Rolling-Horizon Task Allocation for Human–Robot Teams with Mental-State Awareness

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***Abstract*—This paper presents a Mental-State Aware Task Allocation (MSA-TA) framework for human–robot teams in which multiple operators supervise robots executing time-sensitive tasks. Unlike conventional allocation models that treat operators as fixed-capacity resources, the proposed approach includes operator mental state in both the objective function and feasibility constraints. Mental state is represented through a fatigue index and a probabilistic belief over discrete clusters, enabling uncertainty-aware allocation and compatibility with sensing systems such as Brain–Computer Interfaces (BCIs). The problem is solved online through rolling-horizon optimization. Simulation results show that MSA-TA reduces cumulative operator risk exposure and keeps lower fatigue levels than baseline strategies, while preserving competitive task performance.**

***Index Terms*—Task allocation, human–robot teams, mental-state-awareness, cognitive workload, rolling-horizon optimization.**

I. Introduction

Robot fleets, including ground robots and aerial platforms, are increasingly used in warehouses, production floors, and distribution centers [1]. In these systems, performance losses often come from operational decisions rather than robot motion failures: urgent jobs may be delayed, low-priority tasks may be started too early, or one operator may supervise too many robots at once [2]. These issues become more critical when tasks arrive online and deadlines must be respected.

Many task allocation methods treat human supervisors as fixed-capacity resources. However, operators become mentally loaded during a shift, and their attention and decision quality change with monitoring burden, interruptions, and time pressure. This evolution is also operator dependent. Some operators degrade after short periods of high concentration, while others remain stable in short workload bursts but degrade during long repetitive monitoring [3]. Physiological workload and stress markers also vary across subjects, motivating subject-specific models rather than one-size-fits-all assumptions [3], [4].

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This paper proposes an MSA-TA framework for hybrid teams where multiple operators supervise robots executing time-sensitive tasks. Mental state affects the allocation model in two ways: it enters the objective function through fatigue and risk terms, and it affects feasibility through supervision-capacity constraints. The framework is compatible with different mental-state detectors, including BCI-based interfaces for mission-level human–robot interaction [5]. If online estimates are available, the allocator can use them directly. Otherwise, it can rely on a compact load-driven estimator. The main contribution is an uncertainty-aware rolling-horizon formulation in which the human operator is modeled as a dynamic component whose cognitive condition affects both cost and feasibility.

The rest of the paper is organized as follows. Section II reviews related work and states the contribution. Section III presents the system model. Section IV formulates the allocation problem. Section V reports the case study and results. Section VI concludes the paper.

II. Literature review and paper contribution

Multi-Robot Task Allocation (MRTA) has been widely studied for online tasks, timing constraints, uncertainty, and real-time feasibility [6]–[8]. More broadly, AI-driven optimization and sensor-based data analytics are increasingly used to support real-time monitoring, predictive maintenance, query optimization, and decision-making in complex infrastructure systems [9], [10]. In warehouse-style systems, real-time scheduling under limited look-ahead is also central to performance [2]. However, in many of these works, humans are treated as external supervisors or fixed-capacity resources. In warehouse-style systems, real-time scheduling under limited look-ahead is also central to performance [2]. However, in many of these works, humans are treated as external supervisors or fixed-capacity resources.

Human-aware allocation has mainly focused on ergonomics, physical fatigue, and human-centered interaction. Examples include fatigue-aware allocation, ergonomic role allocation, AR-based analysis of engagement with context-aware virtual agents, and haptic/impedance-control mechanisms for safer physical interaction [**?**], [11]–[13]. However, these approaches do not directly address cognitive workload in multi-robot supervision.

Cognitive workload and affective-state estimation have been studied using electroencephalography (EEG), physiological measurements, and multimodal sensing pipelines [14]–[16]. In human–robot collaboration, mental stress and adaptive automation have also been identified as important factors for safety and performance [17]. Recent work also considers workload-aware allocation for multi-human multi-robot teams [18]. Still, cognitive state is often used as a monitoring output or soft objective, rather than as a state that also constrains feasible assignments.

This paper contributes an MSA-TA formulation in which mental state directly affects both the objective and supervision constraints. The allocator only needs a mental-state signal for each operator, which can come from a BCI, another sensing pipeline, or the compact load-driven estimator used here.

III. System Model

Notation: Let $\mathbb{N}$ and $\mathbb{R}_+$ denote the set of natural and positive real numbers, respectively. Calligraphic letters denote sets. For a scalar variable z, the notation $z(t)$ denotes its value at time t. Binary decision variables take values in $\{0,1\}$. Let $\delta(\cdot)$ denote the Kronecker delta function and $H(\cdot)$ the Heaviside step function.

