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Optimal Function and Attention Allocation for Human-AI Collaboration using Computational Cognition-Work Model*

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Abstract— **The paper presents a computational model-based optimization framework for function and attention allocation in collaborative control and decision-making between a human and artificial intelligence (AI). Effective human-AI collaboration (HAC) may depend on structured adaptive function allocation among team members to enhance performance while managing human cognitive limitations, especially attention. Integrating attention allocation is vital for maintaining situation awareness and managing human workload. Various allocation methods rely on heuristics and experimental studies that demand significant resources and domain expertise. To address the function and attention allocation problem in HAC in a systematic way, we propose a computational cognition-work model (CCWM)-based framework. The framework can integrate a qualitative work model and cognitive models to simulate complex team dynamics in temporal semantics. An optimization technique can then improve any task-oriented metrics by exploring the team structure and simulated episodes without requiring exhaustive experimental studies. We present numerical evaluations to demonstrate the proposed framework using a disaster relief drone fleet operation scenario, which provides valuable insights into the early stages of HAC design and the broader domain of HAC.**

I. INTRODUCTION

Teaming represents a work strategy to tackle complex and time-critical challenges as a group of agents. Human organizations have exploited the power of teams to address real-world problems. Effective teamwork relies on proactive collaboration among team members. Recently, advanced artificial intelligence (AI) technologies have introduced a paradigm shift that enables humans to view autonomous agents as teammates, not as mere tools [1]. They have ushered in a new era of human-AI collaboration (HAC).

HAC presents a unique set of challenges due to the distinct capabilities and limitations of humans and autonomous agents [2]. It is not merely a matter of replacing humans with autonomous agents, but HAC creates entirely new cognitive systems through the infusion of AI technologies into a team [3]. Consequently, efficient allocation of roles and resources is a key success factor in HAC while accounting for the characteristics of each agent, interactions, and interdependencies.

Function allocation is a classic problem in the HAC context that aims to determine *who does what*. The Fitts list laid the foundation for addressing the function allocation in human-machine systems [4]. To address criticism on the Fitts list due to its static allocation approach, numerous approaches have been explored to promote situation-based decision-making such as level of automation [5] and adaptive function allocation approaches [6]. While theories and empirical findings support dynamic function allocation approaches, quantitative studies remain rare [3]. Modern manufacturing technology has facilitated collaborative workplaces where humans and robots operate together in the same physical space [7], but further considerations may be needed to address remote operation and effective information flow management.

Attention allocation is another critical issue in HAC to manage humans' limited cognitive resources by adjusting information flow. It is crucial for obtaining situation awareness (SA) while maintaining an appropriate level of workload (WL) [8]. The optimal adaptive attention allocation problem can be likened to an information queuing problem, where autonomous agents request human supervision only when necessary. The optimal attention sequences have been studied but limited to simplified situations [9].

Recent advances in computational models for work and human cognition processes have opened up new opportunities for exploring optimal HAC designs. A computational work model has been developed to simulate and validate the operational concepts of human-AI teams [10]. However, it is limited to testing fixed function allocation policies. In our previous study, we utilized a quantitative work model to optimize adaptive function allocation policies, but it could not address human cognition models and attention allocation [11]. Computational cognition models have been developed independently to predict human cognitive states in dynamic environments [12], [13], [14]. Even though their experimental evidence demonstrates the accuracy of the models, they have not yet been integrated into HAC designs.

We propose a *computational cognition-work model* (CCWM)-based approach. The CCWM integrates work models and human cognition models to build a digital twin of the complex interactions between the environment, humans, and autonomous agents. The CCWM can simulate complex work and human cognitive processes in temporal semantics to explore various function and attention allocation policies through a trial-and-error approach. Thus, HAC designs can be tested and validated for different adaptive allocation policies in simulated environments. The results can be utilized to provide a solid foundation for the followed human-in-the-loop experiments and the CCWM can be refined iteratively

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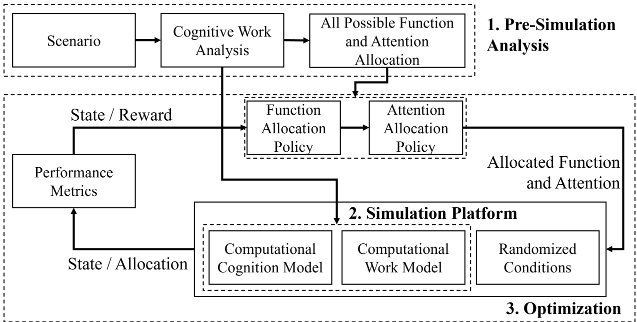

Fig. 1. The proposed framework for optimal adaptive function and attention allocation for HAC.

