


Article

Research of a Multi-Level Organization Human Resource Network Optimization Model and an Improved Late Acceptance Hill Climbing Algorithm

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Abstract: Complex hierarchical structures and diverse personnel mobility pose challenges for many multi-level organizations. The difficulty of reasonable human resource planning in multi-level organizations is mainly caused by ignoring the hierarchical structure. To address the above problems, firstly, a multi-level organization human resource network optimization model is constructed by representing the turnover situation of multi-level organizations in a dimensional manner as a multi-level network. Secondly, we propose an improved late acceptance hill climbing based on tabu and retrieval strategy (TR-LAHC) and designed two intelligent optimization operators. Finally, the TR-LAHC algorithm is compared with other classical algorithms to prove that the algorithm provides the best solution and can effectively solve the personnel mobility planning problem in multi-level organizations.

Keywords: multi-level organization; human resource planning; network optimization model; improved late acceptance hill climbing algorithm; retrieval strategy

MSC: 90B10



Citation: Huang, J.; Li, J.; Du, Y.; Song, Y.; Wu, J.; Yao, F.; Wang, P. Research of a Multi-Level Organization Human Resource Network Optimization Model and an Improved Late Acceptance Hill Climbing Algorithm. *Mathematics* **2023**, *11*, 4813. <https://doi.org/10.3390/math11234813>

Academic Editor: Andrea Scozzari

Received: 20 September 2023

Revised: 23 November 2023

Accepted: 24 November 2023

Published: 28 November 2023



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1. Introduction

The organization is a bounded social entity comprising interconnected elements arranged in a specific manner. Multi-level organizations, characterized by an internal top-down structure and encompassing multiple sectors, have emerged as the predominant form of social organization. These multi-level organizations are characterized by their extensive scale across different countries or regions, intricate job profiles, and diverse workforce composition. Human resource planning constitutes a critical challenge for multi-level organizations to effectively meet their operational requirements and strategic objectives. Human resource planning (HRP), also known as workforce planning [1–4], is an activity that governs and manages the macro perspective to optimize the composition of personnel at all levels within multi-level organizations to achieve a state of equilibrium.

Previously, HRP primarily relied on statistical analysis to address workforce gaps in key positions [5], but it lacked a macro perspective for grasping and optimizing the organizational personnel structure. In recent years, scholars have tackled this issue through mathematical modeling approaches. For instance, Lin [6] models the multi-criteria human resource allocation problem as a multi-stage combinatorial optimization problem and sets the objective function from the organizational standpoint to simultaneously minimize the cost and maximize the benefit of human resource allocation. Hall [7] addresses HRP for U.S. Army officers using the CPLEX11.2 solver, constructing an officer flow network based

on rank and managing personnel flow through recruitment, promotion, and retirement strategies to minimize deviation from target force structure. More current HRP studies will be detailed in Section 2. These studies model and solve the problems according to their respective characteristics and are more scientific and rational than the earlier HRP methods.

However, existing research often overlooks the realistic features and complex characteristics of multi-level organizations when modeling and solving problems. The models and methods studied primarily focus on the lower-level organization, which only represents personnel mobility simplistically. In multi-level organizations, human resources planning necessitates comprehensive control over staff inflow and outflow, as well as the equilibrium of units across all levels of the organization, etc. Due to the multi-level characteristics in such organizations, human resources planning also presents a hierarchical characteristic, i.e., the human resources planning of the next level is related to the previous level, and there are correlations between different levels. The development of these organizations is typically influenced by multiple factors; thus, periodic implementation of human resources planning becomes imperative to maintain a dynamically balanced personnel structure across all organizational levels.

Based on the above characteristics of human resource planning problems in multi-level organizations, the current research in practical application may give rise to the following issues:

- (1) The complexity of a multi-level organizational structure and the presence of numerous low-level units, without consideration, can result in extensive computational requirements due to the substantial size of these units.
- (2) Planning without considering the hierarchical structure may result in an excessive turnover rate within higher-level organizations, such as minimal turnover among the topmost organizations.
- (3) The personnel turnover at each level of the organization typically encompasses various factors, posing challenges in establishing reasonable constraints and objective functions.

Therefore, this paper is based on the realistic characteristics of multi-level organizations and fully considers the personnel flow across levels and units as well as the requirements of HRP. It proposes an optimization problem and model for HRP networks in multi-level organizations, incorporating differentiated objective functions and constraints from both organizational and individual perspectives. Moreover, it expands the application of traditional HRP methods to address the complexities inherent in multi-level organizations. Furthermore, we propose an improved late acceptance hill climbing algorithm based on the tabu and retrieval strategy (TR-LAHC). This approach aims to optimize the organizational personnel structure by effectively allocating limited human resources across different levels and positions, thereby maximizing their overall effectiveness.

The structure of this paper is as follows: Section 2 provides a summary of the existing research on HRP and related algorithms. Section 3 presents the problem of multi-level organization human resource planning and develops a multi-level HRP network optimization model, including an introduction to the model's constraints and objective functions. Section 4 presents the TR-LAHC algorithm, including framework, initialization strategy, neighborhood structure, and retrieval strategy. Section 5 describes the experimental setup and presents the experimental results. Finally, Section 6 concludes this paper with a comprehensive discussion summarizing our findings and discussing future research directions for this problem.

2. Related Work

This paper presents a comprehensive overview of HRP research across four dimensions: authors (year), research object, objective function and solution method, as shown in Table 1. Specifically, about the research object dimension, this section focuses on whether the studies involve multi-level organizations; furthermore, concerning the objective function dimension, this section examines the number of objective functions and whether they are set from an organizational or individual development perspective.

Table 1. Summary of HRP-related studies.

Authors (Year)	Research Object	Objective Function	Solution Method
Lin (2008) [6]	multi-level organization /intra-enterprise staff redeployment across districts	organizational perspective/multi-objective: minimize staffing costs, maximize benefits	multi-objective hybrid genetic algorithm
Nirmala (2010) [8]	non-multi-level organization /organizational HRP recruitment and promotion planning	organizational perspective/single-objective: minimize the recruitment and promotion process costs	dynamic program- ming algorithm
Hall (2015) [7]	multi-level organization/military mobility planning	organizational perspective/single-objective: minimize the deviation of the current state of the human resources strategy from the target state of the human resources strategy.	CPLEX solver
Bastian (2015) [9]	multi-level organization/military medical personnel mobility planning	organizational perspective/single-objective: minimize the deviation of the current state of the human resources strategy from the target state of the human resources strategy.	Excel with the OpenSolver Add-in
Komarudin (2016) [10]	non-multi-level organization /intra-enterprise mobility planning	individual development perspective/ single-objective: maximize job satisfaction and promotion stability	subdivision and delimitation
Zais (2016) [2]	multi-level organization/military mobility planning	organizational perspective/single-objective: dynamic balance of overall personnel structure of the army	Markov chain model
Jaillet (2018) [11]	multi-level organization/HRP in government administration	organizational perspective/single-objective: minimize organizational risk	cut plane method
Abdessameud (2021) [12]	multi-level organization/military mobility planning	organizational perspective/single-objective: minimize the deviation of the current state of the human resources strategy from the target state of the human resources strategy.	CPLEX solver
Dong (2022) [13]	non-multi-level organization /intra-enterprise mobility planning	organizational perspective/single-objective: maximize Performance	fuzzy relationship
Wang (2022) [14]	non-multi-level organization/ intra-enterprise mobility planning	organization perspective/multi-objective: maximize social benefits, economic benefit and environmental benefits	particle swarm opti- mization algorithm