We consider a system composed of M human operators, N robots, and D tasks. Operators are indexed by $i \in \mathcal{I} = \{1,\dots,M\}$, robots by $j \in \mathcal{J} = \{1,\dots,N\}$, and tasks by $d \in \mathcal{D} = \{1,\dots,D\}$. Time is discrete and evolves as $t \in \mathbb{N}$.

A. Task Model

Each task $d \in \mathcal{D}$ is characterized by its processing time $\Delta t_d \in \mathbb{N}$, priority weight $p_d \in \mathbb{R}_+$, and due date $\tau_d \in \mathbb{N}$. The execution state of task d at time t is:

$$x_d(t) = \begin{cases} 0 & \text{task not started,} \\ 1 & \text{task in progress,} \\ 2 & \text{task completed.} \end{cases} \tag{1}$$

Each task also has a remaining processing time:

$$r_d(t) \in \{0,\dots,\Delta t_d\}. \tag{2}$$

When task d starts, its remaining time is initialized to Δt_d. During execution, it evolves as:

$$r_d(t+1) = \max\{r_d(t) - 1, 0\}. \tag{3}$$

When the remaining processing time reaches zero, the task is completed.

B. Robot Model

Robots execute tasks and require operator supervision. The state of robot j is:

$$q_j(t) \in \mathcal{D} \cup \{0\} \tag{4}$$

where $q_j(t) = d$ indicates that robot j is executing task d, while $q_j(t) = 0$ indicates that the robot is idle. The supervising operator is:

$$y_j(t) \in \mathcal{I} \cup \{0\} \tag{5}$$

where $y_j(t) = i$ indicates that operator i supervises robot j, and $y_j(t) = 0$ means that the robot is idle. When robot j starts executing task d, the robot state evolves as:

$$q_j(t+1) = d, \qquad y_j(t+1) = i.$$

When the task finishes, the robot becomes idle and the supervision link is removed:

$$q_j(t+1) = 0, \qquad y_j(t+1) = 0.$$

We introduce the binary variable:

$$a_{ijd}(t) \in \{0,1\}, \qquad i \in \mathcal{I},\ j \in \mathcal{J},\ d \in \mathcal{D}, \tag{6}$$

where $a_{ijd}(t) = 1$ indicates that operator i starts task d on robot j at time t. The assignment dynamics are:

$$a_{ijd}(t) = 1 \Rightarrow \begin{array}{l} q_j(t+1) = d, \\ y_j(t+1) = i, \\ x_d(t+1) = 1, \\ r_d(t+1) = \Delta t_d \end{array} \tag{7}$$

$$\big(q_j(t) = d \wedge r_d(t) = 1\big) \Rightarrow \begin{array}{l} x_d(t+1) = 2, \\ q_j(t+1) = 0, \\ y_j(t+1) = 0. \end{array} \tag{8}$$

C. Operator Model

The supervision load of operator i is:

$$L_i(t) = \sum_{j=1}^{N} \delta\big(y_j(t) - i\big), \tag{9}$$

which represents the number of robots supervised by operator i.

We define K mental-state clusters indexed by $k \in \mathcal{K} = \{1,\dots,K\}$, corresponding for example to fresh, nominal, and tired conditions. Each operator i is associated with the belief vector:

$$b_i(t) = \big(b_{i1}(t),\dots,b_{iK}(t)\big),$$

with

$$b_{ik}(t) \geq 0, \qquad \sum_{k=1}^{K} b_{ik}(t) = 1, \tag{10}$$

where $b_{ik}(t)$ is the probability that operator i belongs to cluster k.

The belief vector is generated through a fatigue index:

$$f_i(t) \in [0,1], \tag{11}$$

where higher values correspond to higher fatigue. The fatigue evolves according to:

$$\tilde{f}_i(t+1) = f_i(t) + \zeta_{\text{up}} \frac{L_i(t)}{L_{i1}^{\max}} - \zeta_{\text{down}} \left(1 - \frac{L_i(t)}{L_{i1}^{\max}}\right), \tag{12}$$