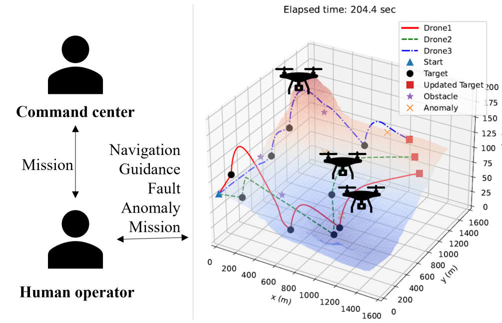

Fig. 2. The simulated environment for package delivery in disaster relief operations using a drone fleet.

with observations from the experiments [15]. The proposed framework uses a three-phase approach as shown in Fig. 1.

Our contributions can be categorized into two main aspects. First, we propose a systematic approach to model the interactions between work, human cognitive processes, and physical states (e.g., vehicle dynamics) as a discrete-time stochastic control process. Second, we introduce an optimization technique to address optimal function and attention allocation in complex HAC designs, considering any performance metrics while accounting for constraints, interactions, and information flow among team members. The results can enhance our understanding of how model parameters and metrics influence the HAC systems.

The paper is organized as follows. In Section II, the proposed framework is formally presented. The computational model can be found in Section III. Section IV provides the illustrative simulation results. Section V concludes the paper.

II. Proposed Approach

A. Application Scenario

To contextualize the problem, we present an application scenario of HAC. We examine a drone fleet operation designed for package delivery within disaster relief scenarios [16], [11]. Fig. 2 depicts a simulated environment with terrain, a start point, target points, obstacles, and environmental anomalies. Within this simulated environment, three entities collaborate as a team: a human operator, three autonomous drones, and a command center. The team's objective is to efficiently and safely visit and stay three seconds to drop packages for each target point using the drones while avoiding obstacles. The team must also address both internal and external anomalies such as actuator faults, adverse weather conditions (e.g., wind gusts), and mission updates (e.g., updated targets). The drones can perform essential tasks such as navigation, guidance, and control. The human monitors the drones under nominal conditions and intervenes under off-nominal situations.

The team needs to obtain, maintain, and share SA. SA can be described as a collection of situation elements (SEs) denoted as $\mathcal{SE}$ [12]:

$$\mathcal{SE} = \{N, G, F, A, M\} \tag{1}$$

where N denotes the navigation information such as drone position, G denotes the guidance information such as mission sequence and waypoints, and F denotes the internal anomaly information encompassing actuator faults that cause degradation of the drone performance (e.g., decreased speed). A is the environmental anomaly information such as wind gusts. M is the mission information shared with the command center such as target points.

We make the assumption that allocation is guided by autonomous drones, and the human always follows the decisions within a fully connected network. While this assumption may be conservative [17], it enables us to focus on the computational decision-making problem related to function and attention allocation with a reasonable level of complexity. Regarding attention allocation, we assume that the autonomous drones convey SEs to the human through a visual interface. Drones possess the capability to adjust the portion and size of the visual interface for each SE to direct the human's attention effectively. This concept is a simplified version of the existing attention allocation model in cognitive science [13].