Lin et al. [6] modeled the multi-criteria human resource allocation problem as a multi-stage combination optimization problem, set the objective function from the organizational perspective to minimize the cost and maximize the benefit of human resource allocation at the same time, and proposed a multi-objective hybrid genetic algorithm to solve this problem. Nirmalad et al. [8] investigated the problem of planning for the recruitment and promotion of personnel in an organization based on a dynamic planning algorithm with an objective function of minimizing the cost incurred by the organization in conducting the recruitment and promotion process of personnel. Hall et al. [7] solved the HRP problem for U.S. Army officers based on the CPLEX11.2 solver, constructed an officer flow network based on the rank level of officers, and controlled the flow of personnel from three perspectives: recruiting, promoting, and retiring to achieve the goal of minimizing the bias value of the personnel structure of the current unit and the target state. Bastian et al. [9] investigated the HRP planning problem in the U.S. Army Medical Department, modeling the problem as a mixed-integer programming model that considers various types of constraints on personnel during the recruitment and promotion process to minimize the deviation of the current personnel structure from the target state. Komarudin et al. [10] aimed at maximizing individual employee job satisfaction and promotion stability and evaluated these two indicators based on fuzzy theory. In modeling and solving, they combined the two objectives into one objective function, modeled this problem as a mixed integer programming problem, and solved it based on the branch-and-bound method. Zais et al. [2] constructed a Markov chain model based on U.S. Army officer turnover data that predicts officer retention based on current personnel status to anticipate measures related to talent retention. This study provides feedback to calculate the pay incentives for officers at differ-

ent stages of their careers based on employment in the civilian sector. Also, it validates the predictive power of the Markov chain model. Jaillet et al. [11] first proposed a method for assessing the riskiness of an organization's current human resource situation and solved this problem based on the cut-plane method to minimize the organizational risk factor. Abdessameud et al. [12] conducted a study on the HRP planning problem in the Belgian army by constructing an army personnel flow network and setting an objective function from an organizational point of view to reach the target state of the organizational structure by controlling the personnel flow. This study modeled this process as a mixed-integer programming problem and solved it based on the CPLEX solver. Dong [13] established an intelligent scheduling model of enterprise human resources based on inverse relationship to meet the needs of human resources enterprises to implement strategies by maximizing employees' performance. Wang [14] aimed at the problem of human resources allocation in the process of enterprise management; this research established a corresponding mathematical model and solved the optimal allocation model of human resources based on particle swarm optimization algorithm.

In terms of research objects, current studies on HRP focus on multi-level organizations, like the military, large enterprises, and government administrations. This characteristic necessitates consideration in modeling and solving HRP problems; however, existing research has not adequately explored the influence of different hierarchical units on personnel mobility.

In terms of the setting of the objective function, most of the studies set the objective function from the perspective of the organization, mainly to make the human resource structure of the organization reach its ideal state. A few studies set the objective function from the perspective of the individual development of the personnel in the organization. In reality, however, multi-level organizations need to achieve a win-win situation for both the organization and the individual in HRP, a situation that still needs to be addressed in existing research. Therefore, this paper represents the multi-level organization personnel flow problem utilizing a multi-level organization personnel flow network, constructs a multi-level human resource network optimization model, and sets the objective function from the perspectives of both the organization and the individual to solve the actual problem.

In terms of solution methods, researchers choose different methods for solving the problem according to the characteristics of their respective research problems, including intelligent optimization algorithms, exact solution algorithms, Markov chain models, etc., and some of the researchers also use commercial solvers for solving the problem, such as CPLEX, OpenSolver, and so on. In the above methods, the intelligent optimization algorithm represented by the metaheuristic algorithm can solve complex problems in a shorter time, and it has become the mainstream method for solving all kinds of complex optimization problems at this stage. After experimental comparison, the overdue acceptance algorithm shows more solving effect and solving speed in solving the optimization model of the human resource network of the multi-level organization. The late acceptance hill climbing algorithm (LAHC) [15,16] efficiently jumps out of the local optimum by accepting the solution before a specific time (step), and has shown excellent solution results in many real-world problems [17–21]. Compared with simulated annealing [22] and the great deluge algorithm [23], the algorithm is simple in principle, which retains the asymptotic convergence of the hill-climbing method and has the intelligence of jumping out of the local optimum.

Among the current research related to HRP, the majority focuses on setting the objective function from an organizational perspective, paying more attention to the balance of personnel structure. Also, a few studies set the objective function from the perspective of individual development. However, in reality, both perspectives need to be considered in human resource planning to achieve a "win-win" situation for both the organization and the individual, which is not yet touched upon in the current research. In addition, in a multi-level organization, personnel mobility also has a multi-level characteristic, which should also be considered in the modeling and solving of HRP problems, and this characteristic has not been sufficiently taken into account in the current research.

This paper focuses on addressing the human resource planning problem within a multi-level organizational context by incorporating multi-level organizations' unique characteristics into the modeling and solving processes. Furthermore, in setting the objective function, considerations are given to both organizational and individual development perspectives, thereby enabling optimization of both the organizational personnel structure and individuals' growth within the organization. Aiming at the characteristics of HRP for multi-level organizations, this paper proposes an improved late acceptance algorithm based on tabu and retrieval strategy and two types of neighborhood operators. The proposed algorithm is applied to solve this problem based on the late acceptance algorithm. It sets up simulation experiments to test the model's performance and the effectiveness of the algorithm.

3. Modeling

In this section, firstly, we present a mathematical representation of the multi-level organizational human resource planning problem. Then, we model the problem as a network and construct an optimization model for the multi-level organization human resource network. Finally, we describe the constraints and objective functions of this model.

3.1. Problem

In order to address personnel mobility across levels and units in a multi-level organization, managers are increasingly concerned with formulating appropriate structures for each level and determining the optimal number of personnel. The key challenge lies in effectively planning and expressing the personnel mobility between units at each level, ensuring a balanced state throughout the organization. HRP in such organizations typically involves controlling internal and external movements of personnel, as well as facilitating transfers between different levels or positions within the organization [24,25]. Various organizational situations often give rise to personnel mobility during practical activities.

- (1) Organizational managers need to respond to the actual situation of organizational development and other corresponding organizational structure distribution adjustments;
- (2) Regular entry and exit of personnel, such as recruitment and dismissal;
- (3) Regular internal mobility, such as promotion and exchange of personnel.

This paper constructs a multi-level staff flow network to address the aforementioned issues to depict personnel mobility within multi-level organizations. This paper constructs a multi-level staff flow network to represent the personnel mobility scenario seen in a multi-level organization. It is based on the assumption that both the organizational structure and staffing levels are predetermined, as illustrated in Figure 1.

This flow network (FN) contains multiple levels, and its structure can be represented in a generalized form, as depicted by Equation (1). Each flow network in level p can be regarded as a set of nodes and edges, as shown in Equation (2).

$$FN = \{FN_1, FN_2, \dots, FN_p, \dots, FN_n\} \quad (1)$$

$$FN_p = (V_p, E_p), \quad p = 1, 2, \dots, n \quad (2)$$

The set FN represents a collection of flow networks, while the set N_p denotes the subset of level p flow networks. Similarly, the sets V_p and E_p represent the nodes and edges in level p flow networks.