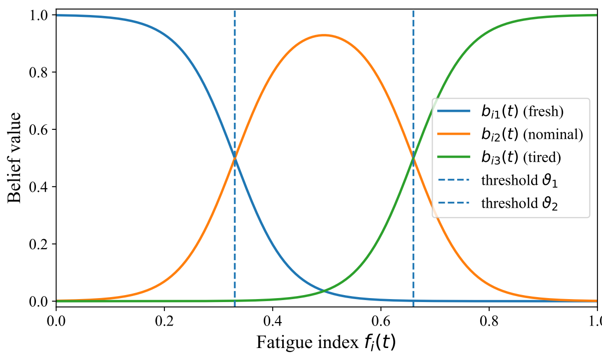

Fig. 1. Mapping from fatigue index $f_i(t)$ to belief vector $b_i(t)$ for $K = 3$ mental-state clusters.

where ζ_{up} controls fatigue accumulation and ζ_{down} models recovery. The value $L_{i1}^{\max}$ is the maximum supervision capacity in the freshest condition. The fatigue index is saturated as:

$$f_i(t+1) = \min\{1, \max\{0, \tilde{f}_i(t+1)\}\}. \tag{13}$$

To obtain the belief vector, let

$$0 = \vartheta_0 < \vartheta_1 < \cdots < \vartheta_K = 1$$

be cluster thresholds and

$$m_k = \frac{\vartheta_{k-1} + \vartheta_k}{2}$$

their midpoints. The belief vector is then computed as:

$$b_{ik}(t) = \frac{\exp\left(-\frac{(f_i(t)-m_k)^2}{2\sigma_f^2}\right)}{\sum_{h=1}^{K} \exp\left(-\frac{(f_i(t)-m_h)^2}{2\sigma_f^2}\right)}. \tag{14}$$

where $\sigma_f > 0$ controls the smoothness of the transition between adjacent clusters. This belief representation can also be updated directly from a BCI or another sensing modality without changing the allocation layer.

IV. Task Allocation Problem

The controller decides, at each time step, which tasks should start, on which robots, and under which operator supervision. The decision variables are the allocation actions $a_{ijd}(t)$. Let T denote the prediction horizon. At each time step τ, decisions are optimized over $\mathcal{H}(\tau) = \{\tau, \tau+1, \ldots, \tau+T-1\}$.

A. Constraints

A task can start only if it has not yet been executed:

$$a_{ijd}(t) \leq \delta\big(x_d(t)\big), \quad \forall i \in \mathcal{I}, j \in \mathcal{J}, d \in \mathcal{D}, t \in \mathcal{H}(\tau). \tag{15}$$

Each task starts at most once over the horizon:

$$\sum_{t=\tau}^{T-1} \sum_{i=1}^{M} \sum_{j=1}^{N} a_{ijd}(t) \leq \delta(x_d(\tau)), \qquad \forall d \in \mathcal{D}. \tag{16}$$

A robot can start a task only if it is idle:

$$\sum_{i=1}^{M} \sum_{d=1}^{D} a_{ijd}(t) \leq \delta\big(q_j(t)\big), \quad \forall j \in \mathcal{J}, t \in \mathcal{H}(\tau). \tag{17}$$

For each operator and mental-state cluster, the supervision limit is:

$$L_{ik}^{\max} \in \mathbb{N}, \qquad 1 \leq L_{iK}^{\max} \leq \cdots \leq L_{i1}^{\max}. \tag{18}$$

Given the belief vector $b_i(t)$, the effective supervision capacity is:

$$\bar{L}_i^{\max}(t) = \sum_{k=1}^{K} b_{ik}(t) L_{ik}^{\max}. \tag{19}$$

This belief-weighted capacity gives a smooth supervision limit and avoids abrupt changes due to mental-state estimation uncertainty. The supervision constraint is:

$$L_i(t) + \sum_{j=1}^{N} \sum_{d=1}^{D} a_{ijd}(t) \leq \bar{L}_i^{\max}(t), \quad \forall i \in \mathcal{I}, t \in \mathcal{H}(\tau). \tag{20}$$

B. Objective Function

The objective combines unfinished-task, fatigue, risk, and overdue costs with a reward for task progress:

$$C(t) = \alpha C_u(t) + \beta C_f(t) + \gamma C_r(t) + \eta C_o(t), \tag{21}$$

where the nonnegative weights $\alpha, \beta, \gamma, \eta$ tune the trade-off between these components.

The unfinished-task cost is:

$$C_u(t) = \sum_{d=1}^{D} p_d \big(1 - \delta(2 - x_d(t))\big). \tag{22}$$

The fatigue cost is:

$$C_f(t) = \sum_{i=1}^{M} \sum_{k=1}^{K} w_k\, b_{ik}(t). \tag{23}$$

The fatigue weights increase with the cluster index:

$$w_k = \Delta w (k-1)^2, \qquad k = 1, \ldots, K.$$

where $\Delta w > 0$ controls the sensitivity to higher fatigue clusters.