B. Pre-Simulation Analysis

The pre-simulation analysis aims to identify the constraints, interdependencies, and all possible function allocation cases. To achieve this, we use cognitive work analysis (CWA), a well-established technique for analyzing socio-technical systems [18]. CWA utilizes a visual representation to describe the work domain hierarchy as shown in Fig. 3 (modified from [11]). This hierarchy delineates the *why-what-how* structure, where each node represents *what* need to be done, the higher-level node elucidates *why* it is necessary, and the lower-level node details *how* it can be accomplished. Within the middle of the hierarchy, the *generalized function* encompasses actions related to all SEs. At the *physical function*, functions are specified along with information about which agents can perform each function. The function allocation problem involves assigning functions that can be performed by both agents. The attention allocation determines which area of the generalized function to be prioritized by the human. Since CWA only identifies a static work domain, we need a simulation platform to analyze team interactions in a temporal context.

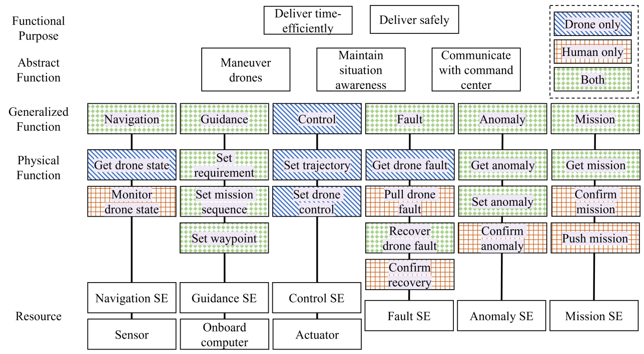

Fig. 3. The abstraction hierarchy of the scenario.

C. Simulation Platform

The simulation platform models the temporal consequences of work based on the pre-simulation analysis. The computational model can simulate three key elements: discrete and continuous decisions made by each agent, the continuous dynamics of the system, and the interactions among team members [10]. Each agent has the capability to *get* information from the environment or their teammates, such as obtaining the velocity of drones or detecting environmental anomalies. Agents can take actions that *set* the environment, such as controlling drone positions or recovering drone faults. These actions can be categorized according to the generalized function. The simulation platform computes the consequences of both *get* and *set* actions to propagate the team's states within the environment. Note that *control* is not considered as an SE in (1) since we assume that the control functions are only managed by the drones as shown in Fig. 3 [19].

The simulation platform represents the team dynamics as a stochastic discrete-time control process:

$$\mathbf{s}_{k+1} = h(\mathbf{s}_k, \mathbf{a}_k) \tag{2}$$

where $\mathbf{s}_k \in \mathbb{R}^n$ denotes the state of the team including all physical states and cognitive states at time step $k \in \mathbb{Z}_{\geq 0}$. The human state includes remaining action time for each function, functions in the waiting queue, WL, and SA. The drone state includes readiness for each generalized function, SA, position, distance to target, and anomaly information [11]. We use discretized variables (i.e., integers) for each state. $\mathbf{a}_k \in \mathcal{A}(\mathbf{s}_k)$ are the possible allocations on function and attention, i.e., decision variables in the proposed framework. $h : \mathbb{R}^n \times \mathcal{A}(\mathbf{s}_k) \to \mathbb{R}^n$ denotes the team dynamics, which could be stochastic. The possible allocation is:

$$\mathcal{A}(\mathbf{s}_k) = \{f_1, \cdots, f_m, a_N, a_G, a_F, a_A, a_M\} \tag{3}$$

where $f_i \in \{\emptyset, \text{human}, \text{drones}\}$, $\forall i \in \{1, \cdots, m\}$, denotes the function allocation decision for m assignable functions. Attention allocation decisions for each SE in (1) can be made only for the functions that require the human's attention:

$$a_i \in \{1, 2, 3\}, \quad \forall i \in \mathcal{SE}_h \tag{4a}$$
$$a_i = 0, \quad \text{otherwise} \tag{4b}$$

where $\mathcal{SE}_h = \{i \in \mathcal{SE} \mid \overline{SE}(f_j), \forall f_j = \text{human}\}$. $\overline{SE}$ denotes the mapping from the physical function to the relevant SE in Fig. 3. $a_i = 0$ implies that the i-th function is not attended by the human. $a_i = \{1, 2, 3\}$ denote low, mid, and high attention to the i-th function, respectively. Section III provides a detailed approach to incorporate the cognitive states and shaping the team dynamics (2).

