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Optimizing Organizational Structures with Artificial Intelligence: Algorithm Design and Application

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ABSTRACT

In the context of globalization and information technology advancement, organizations are confronted with the dual challenges of efficiently allocating resources and promptly addressing internal conflicts. The optimization of organizational structures is identified not only as a strategic measure to enhance competitive advantage but also as a necessary approach to improve decision-making quality and organizational adaptability. This study explores the application of artificial intelligence (AI) technologies in optimizing organizational structures, focusing specifically on the intelligent allocation of human resources and the intelligent identification and resolution mechanisms for internal conflicts. Existing research shows a notable deficiency in resource allocation and conflict resolution, particularly lacking consideration of trust network within organizations and analysis of adaptability to dynamic changes. Addressing these issues, a model based on the fuzzy cerebellar model articulation controller (FCMAC) for the optimization of human resource allocation is proposed. This model is capable of dynamically adjusting strategies in response to the evolving demands of the organization. Concurrently, an intelligent framework for identifying and resolving internal conflicts, which incorporates trust network, has been developed. By quantifying trust relationships, the framework aims to enhance the accuracy of decision-making and the coordination within the organization. Findings suggest that these methodologies significantly improve the efficiency of organizational resource allocation and effectively reduce conflict situations, thereby enhancing overall work efficiency and performance. This research not only offers a new perspective on the role of AI in optimizing organizational decisions but also provides practical solutions for management practices, crucial for aiding organizations to adapt to rapidly changing external environments and enhance their competitiveness.

1. INTRODUCTION

As globalization and the era of information technology progress, the optimization of organizational structures has been recognized as key to enhancing corporate competitiveness and adaptability. The effective allocation of human resources and the efficient resolution of internal conflicts are deemed essential for maintaining organizational flexibility and decision-making efficiency [1-4]. Advances in AI technologies, particularly in machine learning and neural networks, have offered new perspectives and tools for addressing these challenges. The complex nature of current organizational decisions necessitates the continual exploration and utilization of advanced technologies to optimize existing organizational structures and workflows [5-7].

The significance of related research lies in the application of AI technologies to better understand and predict the efficacy of human resources and mechanisms for handling internal conflicts within organizations. Neural network models provide a novel approach to human resource allocation, capable of simulating complex decision processes and optimizing resource allocation [8-11]. Additionally, strategies for identifying and resolving internal conflicts, which take into account trust relationships, are shown to foster a more harmonious working environment, thereby enhancing decision quality and organizational performance [12, 13].

However, existing research often overlooks the factor of trust, lacking in-depth analysis of the impacts of interpersonal interactions and trust network [14-16]. Moreover, traditional methods of human resource allocation are typically static, without the capability to adapt to dynamic organizational changes [17-20]. Such methods fail to fully exploit the potential of AI in learning, prediction, and adaptability, leading to deficiencies in resource allocation and conflict resolution.

This study revolves around two core sections. Initially, a control strategy for human resource allocation based on the FCMAC is explored. This strategy is capable of responding in real-time to changes in organizational needs and optimizing the allocation of resources. Secondly, a strategy for identifying and resolving internal conflicts within organizations, considering trust relationships, is investigated. A decision model incorporating a comprehensive trust metric is proposed to resolve conflicts more accurately. This research holds significant theoretical and practical value for understanding and applying AI in the optimization of organizational decisions, offering new perspectives and solutions for organizational management. Through the findings of this study, organizations are expected to operate more efficiently, adapt better to changes in the external environment, and ultimately enhance overall performance.

2. OPTIMIZATION OF HUMAN RESOURCE ALLOCATION CONTROL STRATEGIES THROUGH AI

In the realm of organizational structure optimization, effective human resource allocation is recognized as a pivotal factor. Traditional approaches often rely on the experience and intuition of human experts, whose knowledge is not always readily translatable into algorithms, resulting in a lack of flexibility and adaptability in human resource allocation. To address this issue, the integration of fuzzy control theory with advanced neural network technologies, such as the Cerebellar Model Articulation Controller (CMAC), is considered. Herein, the FCMAC is employed to learn and simulate efficient human resource allocation rules, thereby achieving optimal matching between internal tasks and employee skills. Specifically, the FCMAC learns the optimal human resource allocation strategies from historical data and continues to optimize its decision-making process with the input of new data. Utilizing expert experience to set initial fuzzy rules and membership functions, the FCMAC is capable of further learning and adjustment, rendering the control strategy more scientific and precise. Through continuous learning, the FCMAC is able to automatically improve the performance of human resource allocation without the need for constant expert intervention. Gaussian basis functions are adopted as fuzzy membership functions, their commendable mathematical properties aiding the FCMAC in rapidly learning and accurately mapping the complex relationships between organizational needs and employee skills.

Within the context of optimizing organizational structures, the FCMAC architecture can be redesigned to suit the needs of human resource allocation control. Specifically, the gap between the demands of various tasks or positions within an organization and the existing capabilities of human resources is denoted by ΔS. For instance, a task may require a specific set of skills, while the existing staff may have deficiencies in some of these skills. The workload or energy level of employees is represented by *TPZ*, which may indicate the current work pressure of employees, or their professional enthusiasm and capacity to undertake additional tasks. The rate of change in organizational needs is denoted by ψ, such as changes in market demand or project priorities, affecting the reallocation of human resources. The input space related to the adjusted organizational structure optimization, denoted by I, encompasses the aforementioned elements. Conceptual memory is represented by Xz, and actual memory by Xo, which store and process information related to rules and weights for human resource allocation. The membership of input variables is indicated by i_u=1,2,…20, characterizing the degree of membership for each input variable to each membership function, aiding in the fuzzification of organizational needs, employee capabilities, and other relevant factors. The addresses mapped to conceptual memory Xz are denoted by x_k,k=1,2,…180, while the weights in actual memory are denoted by q_u,u=1,2,…12. The output variable, represented by b_v, indicates the actual human resource allocation decisions, referring in this document to the proportion of work allocated to each employee for different tasks or projects.