The risk associated with assigning tasks to fatigued operators is:

$$C_r(t) = \sum_{i=1}^{M} \sum_{j=1}^{N} \sum_{d=1}^{D} \left(\sum_{k=1}^{K} \lambda_k\, b_{ik}(t) \right) p_d\, a_{ijd}(t), \tag{24}$$

TABLE I
MAIN SIMULATION PARAMETERS.

Symbol	Value	Description
M	3	Number of operators
N	4	Number of robots
D	24	Number of tasks
T	5	Prediction horizon length
T_f	28	Simulation horizon
K	3	Number of mental-state clusters
Δt_d	3	Task processing time
p_d	$U[0,1]$	Task priority distribution
$f_i(0)$	0	Initial operator fatigue

where:

$$\lambda_k = \frac{k-1}{K-1}.$$

Tasks completed after their due date are penalized through:

$$C_o(t) = \sum_{d=1}^{D} p_d\big(1-\delta(2-x_d(t))\big)H(t-\tau_d). \tag{25}$$

To promote progress on high-priority tasks, the reward is:

$$R(t) = \sum_{i=1}^{M}\sum_{j=1}^{N}\sum_{d=1}^{D} p_d\big(1+\kappa H(t-\tau_d)\big)a_{ijd}(t). \tag{26}$$

where $\kappa \geq 0$ increases the reward for tasks already past their due date.

The stage objective is:

$$J(t) = C(t) - \rho R(t). \tag{27}$$

where $\rho \geq 0$ weights the reward term.

C. Rolling-Horizon Optimization

At each decision time τ, the allocation is obtained by solving a finite-horizon optimization problem. This receding-horizon structure is consistent with predictive-control approaches, where decisions are repeatedly updated using the current system state and a finite prediction window [19]. The belief-weighted costs and supervision limits lead to a deterministic mixed-integer program parameterized by the current belief state:

$$\begin{aligned} \min_{\{a_{ijd}(t)\}_{t=\tau}^{\tau+T-1}} \quad & \sum_{t=\tau}^{\tau+T-1} J(t) \\ \text{s.t.} \quad & \text{integrality constraints (1), (2), (4), (5), (6)} \\ & \text{system dynamics (3), (7)–(14),} \\ & \text{system constraints (15)–(20).} \end{aligned} \tag{28}$$

Only the first allocation decision $a_{ijd}(\tau)$ is implemented. At the next time step, the problem is solved again using updated system information. The process stops when all tasks are completed.

Table I shows the parameters used in this work.

V. CASE STUDY

A. Setup and Baseline

The case study considers $M = 3$ operators, $N = 4$ robots, and $D = 24$ tasks. All tasks require $\Delta t_d = 3$ time steps, and the simulation horizon is $\tau = 0, 1, \dots, T_f$, with $T_f = 28$. Task priorities p_d are sampled uniformly in $[0, 1]$, while due dates τ_d are assigned to create time pressure. The operator mental state is modeled using $K = 3$ clusters, corresponding to fresh, nominal, and tired conditions. All operators start in the fresh state. The hyperparameters of the proposed method are tuned using the Optuna library in Python.

The proposed MSA-TA method is compared with four baselines:

- `Greedy`: tasks are selected by priority and urgency. The highest-ranked feasible task is assigned to an idle robot and to the least-loaded feasible operator. This priority-first logic is common in scheduling, but does not guarantee global optimality, especially in resource-constrained settings with task durations and limited resources [20], [21].
- `Uniform`: supervision load is distributed as evenly as possible among operators [22].
- `Random`: feasible tasks are randomly assigned to robots and operators.
- `NoMental`: the mental-state cost term is removed while the same feasibility constraints are kept.

B. Results

The performance is evaluated using four indicators. The first is completed task priority:

$$\sum_{d=1}^{D} p_d\big(\delta(2-x_d(T_f))\big) \tag{29}$$

The second is cumulative operator risk exposure:

$$\sum_{\tau=1}^{T_f} C_r(\tau) \tag{30}$$

The third is the total overdue penalty:

$$\sum_{\tau=1}^{T_f} C_o(\tau) \tag{31}$$

The fourth is the fatigue evolution $f_i(\tau)$ for each operator.

The results are shown in Figs. 2 and 3. Fig. 2a shows that the greedy heuristic achieves the highest completed priority because it directly favors larger p_d. The proposed MSA-TA approach remains close to the greedy strategy and clearly outperforms the uniform and random baselines.