In the multi-level staff flow network shown in Figure 1, each node v_i represents a unit contained within a multi-level organization, and the edges between the nodes represent the existence of staff flow between units. According to the actual situation of the organization, each node can contain several attributes, such as the name of the unit to which the node corresponds, its priority, the rank of the personnel it contains, and the existing volume. Meanwhile, each node consists of the nodes belonging to the next level, i.e., the subnodes of

the next level together constitute the nodes of the previous level. Similarly, each edge may have several attributes, such as the start and end of the flow, the type of flow, the amount of movement of people, etc.

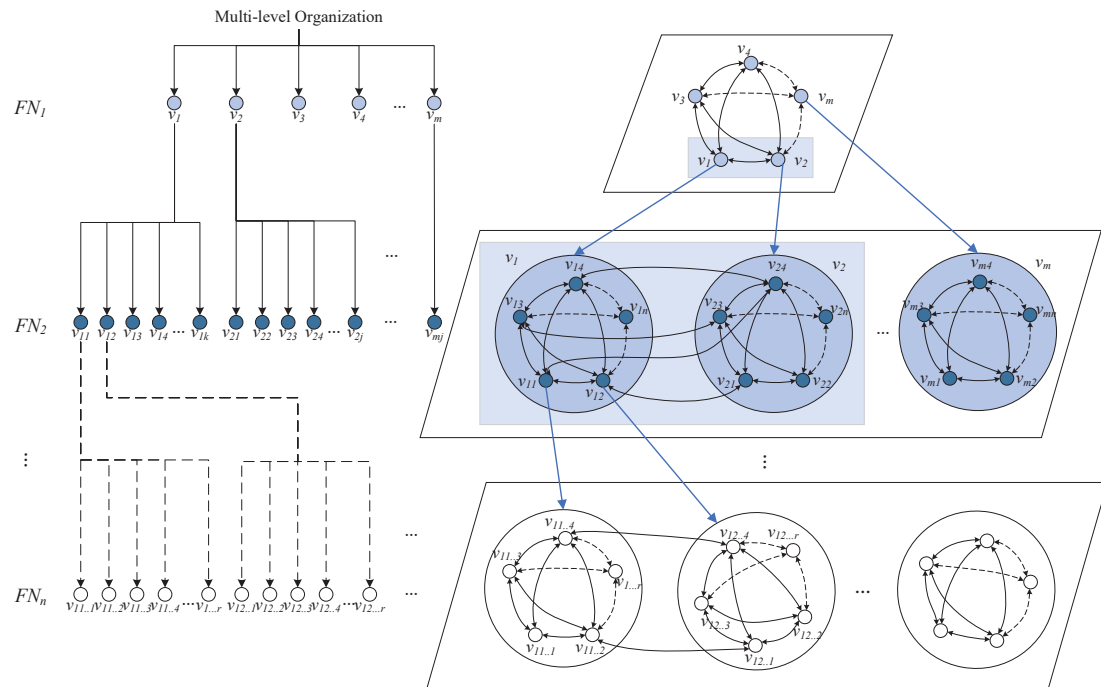


Figure 1. Multi-level staff flow network.

Since the multi-level staff flow network constructed in this paper has multi-level characteristics and the amount of staff flow between nodes should be an integer, the optimization process of this network is modeled as a multi-stage integer planning problem. According to the organizational hierarchical structure, top-down planning of organizational personnel exchange starts from the uppermost network and plans the amount of personnel flow among the nodes of the uppermost network; then, based on the results of the personnel flow planning of the upper network, the amount of personnel flow is allocated to each subnode of each uppermost node, and so on, until the amount of personnel flow is allocated to the lowest hierarchical node. The problem can be generalized and expressed as:

$$\max Z_p \quad \text{or/and} \quad \min Z_p \quad (3)$$

$$\text{s.t.} \quad x_{stkm}^p \leq M \quad (4)$$

$$\text{Cons}_p = \{\text{cons}_p^1, \text{cons}_p^2, \dots, \text{cons}_p^n\} \quad (5)$$

Decision variables: $X = [x_{stkm}^p]$

The set Z_p represents the objective functions, where x_{stkm}^p denotes the number of personnel movements at level p and refers to a set of constraints at level p .

Regarding the constraints of the generalized model, the first condition is that the maximum value of the decision variables in optimizing the entire multi-level staff flow network does not exceed M . The second condition is that the constraints considered in optimizing the multi-level staff flow network at each level need to be set according to the context of the different problems.

3.2. Symbols and Variables

This section gives the symbols, variables, and their corresponding meanings associated with the multi-level human resource network optimization model. The symbols and variables represent the specifics shown in Table 2.

Table 2. Variables and symbols.

Name	Description	Name	Description
v_i	Level p node i	(v_{ik})	Promotion rate of node v_{ik}
$n(v_i)$	Number of personnel movements at node i	N	Set of level p nodes
$n_0(v_i)$	Number of personnel outflows from node i	$ N $	Total number of level p nodes
$n_{sn}(v_i)$	Set number of nodes i	N_i	Set of level $p + 1$ nodes under node i
$n_{pn}(v_i)$	Internal promotion number of node i	$n(v_{ik})$	Number of personnel movements at node k
r_{in}	Ratio of inflows to set number	$n_{in}(v_{ik})$	Number of outflows from node k
r_{out}	Ratio of outflows to set number	$n_{out}(v_{ik})$	Number of inflows from node k
r_{pn}	Ratio of promotions to set number	$X = [x_{ij}]$	Level p decision variables, described in detail as follows
r_{sn}	The ratio of overstaffing or shortfall to a set number	y_{ijkm}	Level $p + 1$ decision variables, described in detail as follows
v_{ik}	Level $p + 1$ node k under level p node i		

$$\text{Decision variables: } X = [x_{ij}] = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1|N|} \\ x_{21} & x_{22} & \cdots & x_{2|N|} \\ \vdots & \vdots & \ddots & \vdots \\ x_{|N|1} & x_{|N|2} & \cdots & x_{|N||N|} \end{bmatrix}.$$

x_{ij} denotes the total number of people flowing from the level p node i to node j , and $|N|$ denotes the total number of the level p nodes.

The decision variables y_{ijkm} denotes the personnel flow from the level $p + 1$ k th node under the level p i th node, to the level $p + 1$ m th node under the level p j th node.

3.3. Constraint

According to the multi-level staff flow network optimization model, the optimization of different levels is interconnected, and the optimization of the following network often needs to be carried out based on the upper network's optimization results, which also affects the setting of the objective function and constraints in each stage of the integer programming problem. Therefore, based on the actual situation, while considering the organization's staff structure and personal development, this part builds a multi-level organization staff flow network optimization model with the following constraints:

3.3.1. Level p Constraints

The level p flow network mainly focuses on controlling the staffing structure of the enterprise from an organizational perspective by controlling the ratio of overstaffing in each type of node within a reasonable limit under the condition that the relevant constraints are satisfied.