D. Optimization

To optimize function and attention allocation using the proposed framework, we define the reward function as:

$$r_k = \boldsymbol{\mu}^T g(\mathbf{s}_k, \mathbf{a}_k) \tag{5}$$

where $\boldsymbol{\mu} = [\mu_1, \cdots, \mu_l]^T \in \mathbb{R}^l$ with $\sum_{i=1}^{l} \mu_i = 1, \mu_i \geq 0$ denotes the weight vector of the reward function. $g : \mathbb{R}^n \times \mathcal{A}(\mathbf{s}_k) \to \mathbb{R}^l$ is the feature function that can include any action-state variables. The team dynamics (2) and the cumulative reward using (5) enable us to formulate an optimization problem for function and attention allocation as a Markov decision process (MDP). The action space includes decisions on function allocation f_i and attention allocation a_j in (3). We utilize a specific optimization technique, called the episodic semi-gradient Sarsa method in reinforcement learning [11], [20], to demonstrate the proposed framework.

III. Computational Cognition-Work Model

We incorporate cognition models to address human cognitive states, WL and SA, within the team dynamics (2). These states are critical in HAC applications [8]. Our goal is to analyze trade-offs, such as minimizing WL while maximizing SA. Cognition models closely interact with the work model, as cognitive processes can affect human execution time. We use the widely recognized adaptive control of thought-rational (ACT-R) architecture [21], though the framework is flexible enough to accommodate alternative architectures.

A. Situation Awareness Model

A well-known model categorizes SA into three levels: perception (Level 1), which involves perceiving individual SEs; comprehension (Level 2), which entails interpreting SEs; and prediction (Level 3), which represents the ability to project the future based on the current understanding of SEs [22]. For consistency, we define SE Level 0 when no information is available.

The SA model provides a detailed depiction of the progress on the SA levels as shown in Fig. 4 [12], [13]. At the beginning, the human lacks access to SE and it is represented as Level 0, denoted by $se_i = 0$ for $i \in \mathcal{SE}$. When the human pays attention to the SE using the visual module and processes it with the declarative memory module, Level 1 is achieved with $se_i = 0.5$. Levels 2 and 3 are reached with $se_i = 1$, as the human completes processing using the procedural memory module to match patterns between the SE and their memory. The human can then execute actions, such as pressing buttons using the motor module, after reaching Levels 2 and 3.

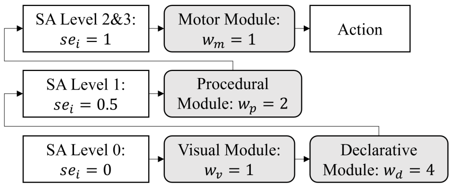

Fig. 4. The sequence of the cognition process including acquisition of levels of SA and action engagement with WL.

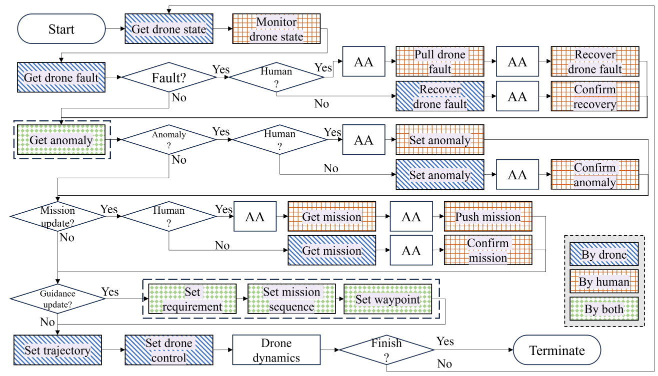

Fig. 5. The flowchart of the work incorporating function allocation ('Human?' conditions) and attention allocation (AA). The functions in the dotted boxes can be allocated independently to both humans and drones with attention allocation determined if allocated to the human.