Fig. 2b shows that MSA-TA gives the lowest cumulative operator risk exposure. The random and uniform strategies lead to higher risk, and the greedy strategy also increases risk despite its high completed priority. Fig. 2c shows that greedy performs best on overdue penalties because it explicitly

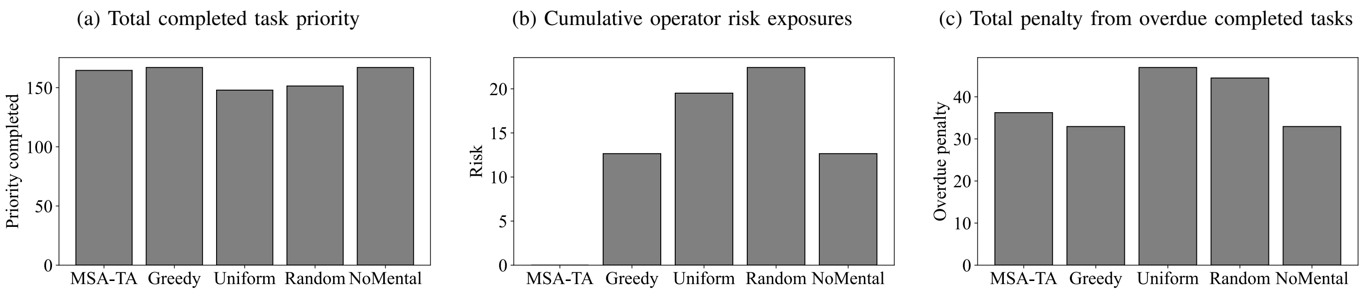

Fig. 2. Comparison of task allocation strategies in terms of system performance.

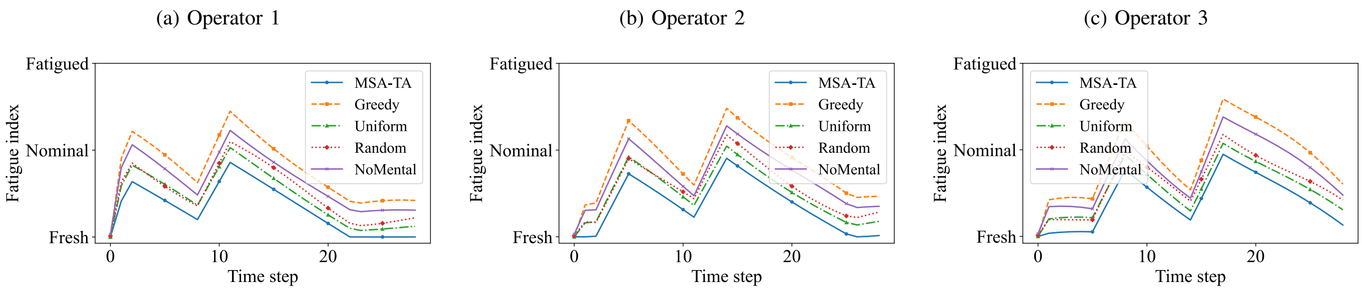

Fig. 3. Mental state dynamics of human operators under different allocation strategies.

prioritizes urgency, while MSA-TA remains competitive and outperforms the random and uniform baselines.

Figs. 3a–3c show that MSA-TA keeps operator fatigue lower and avoids strong peaks compared with the baseline strategies.

C. Discussion

The results show that mental-state awareness reduces risk without severely compromising productivity. This mainly comes from the belief-weighted supervision capacity $\bar{L}_i^{\max}(\cdot)$, which reduces admissible workload when fatigue is likely, and from the risk term, which discourages assigning tasks to fatigued operators.

Baselines that ignore cognitive conditions may concentrate supervision on one operator or assign new tasks when that operator is already fatigued. The fatigue trajectories in Figs. 3a–3c confirm that MSA-TA distributes supervision more safely and reduces fatigue peaks. The same formulation can be applied to larger systems by changing the number of operators, robots, tasks, processing times, priorities, and due dates.

VI. Conclusion

This paper presented a Mental-State Aware Task Allocation (MSA-TA) framework for multi-human multi-robot supervision under time-sensitive workloads. The rolling-horizon formulation represents operator mental state as a belief over discrete clusters and includes this belief in both the objective function and supervision capacity constraints. The mental-state module can be implemented using the load-driven model adopted here or replaced by data-driven estimates, for example from BCI pipelines, without changing the allocation layer. Simulation results show that MSA-TA reduces cumulative operator risk exposure and keeps lower fatigue levels than uniform, random, and greedy baselines, while maintaining competitive priority completion and deadline performance.

Future work will focus on hardware-in-the-loop validation and online mental-state estimation from physiological measurements.

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