Constraints 1: Control the inflow of personnel. To ensure that the inflows to the nodes remain within a reasonable range, it is necessary to ensure that the number of people moving into the nodes does not exceed a certain ratio of the establishment, which depends on the organization.

$$r_{in} = \frac{n_{in}(v_i)}{n_{sn}(v_i)} \leq threshold_i^{in} \quad (6)$$

Constraints 2: Control outflow of personnel. To keep the number of outflows at nodes below a reasonable range, it is necessary to keep the number of outflows from nodes to a certain percentage of the establishment, which depends on the organization.

$$r_{out} = \frac{n_{out}(v_i)}{n_{sn}(v_i)} \leq threshold_i^{out} \quad (7)$$

Constraints 3: Control the internal promotions of personnel. The number of internal promotions must be not less than a certain percentage of the set number, which varies according to the organization.

$$r_{pn} = \frac{n_{pn}(v_i)}{n_0(v_i)} \leq threshold_i^{pn} \quad (8)$$

Constraints 4: Control the overstaffing or shortfall. To prevent overstaffing or shortfalls at the nodes beyond reasonable limits, it is necessary to keep the percentage of overstaffing or shortfalls at each node after turnover from exceeding a predefined threshold, which usually depends on the organizational situation.

$$r_{sn} = \frac{|n(v_i) - n_{sn}(v_i)|}{n_{sn}(v_i)} \leq threshold_i^{sn} \quad (9)$$

3.3.2. Level $p + 1$ Constraints

Since level $p + 1$ network optimization is based on level p network optimization, i.e., the results of optimization of the level p network are the inputs of optimization of the level $p + 1$ network, level $p + 1$ network optimization should mainly satisfy the constraints related to the results of optimization of the level p network:

Constraints 5: Balanced turnover of personnel. The number of personnel movements on each level p edge should equal the total number of movements on the level $p + 1$ edges it contains.

$$n(v_i) = \sum_{k=1}^{|N_i|} n(v_{ik}) \quad (10)$$

Constraints 6: In-degree balance. The in-degree (the number of people moving in) of each level p node should equal the sum of the entry degrees of the level $p + 1$ nodes it contains.

$$n_{in}(v_i) = \sum_{k=1}^{|N_i|} n_{in}(v_{ik}) \quad (11)$$

Constraints 7: Out-degree balance. The out-degree (the number of people moving out) of each level p node should equal the sum of the out-degrees of the level $p + 1$ nodes it contains.

$$n_{out}(v_i) = \sum_{k=1}^{|N_i|} n_{out}(v_{ik}) \quad (12)$$

3.4. Objective Function

3.4.1. Level p Objective Function

The level p staff flow network mainly focuses on controlling the overstaffing or shortfall ratio of each type of node within a reasonable range from the organizational perspective to control the enterprise's personnel structure to satisfy the relevant constraints. Therefore, the objective function of the optimization model of the level p network is set

to minimize the sum of the squares of the overstaffing or shortfall ratios of each node, as shown in Equation (13):

$$\text{minimize} : \sum_{i=1}^{|N|} \left[\frac{n(v_i) - n_{sn}(v_i)}{n_{sn}(v_i)} \right]^2 \quad (13)$$

3.4.2. Level $p + 1$ Objective Function

While considering the balance of the organization's personnel structure, the development of individual employees is also taken into account, and a level $p + 1$ network optimization model is constructed from the perspective of personal development, which promotes the promotion and development of personnel under the premise of satisfying the relevant constraints and requirements so that the gap in the promotion rate of each level $p + 1$ node is reduced as much as possible. Therefore, the optimization objective of the second stage is set to minimize the variance of the promotion rate of the level $p + 1$ nodes, as shown in Equation (14).

$$\text{minimize} : \sum_{i=1}^{|N|} \sum_{j=1}^{|N_i|} [u(v_i k) - \bar{u}]^2 \quad (14)$$

$$\bar{u} = \frac{\sum_{i=1}^{|N|} \sum_{j=1}^{|N_i|} u(v_i k)}{\sum_{i=1}^{|N|} |N_i|} \quad (15)$$

4. Method

To address the issue of turnover in multi-level organizations more effectively, we propose an enhanced late acceptance hill climbing algorithm based on tabu and retrieval strategy (TR-LAHC) and introduce two novel neighborhood structures. This section initially presents the algorithm's framework, then introduces its initialization strategy, and concludes with the proposal of the neighborhood structure and retrieval strategy.

4.1. Framework

The LAHC algorithm performs well in various problem-solving but still has some problems. For example, the algorithm generates new neighborhood solutions through operators during the optimization search, but these neighborhood solutions may be duplicated, causing the algorithm's optimization to be less efficient. Besides that, in the final stage of the algorithm execution, as worse solutions will not be accepted anymore, the scoring function of the historical optimal solution set will be pretty close to each other, which will also make it difficult for the algorithm to jump out of the local optimum and reach a stagnant state. The stagnant state is one in which the results of the search for optimization within r generations are not improved. Therefore, this section proposes TR-LAHC to solve this problem, and its algorithm flowchart is shown in Figure 2.

The pseudocode is illustrated in Algorithm 1:

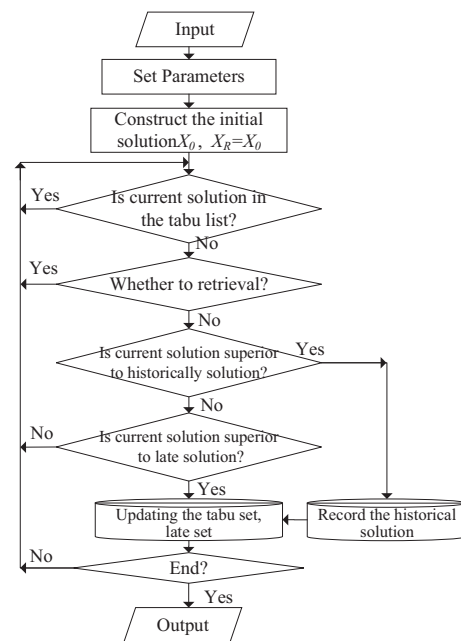


Figure 2. Algorithm flowchart.

Algorithm 1: TR-LAHC

Input: Initial Solution X_0 , Income-based Scoring Functions $F(X)$, Operator Library O , Empty Late Solution Set U_L , Tabu Solution Set U_T , Historically Optimal Solution Set U_X , Parameters r , Termination Conditions

Output: Current Solution X , Historically Optimal Solution Set U_X

```

1  $X \leftarrow X_0$ ;
2  $X_R \leftarrow X_0$ ;
3  $i \leftarrow 0$ ;
4 while not do
5   Select an operator  $o \in O$  from the operator library according to the operator usage.
6   Constructing neighborhood solutions  $X' \leftarrow o(X)$ ;
7   if  $X' \in U_T$  then
8     continue; // Neighborhood solution is forbidden, re-search
9   end
10  if  $F(X') = F(X_R)$  and  $i \geq r$  then
11    //  $X_R$  initial value is  $X_0$ 
12     $X \leftarrow X_R$ ;
13     $i \leftarrow 0$ ;
14    continue;
15  else
16     $i \leftarrow i + 1$ ;
17     $X_R \leftarrow X'$ 
18  end
19  if  $F(X') \geq F(X)$  then
20     $X \leftarrow X'$ ;
21    Based on the FIFO principle,  $X$  is stored in  $U_T$  and  $U_X$  respectively;
22  else if  $F(X') \geq F(X_L)$  then
23    //  $X_L$  is the first element in  $U_L$ 
24     $X \leftarrow X'$ ;
25    Based on the FIFO principle,  $X$  is deposited into  $U_T$ ;
26  end
27  Based on the FIFO principle,  $X$  is deposited into  $U_L$ ; // Each generation deposits
    the current solution into the set of late solutions
28 end
29 return  $(X, U_X)$ 
  
```

Lines 7–9 follow the tabu strategy of the tabu search algorithm, which can improve the algorithm's optimization efficiency and enhance the capability of the LAHC algorithm to jump out of the local optimum. Note that when the number of solutions in the tabu list exceeds the length of the tabu list, the solutions in the list are updated according to the first-in-first-out principle (FIFO). Lines 10–17 incorporate a retrieval strategy that will backtrack the entire solution to the state where the last optimization search occurred for boosting when the algorithm reaches a state of stagnation, i.e., X_R . More inferior solutions will likely be accepted, which can make the algorithm jump out of stagnation. The parameter r needs to be set in the specific context of the problem, generally $r > \text{late acceptance step } l$.