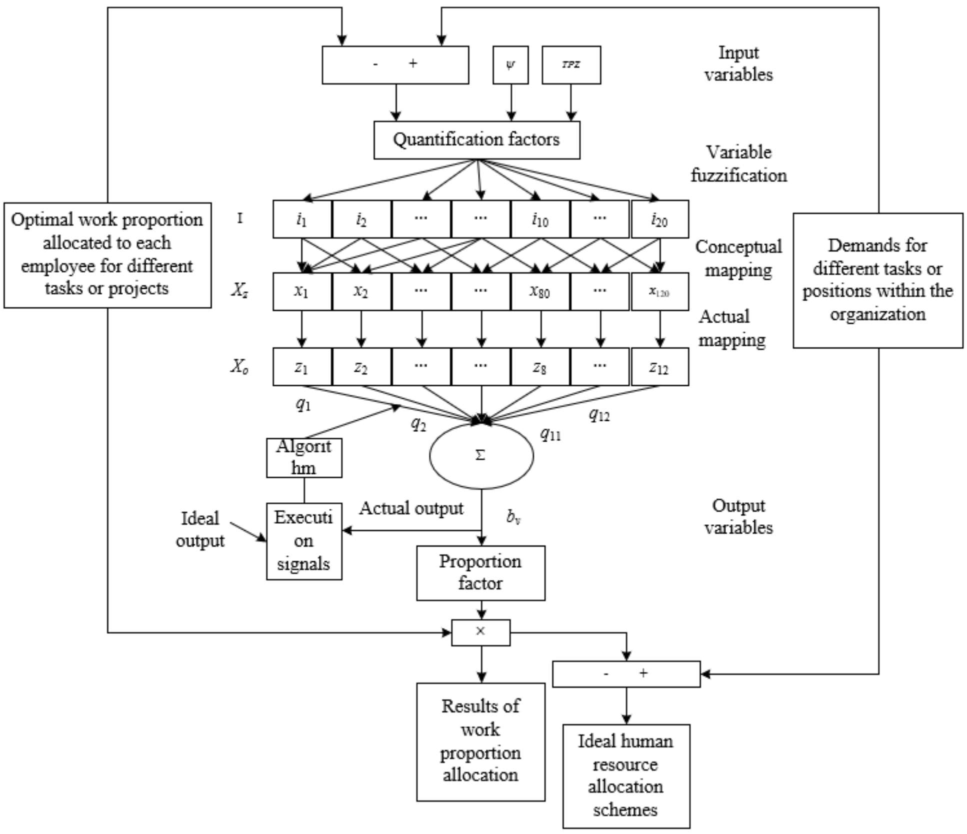

Figure 1. Structure diagram of the FCMAC for human resource allocation control

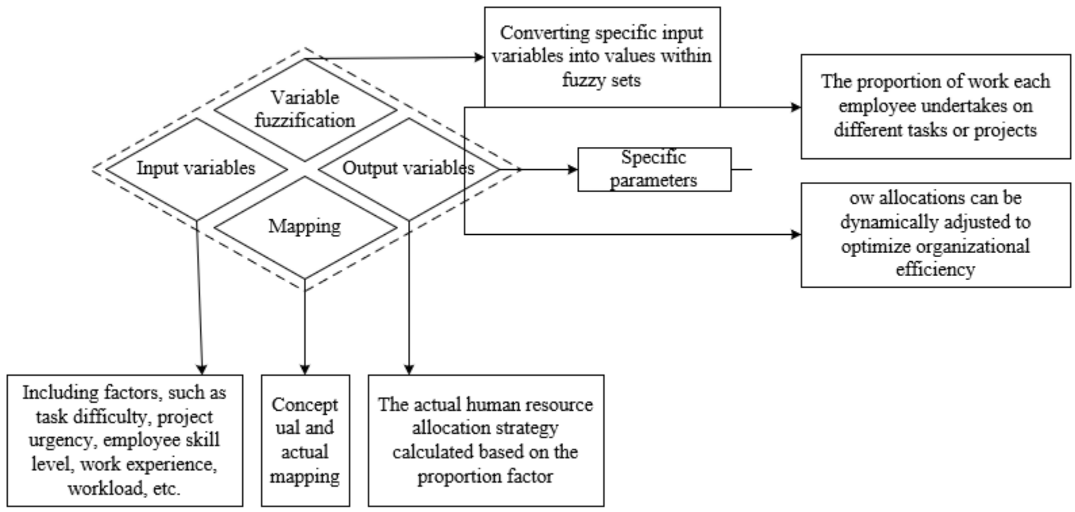

Figure 2. Functional schematic of the FCMAC structure modules

Figure 1 displays the structural diagram of the FCMAC oriented towards human resource allocation control. The basic modules of the FCMAC structure include five components: a) Input variables: which may include factors such as task difficulty, project urgency, employee skill levels, work experience, workload, etc. b) Variable fuzzification: This stage converts specific input variables into values within fuzzy sets. The skill levels of employees can be quantified and output through membership functions as "junior", "mid-level", "senior", and other fuzzy levels. c) Conceptual mapping: In the conceptual mapping stage, the fuzzified input variables are converted into an address in conceptual memory. In human resource allocation, this step can be understood as determining which fuzzy rules apply to the given combination of employees and tasks. d) Actual mapping: Actual mapping converts the results of conceptual mapping into specific actions or outputs. In human resource allocation, this means determining the specific task allocations for employees based on rules and strategies. e) Output variables: These are the actual human resource allocation strategies calculated based on the proportion factor. This equates to determining the proportion of work each employee undertakes on different tasks or projects and how these allocations can be dynamically adjusted to optimize organizational efficiency. Figure 2 illustrates the functional schematic of the FCMAC structure modules.