A quantitative SA model called attention allocation model has been developed [13], [12] to compute human SA as a weighted sum of SEs:

$$SA = \sum_{i \in \mathcal{SE}} e_i se_i \tag{6}$$

where $\sum_{i \in \mathcal{SE}} e_i = 1$ with $e_i \geq 0$ represents the importance factor and $se_i \in \{0, 0.5, 1\}$ based on the levels of SA for each SE. To formulate SEs, we need:

$$p_i = a_i / \sum_{j \in \mathcal{SE}} a_j, \quad \text{if} \sum_{j \in \mathcal{SE}} a_j > 0 \tag{7}$$

where p_i denotes the attention proportion that represents the occurrence probability of paying attention to se_i. Note that $p_i = 0$ if $\sum_{j \in \mathcal{SE}} a_j = 0$. SEs compete with each other to receive more attention since the total attention affects the attention proportion for each SE.

Using the attention proportion p_i, we can compute the expected execution time by the human $t_{e,i}$ for each function:

$$t_{e,i} = t_{v,i} + t_{d,i} + t_{p,i} + t_{m,i} \tag{8}$$

where $t_{v,i} = \Delta t_v / p_i$ is the expected time to pay attention using the visual module. $\Delta t_v = 250$ms is the fixed dwell time [23]. $t_{d,i} = e^{2(\tau - \sum_{j \in \mathcal{SE}} p_j S)}$ is the expected time to achieve Level 1 using the declarative memory module. τ is the threshold and $S = 2 - \ln 3$ is the relationship between the number of SEs related to se_i, respectively. S is assumed to be constant for simplicity [13]. $t_{p,i} = (e^{U_i/\theta} / \sum e^{U_i/\theta})^{-1}$ is the expected time to reach Levels 2 and 3. U_i is the maximum utility and θ is the noise constant [24]. Then, the SA cognition process is modeled in time windows:

$$se_i(t) = \begin{cases} 0 & \text{if } t \leq t_{v,i} + t_{d,i} \\ 0.5 & \text{if } t_{v,i} + t_{d,i} < t \leq t_{v,i} + t_{d,i} + t_{p,i} \\ 1 & \text{if } t_{v,i} + t_{d,i} + t_{p,i} < t \end{cases} \tag{9}$$

where $t = k\Delta t$ is the continuous elapsed time with the discrete-time interval Δt, and it can be omitted for simplicity when representing $se_i(t)$. We use $\Delta t = 0.1$s.

B. Workload Model

A WL model based on ACT-R offers an integrated perspective along with the SA model [14]. The WL model formulates the instantaneous WL for each module. When the human engages with the visual and motor modules, the WL is relatively low, quantified with WL weighting factors: $w_v = w_m = 1$. When the human accesses the declarative memory module, the WL reaches its maximum value with a weighting factor of $w_d = 4$. The procedural memory module has a weighting factor of $w_p = 2$ for selecting actions. The instantaneous WL is computed as a weighted sum of activated modules:

$$WL = \sum_{j \in \mathcal{SE}_h} \sum_{i \in \mathcal{M}} w_i A_{i,j} \tag{10}$$

where $\mathcal{M} = \{v, d, p, m\}$ denotes the set of all modules (i.e., visual, declarative, procedural, and motor), with associated weighting factors $\{w_v, w_d, w_p, w_m\} = \{1, 4, 2, 1\}$. $A_{i,j} \in \{0, 1\}$ serves as the activation indicator for the corresponding function and module, where $A_{i,j} = 0$ when the module is inactive and $A_{i,j} = 1$ when the module is active, respectively.

C. Integration of Cognition and Work

Human cognition processes influence the given work by affecting the expected time required to perform functions, which is computed based on the allocated attention. Therefore, the CCWM introduces an additional dimension to the state $\mathbf{s}_k$ (i.e., cognitive states) and the control space $\mathbf{a}_k$ (i.e., attention allocation), respectively. Fig. 5 illustrates the progression of the work over time. The generalized functions are executed sequentially. When a function is allocated to the human, attention allocation needs to be determined. The cognitive state models in (6) and (10) are employed to propagate SA and WL, respectively. The physical states are propagated by the drone dynamics once the *set drone control* function is engaged in each time step. Subsequently, the team dynamics in (2) can be fully simulated.