4.2. Initialization Strategy

The paper proposes an algorithm initialization strategy to generate an initial solution for the input of the local search algorithm.

4.2.1. Level p Initialization Strategy

Firstly, nodes that meet the promotion criteria are stochastically selected using Russian roulette. A random edge of the node is chosen, and one individual flows to the targeted node until all eligible nodes have had an outflow of one individual. If the number of eligible nodes is fewer than the number of individuals who entered, an overqualified node is then randomly selected and assigned one individual along an edge pointing towards a vacant node that satisfies the conditions. This process continues until all super-nodes capable of pointing to a vacant node have been depleted by one individual.

4.2.2. Level $p + 1$ Initialization Strategy

The level $p + 1$ optimization model takes as input the optimal solution of the level p optimization model, so the initial solution is the level p optimization model solution.

4.3. Neighborhood Structure

In this section, based on the decision matrix of the multi-level staff flow network optimization model, the neighborhood formed by a 3×3 decision matrix (i.e., a staff flow network optimization problem with three nodes) is used as an example to visualize the algorithmic neighborhood structure and the two operators designed in this section:

4.3.1. Move Operator

The Move operator can randomly change the value of a decision variable in the decision matrix, e.g., changing the value of the decision variable x_{12} from 1 to 3 in the decision matrix X as shown in Figure 3. In the multi-level staff flow network optimization model mentioned above, the actual meaning of this operator is that the number of people flowing from the first node to the second node (i.e., the number of flows is changed from 1 to 3) in a given level is changed. In this section, the operator is designed to be the most basic optimization operator, and any complex operator can be formed by combining multiple Move operators.

$$X = \begin{bmatrix} x_{11} & x_{12} = 1 & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{23} & x_{33} \end{bmatrix} \Rightarrow X' = \begin{bmatrix} x_{11} & x_{12} = 3 & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{23} & x_{33} \end{bmatrix}$$

Figure 3. Move operator.

4.3.2. Swap Operator

The Swap operator can randomly swap the values of one or a series of decision variables in the decision matrix, which can be further categorized into three types as random, homotopy, and whole rows of swap operators, as shown in Figure 4. In the

multi-level staff flow network optimization model, the actual meaning of this operator is that the number of people moving on a particular two edges is exchanged. This operator is the same as the Move operator in its basic principles and can be regarded as a combined form of several Move operators.

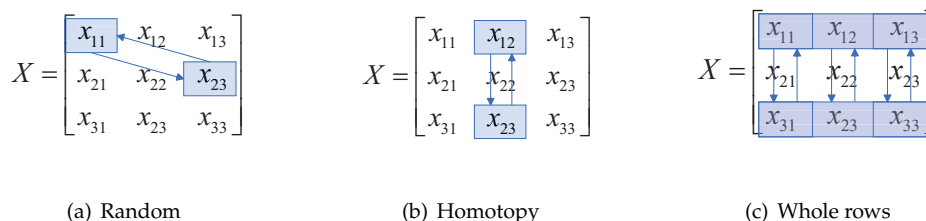


Figure 4. Swap operator.

4.4. Retrieval Strategy

Although the LAHC algorithm can effectively jump out of the local optimal solution by receiving the solution before the specified step length, it may still not be able to jump out of the local optimal solution if it exceeds this step length. Therefore, in this paper, the taboo strategy and retrieval strategy are added to the LAHC algorithm to improve the ability of the algorithm to jump out of the local optimal solution.

The retrieval strategy makes the algorithm backtrack after a certain number of generations r of stagnation to a state r generations ago, i.e., X_R , which means that there will be worse solutions that may be accepted for the algorithm to jump out of the stagnation state—generally, the number of backtracking generations $r >$ late acceptance step l .

5. Experiments

To verify the effectiveness of the multi-level staff flow network model, the multi-level organization staff flow optimization model, and the TR-LAHC algorithm, we designed a series of experiments and used five commonly used algorithms for comparison.

5.1. Setup

The experimental setup for this paper is Core i7-10510U 1.8 GHz, 16 GB RAM, Windows 10 operating system laptop, coding environment is Java 8, and all of the algorithms are run under the same system configuration.

Constraint threshold setting: The thresholds of constraints 1 to 4 in the optimization model can be adjusted according to the actual situation of the organization. To ensure the experiments are carried out successfully, the constraint thresholds are set as shown in Table 3:

Table 3. Constraint threshold settings.

Name	Describe	Value
$threshold_i^{in}$	Ratio of inflow at the nodes	0.2
$threshold_i^{out}$	Ratio of outflow at the nodes	0.2
$threshold_i^{pn}$	Ratio of promotions within nodes	0.5
$threshold_i^{sn}$	Ratio of overstaffing or shortfall in nodes	0.3

Experimental examples: To validate the multi-level staff flow network model, multi-level organization staff flow network optimization model, and TR-LAHC algorithm, comprehensively considering various situations in reality, this paper designed the experimental data as shown in Table 4, according to the organizational size and the number of personnel within it. A total of 9 groups of examples with distinct characteristics were included.

Table 4. Feature descriptions of examples.

Case	Level p Nodes	Level $p + 1$ Nodes	Set Number of Level $p + 1$ Nodes	Personnel Types	Job Classes
1	6	5–7	100–200	3	5
2	6	5–7	200–300	3	5
3	6	5–7	300–500	3	5
4	9	8–12	100–200	3	5
5	9	8–12	200–300	3	5
6	9	8–12	300–500	3	5
7	12	14–18	100–200	3	5
8	12	14–18	200–300	3	5
9	12	14–18	300–500	3	5

The node and edge attributes for each level are shown in Table 5 and Table 6, respectively:

Table 5. Node attributes and descriptions.

No.	Attribute	Description
1	Node No.	Unique identifier for this node
2	Name of unit	Unit name of the node
3	Unit priority	Importance of the node and its subordinate nodes
4	Personnel type	Types of staff positions in the node, categorized as Types 1–3
5	Job level	Personnel job levels in this node, categorized as levels 1–5
6	Number of existing personnel	Total number of persons on duty at the node
7	Set number of personnel	Total set number at the node
8	Number of promotions available	Total number of promotions available at the node
9	Maximum overstaffing or shortfall ratio	Maximum percentage of overstaffing or understaffing permitted for the node

Table 6. Edge attributes and descriptions.

No.	Attribute	Description
1	The start of personnel flow	A unit node
2	The end of personnel flow	A unit node
3	Type of flows	Divided into three categories: mobile rotations, mobile promotions and internal promotions
4	Number of personnel flows	Total number from beginning to endpoint

Algorithm comparison: In this section, algorithm comparison experiments are conducted to solve the above cases based on commonly used algorithms such as tabu search (TS); late acceptance hill climbing (LAHC); improved late acceptance hill climbing algorithm with tabu Strategy, T-LAHC; simulated annealing (SA); and genetic algorithm (GA).