Within this structure, the FCMAC for human resource allocation control optimizes the configuration of human resources by learning and adjusting fuzzy rules and weights. It must process varying employee characteristics, task requirements, and organizational goals, finding the optimal match among them to achieve the strategic objectives of the organization.

In the network, input variables are first discretized through quantification factors to match corresponding fuzzy sets [VY,VT,CR,OT,OY], representing different levels of evaluation, from "very low (VY)" to "very high (OY)" in terms of skill levels. These inputs are further fuzzified through Gaussian membership functions to be converted into a form that can be processed by fuzzy logic systems. Quantification factors, serving as tuning parameters, refine the segmentation of fuzzy sets, ensuring input values are mapped to the correct degree of membership. Thus, the neural network can more accurately process different levels of input variables, effectively analyzing employee skills, task urgency, and other variables. This approach provides more rational human resource allocation strategies for organizational structure optimization, aiming to enhance organizational efficiency and adaptability. The expression for the Gaussian membership function is as follows:

$$d\left(a,\delta,z\right)=e^{-\frac{(a-z)^2}{2\delta^2}} \tag{1}$$

where, δ is typically positive, and z is used to determine the center of the curve.

In the FCMAC for human resource allocation control, the mapping steps are crucial processes that ensure inputs such as employee capabilities, task urgency, and individual adaptability are effectively transformed into the network's output, namely the decisions for human resource allocation. The following outlines the mapping steps for the FCMAC in human resource allocation control:

Step 1: Introduction of fuzzy membership vector

Initially, a vector of fuzzy membership functions is introduced into the input space I. The input space I is divided into 20 storage units, each corresponding to a fuzzy membership degree vector. The configuration of these storage units allows the network to identify and locate the storage unit address corresponding to the input vector.

Step 2: Conceptual mapping ($I \Rightarrow X_Z$)

Within the input space I, by applying rule segmentation to the fuzzy membership functions, several different states can be obtained. Each state corresponds to a pointer, which maps the state to multiple storage units in the conceptual memory X_Z. Through this mapping, a unique storage address can be found for each state.

Step 3: Actual mapping ($X_Z \Rightarrow X_o$)

For the states obtained after conceptual mapping, the modulus residue method from scatter code techniques is used to determine the storage address. Specifically, the address value of the activated state is added to a constant k, then divided by a large prime number V, which is less than the length l of the hash table. The remainder plus one results in the storage address in the actual memory X_o, thereby mapping these states into the storage units of X_o. Assuming the storage address in actual memory X_o is represented by $xf(k)$, the address of the activated unit by x_k, the unit after conceptual mapping by k, and the modulus function by Matlab as *LPF*, the expression is given as:

$$xf(k) = \left[(x_k + k) LPF\ V \right] + 1k = 1, 2, ..., z \quad (2)$$

Step 4: Output mapping ($X_o \Rightarrow b_v$)

The output function of the FCMAC can be defined according to actual needs. In the context of human resource allocation, the output function will determine the most suitable employee allocation plan to optimize the organizational structure and enhance efficiency. Assuming the product of the membership function mapping is represented by x_j, and the corresponding weight by μ_a, the expression for the output function is given as:

$$b_v = \sum_{j=1}^{z} \mu_j x_j \quad (3)$$

In practical human resource allocation systems, the FCMAC receives a series of predefined discrete signals, representing key indicators in the process of organizational structure optimization. These input signals are processed according to a specific sampling period to accommodate dynamically changing organizational needs. The output signals of the FCMAC correspond to the actual human resource allocation plans. In the optimization process, the ideal human resource allocation plan is predefined based on organizational goals and employee capabilities. This ideal output is considered a set of desired allocation coefficients, reflecting the optimal configuration of human resources. However, in practice, due to various uncertainties such as employees' actual performance and unforeseen events, there might be deviations between the actual human resource allocation plan and the ideal plan. Thus, the task of the FCMAC is to compute a deviation value R by comparing the difference between the ideal and actual outputs. This deviation value R serves as an execution signal for adjusting and optimizing human resource allocation, aiming to minimize the gap between ideal and actual outcomes, thereby enhancing organizational efficiency and effectiveness. The definition formula for the error function is provided as follows:

$$R = \left[b(s) - b_v(s) \right]^2 / 2 \quad (4)$$

This study opts for the δ learning rule to adjust the weights of the output. Assuming the learning rate is represented by $Y \in (0,1]$. The error is denoted by r, the ideal output by $b(s)$, the inertia coefficient by ϕ, and $k = xf(u)$, $u = 1,2,...,z$. The following expressions are obtained:

$$\Delta\mu_u(s) = -\alpha \frac{\partial r}{\partial \mu_u} \omega_u = \alpha \frac{\left[b(s) - y_n(s) \right]}{c} \frac{\partial b_u}{\partial \mu_u} \omega \quad (5)$$

$$\mu_k(s) = \mu_k(s-1) + \Delta\mu_k(s) + \varphi\left(\mu_k(s-1) + \mu_k(s-2) \right) \quad (6)$$

In the context of human resource allocation control, the FCMAC employs a supervised learning algorithm. After each control loop is completed, the control system needs to evaluate its effectiveness. In each control cycle, the control system obtains a learning signal $r(s)$ by comparing the ideal human resource allocation plan $b(s)$ with the actual efficiency of human resource allocation $b_v(s)$, indicating the deviation between them. This deviation signal $r(s) = b(s) - b_v(s)$ guides the learning process. Furthermore, combined with the fuzzy membership $\omega(s)$ of each task or employee, the controller adjusts the weights of its output, which can be viewed as a fuzzy learning process. The fuzzy membership $\omega(s)$ is based on factors such as employee skill levels, experience, task urgency, and importance. The goal of learning is to minimize the difference $r(s)$ between the ideal human resource allocation plan $b(s)$ and the actual efficiency of human resource allocation $b_v(s)$, ensuring that the organization's human resources are utilized as effectively as possible.