Table I provides parameters associated with the physical functions. To simulate differences in capabilities between humans and drones, we utilize the skill-rule-knowledge taxonomy [19]. Autonomous agents typically excel in skill and rule-based functions, such as optimizing solutions for guidance and control in nominal conditions. Conversely, humans can leverage their knowledge to address the complexities of off-nominal scenarios.

The drone dynamics is modeled in the three-dimensional space using a double integrator, with the maximum speed and acceleration set at $20 m/s$ and $5 m/s^2$, respectively. In the

TABLE I

THE PHYSICAL FUNCTION PARAMETERS FOR DRONES (DURATION) AND HUMAN ($\{\tau, t_{p,i}, t_{m,i}\}$).

Physical Function	Duration (s)	τ	$t_{p,i}(s)$	$t_{m,i}(s)$
Get drone state	Δt	-	-	-
Monitor drone state	-	1.5	2	1
Set requirement	1	1.0	4	1
Set mission sequence	1	1.0	8	1
Set waypoint	1	1.0	8	1
Confirm guidance	-	1.0	-	-
Set trajectory	1	-	-	-
Set drone control	Δt	-	-	-
Get drone fault	1	-	-	-
Pull drone fault	-	1.0	4	1
Recover drone fault	60	2.0	8	1
Confirm recovery	-	2.0	-	-
Get anomaly	1	1.5	1	1
Set anomaly	1	1.5	2	1
Confirm anomaly	-	1.5	-	-
Get mission	1	2.0	2	1
Confirm mission	-	1.0	-	-
Push mission	-	1.0	2	1

event of a fault, the speed is limited to $2m/s$. Target point sequences are computed through brute-force optimization, and trajectories are determined by connecting waypoints while avoiding obstacles and terrain using a potential field method [25]. Trajectory tracking is performed using a proportional-derivative controller. The drones can detect obstacles within a $50m$ range, while humans have a broader anomaly detection range of $500m$.

IV. NUMERICAL SIMULATION EVALUATION

We present simulation results demonstrating that different reward functions lead to distinct allocation policies. In a physical space of dimensions $1600m \times 1600m \times 200m$, nine target points are randomly generated with a fixed start point, as shown in Fig. 2. Three extra target points are randomly generated with varying update times. Three obstacles and three anomalies are also randomly positioned. Three distinct drone faults can occur, each with a probability of 0.5. Throughout all trade-off studies, we utilize a consistent set of 3000 episodes for training and another set of 100 episodes for testing.

A. Trade-off Analysis

A reward function is structured as:

$$r_k = \mu_1(-1) + \mu_2(-WL_k^2) + \mu_3(-(SA_k - 1)^2) \quad (11)$$

where μ_i is the weighting factor. WL_k and SA_k denote the WL and SA at time step k, respectively. We choose the importance factors $e_i = 0.2$ for all $i \in \mathcal{SE}$ in (6). The study cases are as follows:

- R_{human}: all functions that the human can perform are assigned to the human. Attention is equally allocated to each generalized function.
- R_{drone}: all functions that the drones can perform are assigned to the drones. Attention is equally allocated to each generalized function.

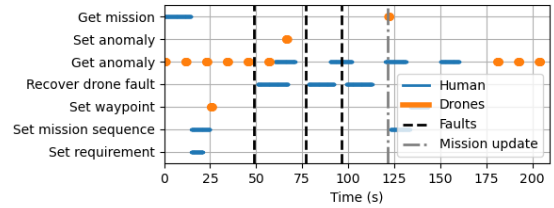

Fig. 6. The function allocation for an exemplar episode with R_{time}.

- R_{time}: $\{\mu_1, \mu_2, \mu_3\} = \{1, 0, 0\}$.
- R_{WL}: $\{\mu_1, \mu_2, \mu_3\} = \{0, 1, 0\}$.
- R_{SA}: $\{\mu_1, \mu_2, \mu_3\} = \{0, 0, 1\}$.
- $R_{\text{WL-SA}}$: $\{\mu_1, \mu_2, \mu_3\} = \{0, 0.5, 0.5\}$.