Algorithm parameter settings: This experiment is divided into two stages. After the preliminary experimental comparison, the optimal parameters of each algorithm are selected within the two stages for the final performance comparison of algorithms. The parameter settings of the algorithms in each phase are listed as follows.

In the first stage, the number of iterations and late steps of TR-LAHC, T-LAHC and LAHC algorithms are 500,000 and 500, the size of tabu list at TR-LAHC and T-LAHC is 10, and the retrieval step of TR-LAHC algorithm is 1500; the iteration number of TS is 10,000, and the length of tabu list is 10; the iteration number of SA algorithm is 100,000, and the annealing type is equal variance; the GA algorithm has 500 evolutions, population size of 100, crossover probability of 0.8, and mutation probability of 0.01.

In the second stage, the number of iterations and late step of TR-LAHC, T-LAHC, and LAHC algorithms are 1,500,000 and 800, the size of tabu list of TR-LAHC and T-LAHC

is 15, and the retrieval step of TR-LAHC algorithm is 1000; the number of iterations of TS algorithm is 50,000, and the length of tabu list is 15; the number of iterations of SA algorithm is 500,000, and the annealing type is equal variance; the GA algorithm has 600 generations, a population size of 100, a crossover probability of 0.8, and a mutation probability of 0.01.

Evaluation indicator: The performance of the algorithms is evaluated by running each algorithm case times. Evaluation indicators, including the best profit (Best), average profit (Mean), and standard deviation (Std.), are used to compare the results of each algorithm.

5.2. Result

After computation, Table 7 shows the comparison results of each algorithm in level p network optimization, where Figure 5 shows the iteration progress in the horizontal coordinate and the corresponding profit in the vertical coordinate, and Figure 6 shows the algorithm in the horizontal coordinate and profit in the vertical coordinate.

The above results indicate that the TR-LAHC algorithm exhibits the lowest termination objective function profit and achieves superior optimization outcomes, thereby enabling more effective optimization of the level p staff flow network compared to other algorithms.

In order to control the variables, the performance of several algorithms in level $p + 1$ network optimization will be compared using the results of level p staff flow planning obtained by the best result TR-LAHC algorithm as an input in the comparison experiments of level $p + 1$ network optimization. After computations, the results are shown in Table 8, Figures 7 and 8, where Figure 7 shows the iteration progress in horizontal coordinates and the corresponding profit in vertical coordinates, and Figure 8 shows the algorithms in horizontal coordinates and the profit values in vertical coordinates.

Table 7. Level p network optimization results.

Case	Initial Profit	TR-LAHC			Tabu-LAHC			LAHC		
		Best	Mean	Std.	Best	Mean	Std.	Best	Mean	Std.
1	6157	1209	1246.00	34.64	1214	1241.20	39.89	1848	2064.40	140.95
2	4673	1009	1031.20	18.42	1022	1093.10	51.40	1080	1187.00	60.85
3	5911	3186	3552.00	239.40	3424	3789.50	251.33	3319	3902.10	291.04
4	11,159	2492	2506.70	7.90	2549	2752.90	206.14	2883	3562.10	379.77
5	4478	1431	1512.30	66.26	1585	1728.50	203.67	1453	1607.90	198.57
6	6773	4443	4780.60	182.97	4891	5144.50	172.66	4778	5208.60	230.56
7	13,914	3786	3799.20	8.08	3839	4013.70	202.80	4082	4469.40	265.27
8	5710	2578	2681.10	63.73	2718	2975.80	173.26	2594	2777.30	131.20
9	9610	7396	7631.20	156.64	7792	8137.20	142.54	7724	8132.80	156.61
Case	Initial Profit	TS			SA			GA		
		Best	Mean	Std.	Best	Mean	Std.	Best	Mean	Std.
1	6157	1682	2034.90	310.81	1353	1447.10	41.97	2234	2641.90	226.08
2	4673	1036	1168.60	60.34	1234	1393.30	124.61	1546	1674.80	85.77
3	5911	3730	3999.70	253.19	3746	4237.50	239.47	4174	4575.10	217.72
4	11,159	2779	3232.50	284.28	2833	2944.40	86.76	5561	6791.30	584.99
5	4478	1434	1644.90	226.51	1952	2197.20	183.87	2348	2867.30	226.45
6	6773	4661	4972.50	220.89	5419	5562.90	127.98	5609	6040.20	209.25
7	13,914	3827	3888.20	63.71	4165	4492.80	252.52	8364	9890.80	819.50
8	5710	2666	2738.80	66.34	3294	3473.60	128.65	4088	4528.10	233.09
9	9610	7518	7833.60	186.25	8296	8500.50	122.22	8900	9091.00	96.37