The control process of the FCMAC unfolds as follows:

a) At the initial run of the human resource allocation system, initial weights are set to $q=0$, implying that the FCMAC's output on the efficiency of human resource allocation, $b_v(s)$, equals 0. During this initial stage, the actual allocation plan $b(s)$ equals the FCMAC's output $b_v(s)$, as no allocation has yet been made.

b) Subsequently, key parameters under the current work scenario of the organization, ΔS, TPZ, and x, are input into the FCMAC. These parameters, after being processed by quantification factors, are inputted. Through address mapping, z corresponding actual addresses are located in the FCMAC memory for storing the membership $\omega_u(s)$ and weights $\mu_k(s)$. Following computation by the FCMAC function, the FCMAC's output $b(s)$ is obtained, representing the ideal human resource allocation plan.

c) Upon completion of each control loop, the FCMAC's actual output $b_v(s)$ is calculated and compared with the ideal allocation plan $b(s)$, yielding a deviation $r(s)$ as a learning signal. Consequently, the system begins to learn and adjust weights, with the ongoing learning of the FCMAC aimed at minimizing the value of deviation $r(s) = b(s) - b_v(s)$.

d) The actual efficiency of human resource allocation $b_v(s)$ is adjusted through a proportion factor so that the required adjustment in human resources can be calculated based on control needs. By performing a subtraction operation on the organization's total human resource demand S_{RE} and the obtained human resource allocation S_r, the amount of human resources that need further allocation or adjustment within the organization, $S_{RE} - S_r$, can be determined. Further calculations can identify the human resources required by different departments or tasks, thereby achieving optimized allocation of human resources within the organization.

3. IDENTIFICATION AND RESOLUTION STRATEGIES FOR INTERNAL CONFLICTS CONSIDERING TRUST RELATIONSHIPS

3.1 Conflict identification

Against the backdrop of practical needs for organizational structure optimization, the resolution of decision preference conflicts is imperative, as it directly impacts the quality and effectiveness of organizational decision-making. Compared to preference conflicts in general group decision-making processes, internal organizational decision conflicts are often more complex, involving not only individual-level concerns but also a multitude of organizational-level factors. Decision-making within an organization frequently encompasses multi-level structures, potentially including differences between senior managers and ground-level employees. Moreover, decision-makers within an organization usually need to maintain cooperative relationships over an extended period, making the resolution of conflicts lean towards seeking long-term and sustainable solutions.

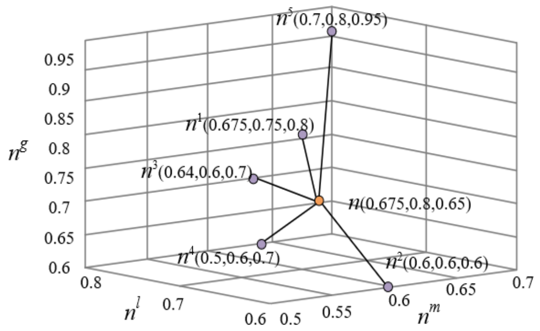

Figure 3. Visualization process of aggregating internal organizational decision-makers' preferences

The main distinction between preference conflicts in internal organizational decision-making and other group decision-making lies in the involvement of a more complex network of stakeholders within the organization. The decision-making process requires a balance of diverse factors, including but not limited to, hierarchical positions, departmental interests, organizational culture, and long-term strategic goals. Therefore, resolving these preference conflicts necessitates a comprehensive consideration of organizational structure, communication processes, and decision-making mechanisms. It is assumed that the similarity of evaluations between two decision-makers, r_u and r_k, regarding all options, specific options, and option attributes is represented by t_{uk}, $t(z^{uk}{}_{\beta})$, and $t(j^{uk}{}_{\alpha})$, respectively. The similarity of preferences between decision-maker r_u and the decision group regarding all options, specific options, and option attributes can be represented by t_u, $t(z^{u}{}_{\beta})$, and $t(j^{u}{}_{\alpha})$, respectively. This study focuses on defining and quantifying the degree of preference conflicts among internal organizational decision-makers at the attribute level, the option level, and the decision-maker level. Figure 3 demonstrates the visualization process of aggregating internal organizational decision-makers' preferences.

a) Preference conflict degree at the attribute level: Within an organization, when a decision-maker, referred to as r_u, and other team members exhibit significant differences in the importance or evaluation of a specific attribute, it is termed as preference conflict degree at the attribute level. For instance, one decision-maker might prioritize cost-effectiveness, while other team members may value the innovation or sustainability of a project more highly. The preference conflict degree at the attribute level reflects the divergence between an individual and the group when evaluating a specific attribute α of a particular option β. The formula is expressed as follows:

$$D_{\beta}^{i}=\left|ls(k_{\beta}^{i})-\sum\nolimits_{i=1}^{n}w_i s(k_{\beta}^{i})\right| \tag{7}$$

b) Preference conflict degree at the option level: Preference conflict degree at the option level refers to the degree of inconsistency between a decision-maker's overall evaluation of an option and the collective opinion of the group. Within an organization, this may manifest as divergent overall evaluations of the same option by different teams or departments. For example, the marketing team might prioritize market acceptance, while the product team might be more concerned with technical feasibility. The formula is represented as:

$$F_{\beta}^{u}=\frac{1}{b}\sum_{\alpha=1}^{b}F_{\alpha}^{u} \tag{8}$$

c) Preference conflict degree at the decision-maker level: Preference conflict degree at the decision-maker level reflects the overall difference in opinion of a particular decision-maker, across all option evaluations, in comparison with the entire team or other members within the organization. This degree of conflict can illustrate a decision-maker's overall position within the organizational decision-making culture and their influence on group consensus. The formula is expressed as:

$$F^{u}=\frac{1}{a}\sum\nolimits_{\beta=1}^{a}F_{\beta}^{u} \tag{9}$$

Within the context of organizational structure optimization and given the uniqueness of the decision-making process, it is understood that preference conflicts are not only inevitable but also beneficial for fostering high-quality decisions within a moderate range. However, preference conflicts exceeding a certain degree can hinder the decision-making process, leading to decreased decision-making efficiency or even paralysis. The setting of a threshold η is intended to quantify the presence of preference conflicts. If the degree of preference conflict F^u for a decision-maker in evaluating options is less than or equal to η, it is considered that the decision-maker's preferences are consistent with the group; conversely, if F^u exceeds η, significant preference conflicts are deemed to exist.