R_{time}, R_{WL}, and R_{SA} are chosen to illustrate the different cases, i.e., minimizing mission completion time, minimizing WL, and maximizing SA, respectively. $R_{\text{WL-SA}}$ is designed to test a trade-off between WL and SA. An exemplary function allocation over time for R_{time} is presented in Fig. 6.

Fig. 7 shows that R_{time} can improve mission completion time by leveraging the adaptive function allocation. R_{WL} presents the lowest range of WL, even when compared to R_{drone}. In R_{drone}, the human needs to interact with the drones to confirm the team state. This finding provides an interesting insight that the proposed framework can computationally improve a target performance metric in a complex HAC designs. R_{human} and R_{SA} demonstrate the highest range of WL and SA. This fact indicates that the human needs to perform more functions to obtain a higher level of SA. R_{WL} and R_{SA} exhibit a trade-off relationship between WL and SA, where higher WL is required to achieve a higher level of SA. The proposed framework can successfully find the optimal allocation policy for $R_{\text{RW-SA}}$ that balances WL and SA.

B. Robustness to Model Parameter Uncertainties

We conduct a robustness study to examine how errors in human parameters in Table I impact the proposed framework. Suppose that the expected time parameters for reaching each SA in (9) are susceptible to multiplicative errors:

$$\tilde{t}_{i,j} = (1 + \tilde{e})t_{i,j} \quad (12)$$

where $t_{i,j}$ is the nominal expected time for $i \in \mathcal{M}$ and $j \in \mathcal{SE}$. $\tilde{e}$ is the scale factor error, with $\tilde{e} \sim \mathcal{N}(\bar{e}, 0.1^2)$, where $\bar{e}$ denotes the mean of the scale factor error. In the robustness study, we use the nominal expected time for training and the randomized expected time in (12) for testing. An identical set of 100 randomized episodes is utilized for all testing cases.

The mission completion time gaps between different study cases are presented in Fig. 8. The results reveal that the allocation policy trained in R_{time} outperforms the fixed allocation policy in R_{human}, regardless of the size of the error. The result means that even if it is difficult to find accurate human parameters, we can find sufficiently reasonable allocation policies using the proposed framework.

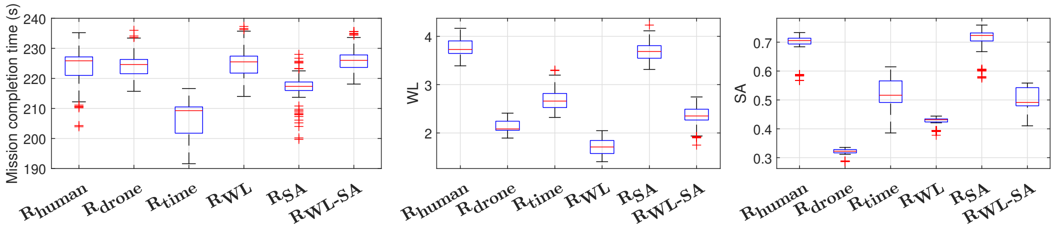

Fig. 7. The group comparison for mission completion time, WL, and SA.

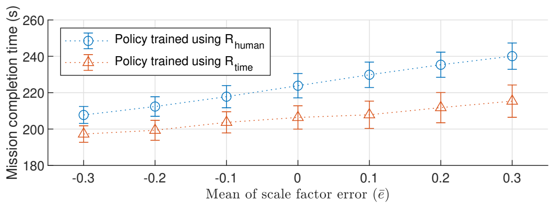

Fig. 8. Mean mission completion time and its standard deviation (error bars) for the policies trained in R_{human} and R_{time} in relation to the mean scale factor error $\bar{e}$.

V. CONCLUSIONS

We proposed a computational model-based optimization framework for investigating role and resource allocation in complex human-AI collaboration (HAC) scenarios. The proposed framework provides the flexibility to optimize any metrics using any parameters to explore the team's trade-space. It can serve as a valuable tool for gaining insights into HAC design during the early phases. Our ongoing work involves validating the proposed model through human user studies, focusing on inferring cognitive states using physiological sensors. Since internal human states are not directly observable, non-invasive sensors, such as heart rate sensor and camera, are used to assess cognitive states.

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