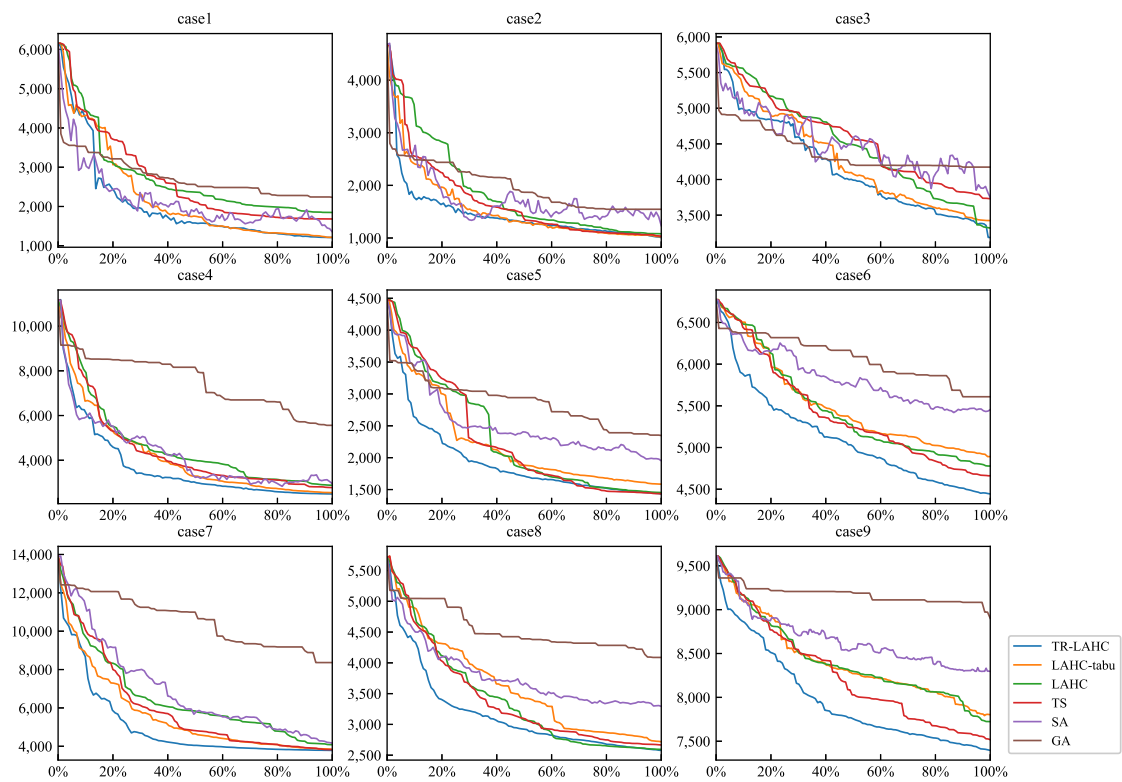
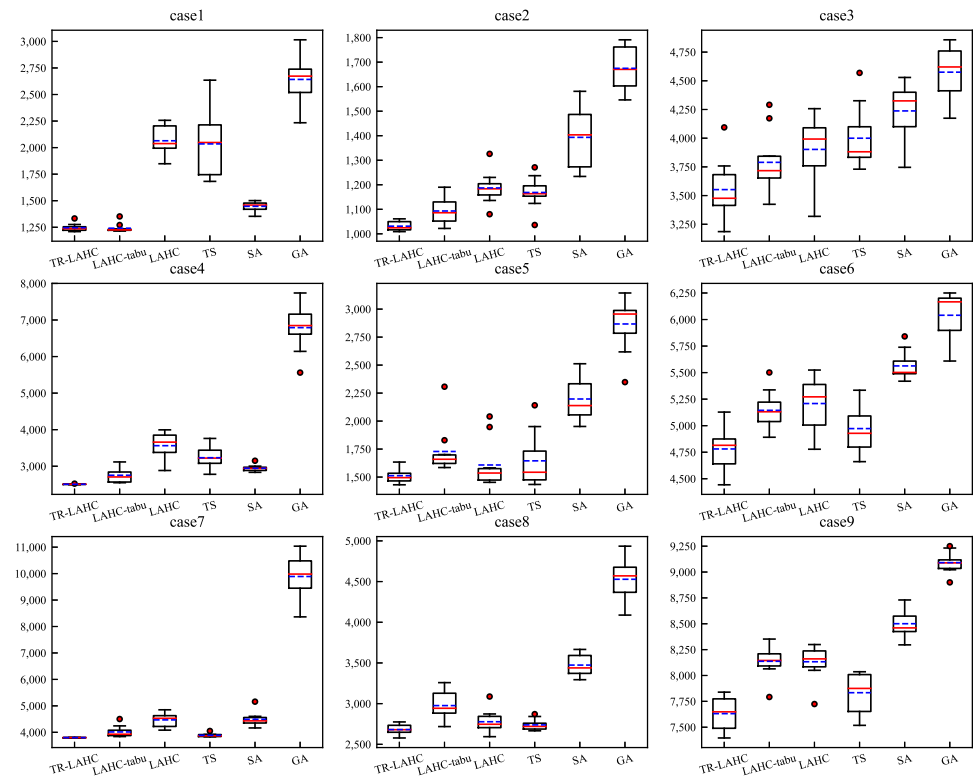
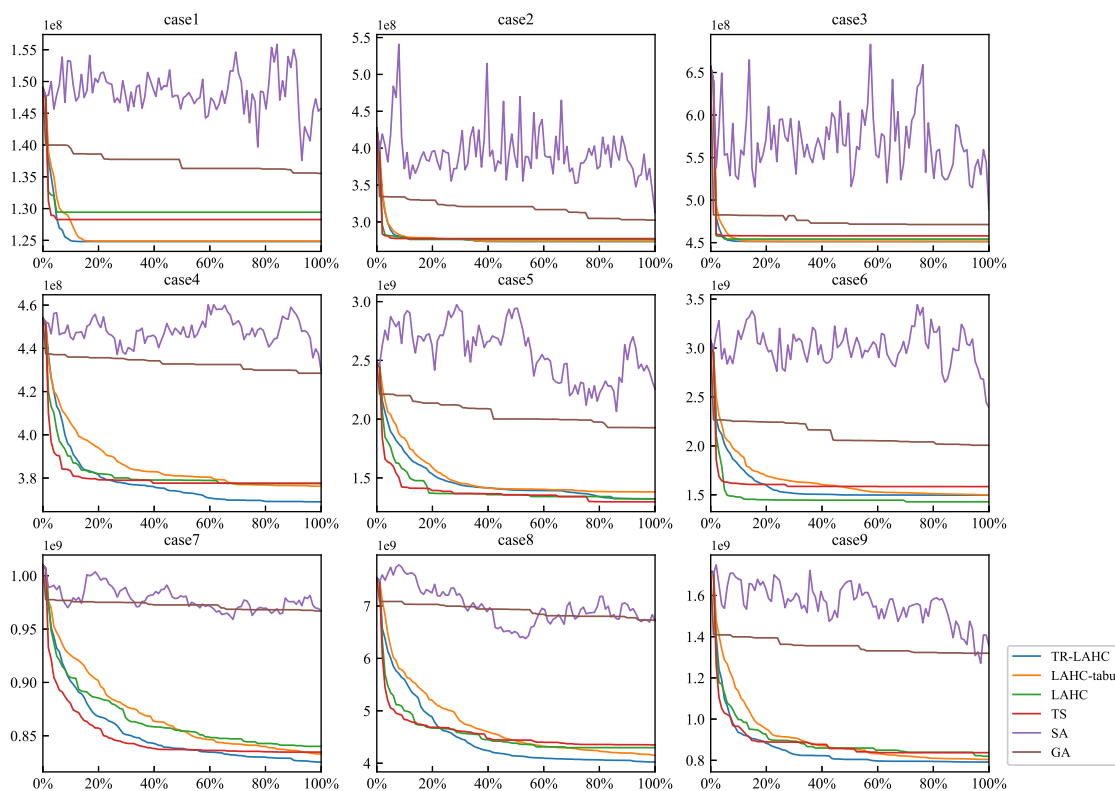
Figure 5. Level p optimization iteration diagram.Figure 6. Level p profit box-line diagram.

Table 8. Level p network optimization results.

Case	Initial Profit	TR-LAHC			Tabu-LAHC			LAHC		
		Best	Mean	Std.	Best	Mean	Std.	Best	Mean	Std.
1	1.49×10^8	1.25×10^8	1.28×10^8	1.59×10^6	1.25×10^8	1.27×10^8	1.91×10^6	1.29×10^8	1.31×10^8	9.30×10^5
2	4.27×10^8	2.73×10^8	2.76×10^8	2.17×10^6	2.74×10^8	2.77×10^8	2.77×10^6	2.76×10^8	2.78×10^8	1.95×10^6
3	6.57×10^8	4.51×10^8	4.54×10^8	2.38×10^6	4.51×10^8	4.55×10^8	3.02×10^6	4.54×10^8	4.60×10^8	2.70×10^6
4	4.54×10^8	3.69×10^8	3.74×10^8	2.40×10^6	3.76×10^8	3.80×10^8	3.39×10^6	3.77×10^8	3.84×10^8	2.99×10^6
5	2.48×10^9	1.32×10^9	1.40×10^9	6.11×10^7	1.38×10^9	1.44×10^9	5.29×10^7	1.32×10^9	1.42×10^9	5.43×10^7
6	3.07×10^9	1.50×10^9	1.56×10^9	4.71×10^7	1.50×10^9	1.57×10^9	5.63×10^7	1.43×10^9	1.60×10^9	8.36×10^7
7	1.01×10^9	8.25×10^8	8.36×10^8	8.16×10^6	8.33×10^8	8.48×10^8	7.22×10^6	8.40×10^8	8.52×10^8	6.38×10^6
8	7.54×10^9	4.02×10^9	4.15×10^9	9.41×10^7	4.15×10^9	4.29×10^9	5.46×10^7	4.30×10^9	4.58×10^9	1.33×10^8
9	1.72×10^9	8.08×10^8	8.40×10^8	2.56×10^7	8.04×10^8	8.50×10^8	3.86×10^7	8.20×10^8	8.74×10^8	2.86×10^7