The distinction between decision conflicts within an organization and other group decision conflicts mainly lies in the more fixed relationships among decision participants, and their decisions are often influenced by organizational culture, internal politics, and organizational structure. Therefore, when resolving preference conflicts within an organization, greater attention needs to be paid to the interaction process among decision-makers and their roles and statuses within the organization. Hence, in determining the threshold η, differences in decision-making weights among various levels, departments, and individuals should be considered. That is, the threshold η should reflect the organization's decision-making culture, strategic objectives, and overall attitude towards conflict tolerance. This threshold can be determined through methods such as historical data analysis, expert consultation, and simulation of decision-making experiments. In calculating F^u, the difference between a decision-maker's evaluations and the group's average evaluations should be taken into account.

Considering the characteristics and needs within an organization, this study adjusts the conflict identification process into the following three steps:

Step 1: Conflict identification at the decision-maker level

Internally, this step involves analyzing factors such as the decision-maker's personal background, position, power structure, personal interests, and values. It is important to note that within an organization, decision-makers may have more complex interests and motivations, which may differ from the motives and behavior patterns of individuals in other types of group decision-making. The set of decision-makers whose degree of conflict exceeds the threshold η is represented by *FZMS*, with the formula given as:

$$FZMS = \{u \mid F^u > \eta\} \tag{10}$$

Step 2: Conflict identification at the option level

This step focuses on the evaluation differences between various decision options. Internal evaluation of options may be influenced by the existing organizational structure, resource allocation, historical performance, and future development plans. Utilizing algorithms to analyze differences between options and their potential impacts on different departments or business lines within the organization can help identify potential conflict points caused by options. The set of options whose degree of conflict exceeds the threshold η is represented by *XZMS*, with the formula given as:

$$XZMS = \{(u,\beta) \mid u \in DZMS \wedge F_\beta^u > \eta\} \tag{11}$$

Step 3: Conflict identification at the attribute level

Internally, the attribute level primarily refers to specific factors involved in the decision-making process, such as cost, risk, time frame, technical requirements, etc. Internal decision-making often requires balancing different business attributes. The set of attributes whose degree of conflict exceeds the threshold η is represented by *OZMS*, with the formula given as:

$$OZMS = \{(u,\beta,\alpha) \mid (u,\beta) \in XZMS \wedge F_\alpha^u > \eta\} \tag{12}$$

Once the specific levels at which conflicts exist are identified, the organization can take targeted measures to manage and mediate conflicts. For example, providing more information through decision support systems, changing the power structure by adjusting decision processes, or increasing consensus on organizational goals and option evaluations through training and communication.

3.2 Conflict resolution

Within the context of organizational structure optimization, the conflict resolution process does not merely seek complete unanimity of preferences among decision-makers. Instead, it aims to accurately identify and analyze the attributes, opinions, and preferences of decision-makers at all levels within the organization, striving to minimize the degree of conflict between individuals and the group, different management levels, and diverse functional departments. Compared to conflict resolution in general group decision-making, internal organizational conflict management places greater emphasis on maintaining decision efficiency and consistency with organizational goals, while fully considering organizational culture, power structures, and the synergistic effects between individuals. Figure 4 presents a flowchart for conflict resolution aimed at organizational structure optimization.

Within an organization, conflict resolution is a dynamic, iterative process that considers trust relationships, involving decision-makers adjusting their preferences through trust network after understanding and evaluating the assessments or preferences of other members. The main difference between internal organizational decision conflicts and general group decision conflicts lies in the focus on maintaining coordination and trust between individuals and the whole, seeking optimization and consensus of solutions while preserving decision efficiency and alignment with organizational goals. In this study, decision-makers adjust their preferences based on the strength and direction of trust relationships, encompassing self-assessment and consideration of preferences of leaders or influential members, as well as consensus on the overall organizational objectives and value judgments. The selection of adjustment coefficients and criteria is determined by the internal trust network structure, decision-making levels, and the complexity of interactions among members, ensuring that the final resolution of conflicts not only reduces the individual conflict degree but also strengthens the organization's synergistic effect and decision-making efficiency, promoting optimization of the organizational structure and enhancement of decision quality.