Case	Initial Profit	TS			SA			GA		
		Best	Mean	Std.	Best	Mean	Std.	Best	Mean	Std.
1	1.49×10^8	1.28×10^8	1.31×10^8	1.16×10^6	1.38×10^8	1.40×10^8	1.29×10^6	1.36×10^8	1.38×10^8	1.54×10^6
2	4.27×10^8	2.77×10^8	2.82×10^8	3.62×10^6	3.13×10^8	3.28×10^8	1.04×10^7	3.02×10^8	3.14×10^8	4.87×10^6
3	6.57×10^8	4.58×10^8	4.62×10^8	2.77×10^6	4.89×10^8	4.97×10^8	7.01×10^6	4.71×10^8	4.76×10^8	3.50×10^6
4	4.54×10^8	3.78×10^8	3.82×10^8	3.39×10^6	4.30×10^8	4.35×10^8	3.73×10^6	4.28×10^8	4.33×10^8	2.92×10^6
5	2.48×10^9	1.30×10^9	1.41×10^9	5.79×10^7	2.07×10^9	2.29×10^9	9.63×10^7	1.93×10^9	2.02×10^9	6.17×10^7
6	3.07×10^9	1.58×10^9	1.66×10^9	3.45×10^7	2.39×10^9	2.58×10^9	9.57×10^7	2.01×10^9	2.20×10^9	1.05×10^8
7	1.01×10^9	8.35×10^8	8.44×10^8	6.46×10^6	9.59×10^8	9.70×10^8	5.92×10^6	9.67×10^8	9.75×10^8	4.07×10^6
8	7.54×10^9	4.35×10^9	4.49×10^9	8.19×10^7	6.38×10^9	6.63×10^9	1.15×10^8	6.73×10^9	6.79×10^9	6.41×10^7
9	1.72×10^9	8.37×10^8	8.88×10^8	3.21×10^7	1.27×10^9	1.34×10^9	4.06×10^7	1.32×10^9	1.38×10^9	3.25×10^7

Figure 7. Level $p + 1$ network optimization iteration diagram.

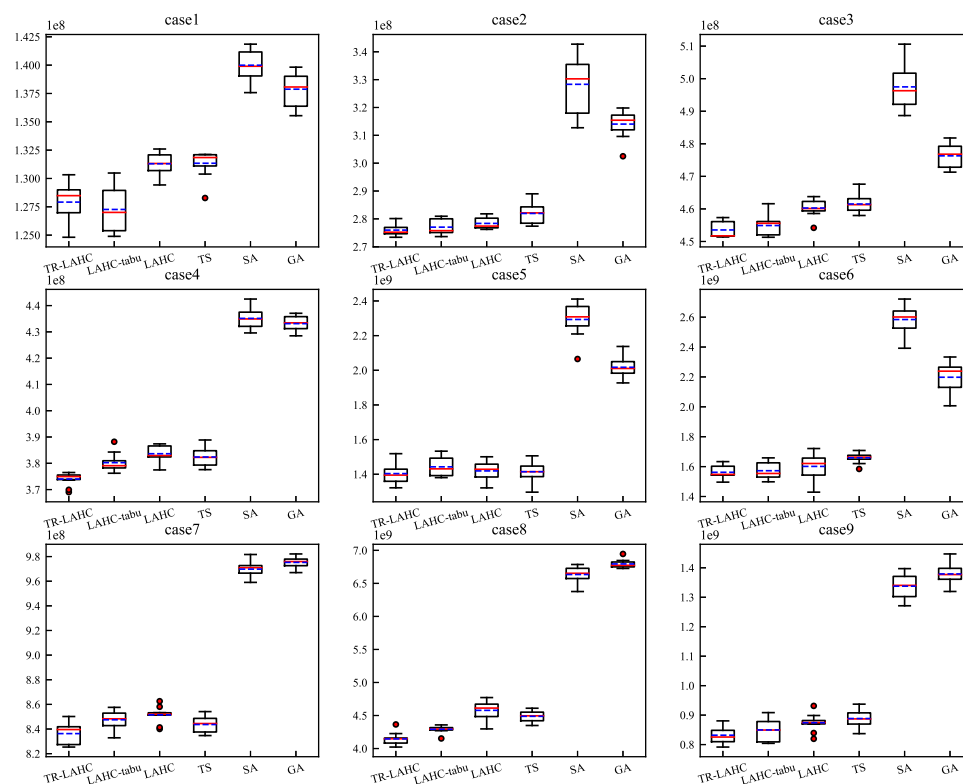


Figure 8. Level $p + 1$ profit box-line diagram.

The above results show that compared to other algorithms, the TR-LAHC algorithm has the lowest termination objective function value and the best optimization as opposed to the other algorithms in optimizing the level $p + 1$ staff flow network.

Meanwhile, the experiment also validates the efficacy of the multi-level organizational human resource network optimization model constructed in this study. In level p , the reduction in the objective various sizes of multi-level organizations indicates a decrease in overstaffing or shortfall at level p nodes, effective filling of vacant positions, and a reduction in overstaffed positions. This enhances the overall macro-level structure of the organization and promotes more efficient functioning. At level $p + 1$, a decrease in the objective function signifies a significant improvement in promotion rates at level $p + 1$ nodes, facilitating personnel promotion and development while meeting constraints and requirements.

The level p and $p + 1$ decision variables $[x_{ij}]$ and y_{ijkm} represent personnel mobility between the nodes, and the rate of overstaffing or shortfall of the optimization solution for level p is not higher than the original value, so in the application of the optimization solution, the organization can control the internal personnel mobility through the optimization results of the level $p + 1$ bottom-up, and has achieved the optimization of human resources within the organization.

6. Discussion

This paper analyzes the characteristics of staff flow in multi-level organizations, constructs a multi-level staff flow network to describe the process of staff flow in multi-level organizations, and models the optimization problem of this network as a human resource network optimization model for multi-level organizations while setting the objective function from the perspective of the organization and personal development. In this paper, this planning problem is solved to control the flow of personnel in multi-level organizations to optimize the overall personnel structure of the organization. In the design of the solution method, we propose an improved late acceptance hill climbing based on tabu and retrieval strategy (TR-LAHC). Based on the above method, this paper solves the case of multi-level

organization in different situations and compares it with other classical algorithms. The experimental results show that the TR-LAHC algorithm has an excellent solving effect and can effectively perform multi-level organization staff flow planning.

Current works have verified the validity of the multi-level organization human resource network optimization model, but there are various shortcomings and special situations in practical application. For example, (1) the organization's existing personnel and their attributes may not always be able to match the expectations, (2) multiple objective functions and their influence on each other are often found in human resource planning, and (3) time also has an impact on personnel mobility in multi-level organizations. Therefore, in future research, more levels and objective functions will be considered, and multi-objective planning algorithms will be introduced to dynamically solve the multi-level organization personnel mobility problem by considering the movement of personnel in and out of the organization caused by changes in time.

Author Contributions: Conceptualization, J.H. and Y.D.; data curation, J.L. methodology, J.H. and J.L.; supervision, F.Y. and P.W.; visualization, P.W.; investigation, Y.S.; software, J.H. and Y.D.; validation, J.W.; writing—original draft, J.H. and J.L.; writing—review and editing, Y.D., Y.S., J.W., F.Y. and P.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (No. 72201272), Science Foundation of National University of Defense Technology (ZK22-48 and 2021-JCJQ-JJ-0049).

Data Availability Statement: All data in this paper are publicly available.

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

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