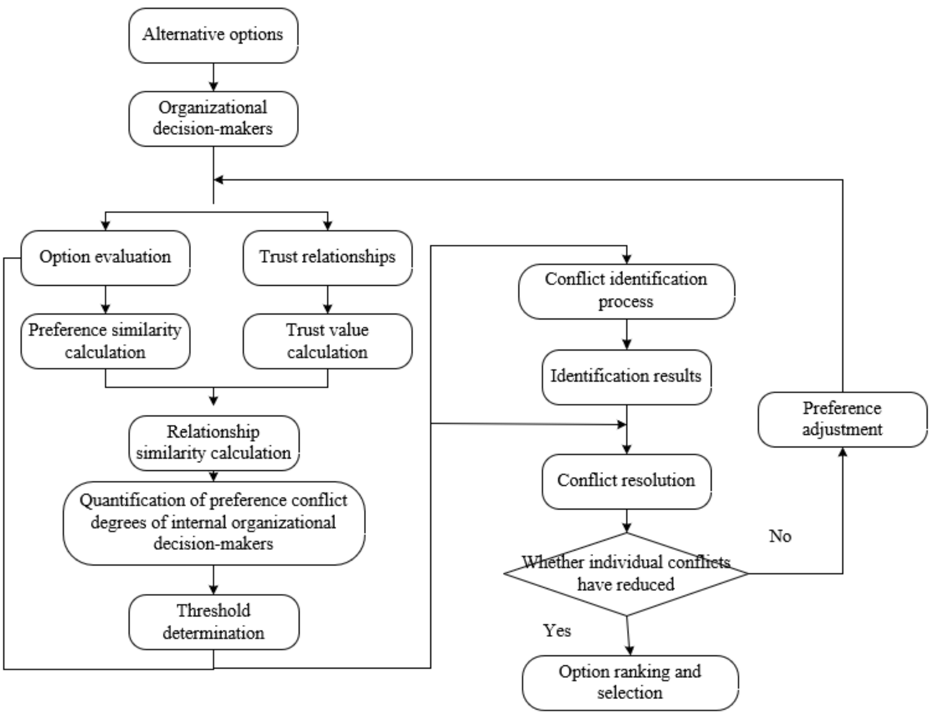

Figure 4. Flowchart for conflict resolution aimed at organizational structure optimization

In the process of resolving internal organizational decision conflicts considering trust relationships, each decision-maker's preferences are influenced not only by their initial evaluations but also significantly by the preferences of their most trusted colleagues or leaders. This dynamic adjustment of preferences is based on dual factors: the individual's preference similarity for options and the level of trust with other decision-makers. This trust level is then reflected through an adjustment coefficient, determining the extent of influence trusted decision-makers have on individual preference adjustments. Unlike ordinary group decision conflicts, the resolution of internal organizational decision conflicts places greater emphasis on the construction and utilization of trust network, capturing not only the consistency of preferences but more importantly, reflecting the trust relationships between different decision-makers. In this process, the practical needs of organizational structure optimization require decision-makers to make conscious preference adjustments based on mutual trust, to foster harmony and efficiency in the decision-making process, ensuring that solution optimization enhances the organization's decision quality and achieves structural optimization.

Assuming two decision-makers, r_u and r_k, where r_k is another decision member most trusted by r_u, and their respective evaluations or preferences for options are n^u and n^k, with r_u's degree of conflict exceeding η, r_u needs to adjust decisions to reduce n^u. The formula for r_u's preference adjustment is given as:

$$n^u(P+1)=(1-\varphi)n^u(P)+\varphi n^k(P) \tag{13}$$

Assuming the number of decision-makers is represented by v, the preference adjustment coefficient ϕ can be calculated as follows:

$$\varphi=\frac{\max(s_{uk})}{\sum_{k=1}^{v}s_{uk}} \tag{14}$$

4. EXPERIMENTAL RESULTS AND ANALYSIS

Based on the data from Figure 5, it is observed that with an increase in the number of control cycles, the testing error in human resource allocation control by the FCMAC shows an overall decreasing trend. Starting from an error rate of 8.30% at 6 cycles, the rate steadily declines to 7.68% at 11 cycles, indicating that with more iterations, the FCMAC becomes more precise in predicting and controlling the allocation of human resources. Particularly, when the number of cycles increases from 10 to 11, the decrease in error is notably significant, dropping from 7.80% to 7.68%. However, as the number of cycles continues to rise to 12 and 13, a slight increase in error rates is observed, reaching 7.79% and 7.81%, respectively. This suggests that excessive iteration may not necessarily lead to better outcomes, possibly due to the model beginning to overfit or other factors causing a slight decrease in performance. The experimental results demonstrate the effectiveness of the human resource allocation control strategy based on the FCMAC proposed in this study. Increasing the number of control cycles within a certain range can enhance the accuracy of the strategy. The FCMAC model is capable of adapting to changes in organizational needs and optimizing resource configuration, especially when the number of control cycles reaches 11, where the model achieves the lowest testing error, proving the potential of this strategy in practical applications.

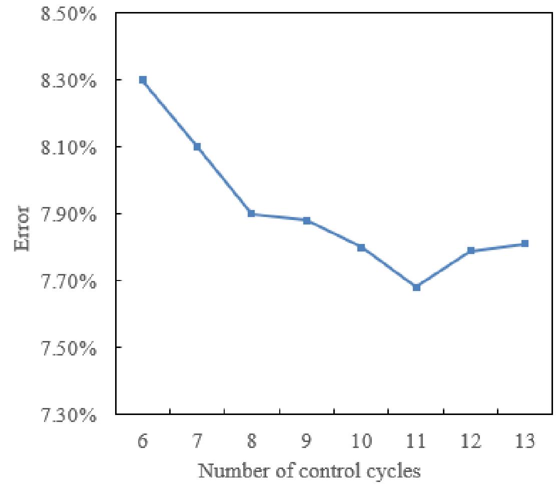

Figure 5. Testing error of the FCMAC under different numbers of human resource allocation control cycles

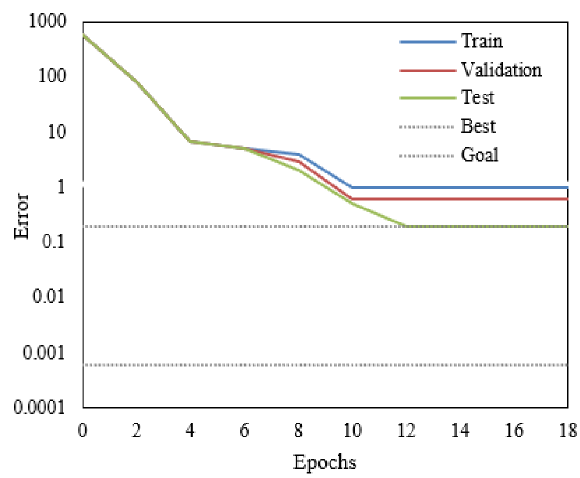

Figure 6. Convergence of the FCMAC during the testing process

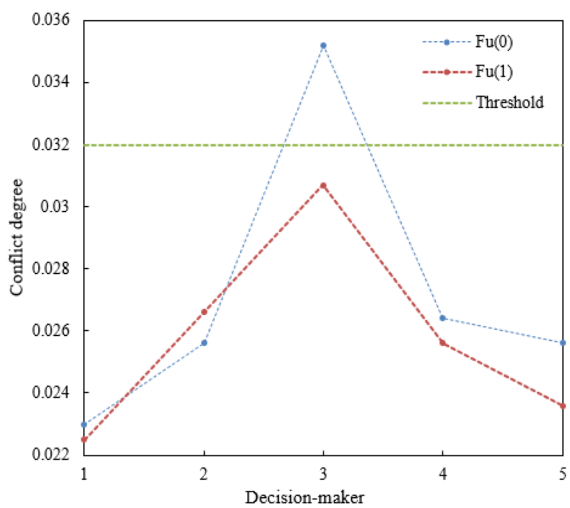

Figure 7. Change in conflict degrees of different decision-makers

Table 1. Sample data after optimization of human resource allocation control

Sample ID	Employee Satisfaction	Training and Development Needs	Change in Productivity or Service Efficiency	Human Resource Costs	Change in Project Delivery Time	Change in Workload Balance	Change in Employee Work Proportion
1	7	1156	4%	31256	9*h*	47	14%
2	6	1248	7%	32147	7*h*	48	12%
3	7	912	8%	35698	11*h*	28	12%
4	6	1245	9%	28956	6*h*	51	13%
...	...	...	...	...	...	...	...
2256	7	1689	5%	35647	6*h*	43	13%

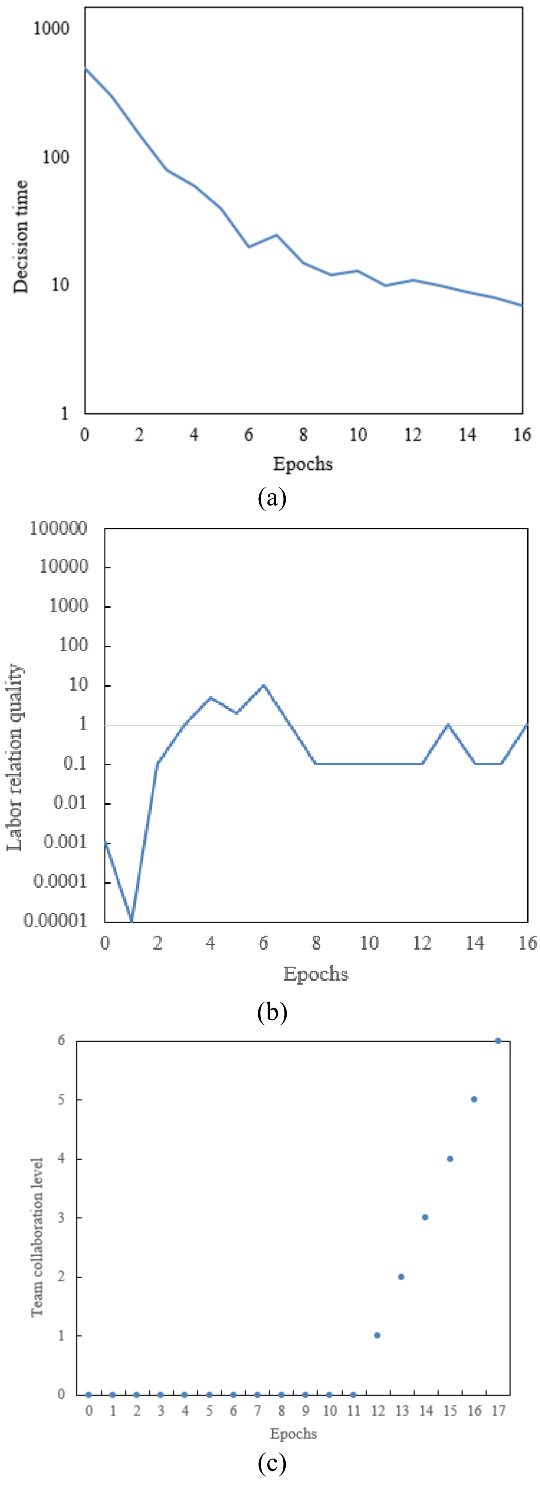

Figure 8. Optimization of decision time, labor relation quality, and team collaboration level after internal conflict resolution

Figure 6 displays the convergence behavior of the FCMAC during the training process of the human resource allocation control strategy, with data indicating a significant reduction in errors across the training, validation and test sets as epochs increase. In the initial phase of training (0-2 epochs), the error rapidly decreases from 600 to 80, demonstrating the FCMAC's ability to learn and adjust swiftly. With further training (4-10 epochs), the error continues to decrease across all data sets, reaching levels of 1, 0.6, and 0.5 at 10 epochs, respectively, showcasing excellent learning capabilities and efficient convergence speed. Continuing the training up to 18 epochs, the model's error stabilizes at 0.6 and 0.2 on the validation and test sets, respectively, while the training set error remains at 1, indicating the model has achieved stable generalization performance. Moreover, compared to the predefined target error (0.2), the error on the test set has already met the target, while the best error recorded at 0.0006 is significantly lower than the target error. These experimental results thoroughly demonstrate the effectiveness of the human resource allocation control strategy based on the FCMAC. The model not only learns quickly and adapts to the training data but also exhibits good generalization capabilities in subsequent validation and testing, which is key to the success of the control strategy. The stable decline in error and test results below the target error indicate that the strategy can respond in real-time to changes in organizational needs and optimize resource configuration in practical scenarios.

Table 1 provides sample data following the optimization of human resource allocation control, including key indicators such as employee satisfaction, training and development needs, changes in productivity or service efficiency, human resource costs, changes in project delivery time, workload balance and proportion of employee work. From the sample data, it is observed that employee satisfaction generally remains at a high level (e.g., satisfaction of 7 for samples 1 and 3), while project delivery times have been reduced (e.g., from standard time to 7 hours for sample 2), improvements in workload balance are evident (e.g., a workload balance of 51 for sample 4), and changes in the employee work proportion are maintained within a reasonable range (between 12%-14%). These improvements indicate that in the optimized human resource configuration, all indicators have shifted in a positive direction, reflecting the efficiency of human resource allocation and the improvement of employee work conditions. From this data analysis, it can be concluded that the human resource allocation control strategy based on the FCMAC effectively enhances key human resource management indicators, such as increasing employee satisfaction, optimizing the match between training and development needs and resources, enhancing productivity or service efficiency, and while controlling human resource costs, shortening project delivery times, achieving workload balance. These positive changes not only enhance the overall operational efficiency of the organization but may also bring long-term economic benefits and improve employee welfare. Therefore, the human resource allocation control strategy based on the FCMAC proposed in this study not only demonstrates efficiency in laboratory tests but also proves its effectiveness in optimizing human resource configurations in practical applications.

Figure 7 shows the conflict degree values of five decision-makers at two different time points, as well as the conflict degree threshold they need to meet. At the initial state $Fu(0)$, the conflict degree of Decision-Maker 3 (0.0352) is slightly above the threshold (0.032), while the conflict degrees of the other decision-makers are below the threshold. This indicates that before the implementation of the resolution strategy, the conflict levels of most decision-makers were already within an acceptable range. In the state $Fu(1)$ after strategy implementation, the conflict degree values of all decision-makers are below the threshold, and compared to the initial state, except for a slight decrease in the conflict degree of Decision-Maker 1, other decision-makers experienced various degrees of reduction, especially Decision-Maker 3, whose conflict degree decreased from above the threshold at 0.0352 to 0.0307. This demonstrates the effectiveness of the strategy in reducing their conflict degrees. From this data analysis, it is evident that the internal conflict identification and resolution strategy proposed in this paper is effective in reducing the conflict degrees of decision-makers. Especially for those whose initial conflict degrees exceeded the threshold, the implementation of the strategy significantly reduced their conflict degrees to an acceptable level. This indicates that the decision model incorporating trust metrics can accurately identify and resolve conflicts within the organization. Through the quantification and management of trust relationships, decision-makers are able to make more harmonious and consistent decisions in the context of conflict, thereby enhancing the overall decision-making efficiency and internal coordination of the organization.

Figure 8(a) records a significant reduction in internal decision-making time within the organization as the model training progresses. Starting from an initial decision time of 500 units, a rapid decrease is observed with the increase in epochs, reducing to only 12 units of time by the 10^{th} epoch. Although the reduction in decision time slows down thereafter, a decreasing trend continues, reaching 7 units of time by the 16^{th} epoch. This change indicates that with the training of the FCMAC model, the internal decision-making process becomes more efficient, reflecting the model's learning on how to resolve conflicts more swiftly. Figure 8(b) reflects the changes in labor relation quality as the FCMAC model training progresses. At the beginning of model training, the quality of labor relations was very low (0.001), which could indicate serious labor relations issues or conflicts. With the increase in epochs, the quality of labor relations experiences fluctuations but overall shows a significant upward trend, especially between the 4^{th} and 12^{th} epoch, where this indicator grows from 0.1 to 10, then stabilizes between 0.1 and 1 after the 14^{th} epoch. This fluctuation might suggest that the model, during its learning and adaptation process, continuously adjusts the human resource allocation strategy to achieve optimal quality of labor relations. Figure 8(c) displays the changes in team collaboration level as the model training epochs increase. In the first 12 epochs, the level of team collaboration remains at 0, implying that internal conflicts may not have been effectively identified or resolved during this stage, leading to inactive team cooperation. However, starting from the 13^{th} epoch, the level of team collaboration begins to show significant positive growth, gradually increasing from 1 to 5 by the 16^{th} epoch. This continuous upward trend indicates that after a series of iterative learning, the FCMAC's human resource allocation control strategy begins to take effect, gradually enhancing the collaborative capabilities among team members.

Combining the above experimental results, it can be concluded that the human resource allocation control strategy based on the FCMAC is not only effective for the optimal allocation of human resources but also significantly improves internal decision-making efficiency, as well as enhancing the quality of labor relations and team collaboration. The notable reduction in decision time confirms the model's capability in understanding and addressing internal trust and conflict relations. Furthermore, as the model undergoes further training, its effectiveness continues to improve. Although improvements in labor relation quality are not constant, the stable performance in the later stages of model training illustrates that the strategy can sustain high-quality labor relations after initial adjustments. With the continuous application of the strategy and ongoing optimization of the model, a significant improvement in the level of team collaboration has been achieved.

5. CONCLUSION

This paper explores a human resource allocation control strategy based on the FCMAC, providing an effective method for responding in real-time to organizational demand changes and optimizing resource configuration. The feasibility and efficiency of the FCMAC in human resource allocation have been demonstrated through the analysis of network test errors under different control cycle numbers and discussions on convergence. Experimental results indicate that the optimized human resource allocation plan can significantly enhance organizational efficiency.

Furthermore, the internal conflict identification and resolution strategy considering trust relationships, introduced through a decision model incorporating comprehensive trust metrics, offers a new perspective for the precise handling of organizational conflicts. Experimental data show that this strategy not only effectively reduces the conflict degree of decision-makers but also improves decision time, labor relation quality, and team collaboration level after conflict resolution.

Overall, this study not only enriches the theoretical domain of human resource allocation and organizational conflict management but also provides specific guidance for practical application. However, the research also has limitations, such as potential restrictions to specific organizational types and sizes, as well as factors related to model parameter selection during experimental validation. Future research could validate the universality and stability of the model across a broader range of organizational types and sizes. Further exploration could also examine the impact of model parameters on experimental outcomes, as well as how to integrate more advanced technologies such as machine learning to enhance the model's predictive capabilities and application scope.

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