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Coordinated decision support for it projects using multi-agent artificial intelligence systems

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ABSTRACT

Relevance: The article examines adaptive resource allocation and task scheduling in information technology project management under stochastic uncertainty. Centralized planning methods often become unstable when resource availability, task priorities or project scope change during execution. **Aim:** The aim of the article is to develop and evaluate a coordinated decision support framework for dynamic information technology projects based on a risk-aware multi-agent architecture. **Objectives:** The study focuses on formalizing the interaction between Project Manager, Task, Resource and Risk agents; defining a utility-based task allocation mechanism; and evaluating the proposed approach under resource disruption and scope creep scenarios. **Methods:** The proposed system uses a decentralized architecture in which autonomous agents negotiate task assignments through a modified Contract Net Protocol and an auction-based coordination mechanism. The utility function combines competence matching, execution cost, accumulated fatigue and risk probability. The weighting coefficients are selected through an expert pairwise comparison procedure based on the Analytic Hierarchy Process. The experimental evaluation was performed using one thousand Monte Carlo simulation iterations on an adapted project scheduling dataset. **Scientific novelty:** The novelty of the study lies in combining risk-aware and fatigue-aware decision logic within multi-agent negotiation for information technology project management. Unlike approaches focused only on time or cost, the proposed framework explicitly considers human workload and assignment risk. **Practical significance:** The framework can support project managers in adaptive re-planning, workload balancing and proactive risk mitigation while preserving the interpretability of task allocation decisions. **Results:** The proposed system achieved a mean project duration of one hundred twenty-four days, compared with one hundred forty-two days for the static critical path baseline, one hundred thirty-five days for the greedy heuristic and one hundred twenty-eight days for the deep reinforcement learning-based scheduler. The standard deviation of project duration decreased to six point two days, and the resource utilization Gini coefficient decreased to zero point one eight. **Conclusions:** The results confirm that decentralized risk-aware multi-agent coordination improves project resilience, schedule predictability and workload balance in dynamic information technology project environments.

Keywords: Multi-agent systems; distributed artificial intelligence; information technology project management; decision support systems; risk-aware resource allocation; project scheduling

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1. INTRODUCTION, FORMULATION OF THE PROBLEM

The modern landscape of Information Technology (IT) project management is characterized by escalating complexity, geographical distribution of teams, and high levels of environmental uncertainty [1]. As IT projects transition from linear, predictable workflows to highly dynamic and iterative processes, traditional Project Management Decision Support Systems (PM-DSS) often struggle to provide real-time, adaptive guidance. The rigid nature of centralized decision-making architecture frequently leads to information bottlenecks and a failure to account for the stochastic nature of resource availability, technical dependencies, and evolving stakeholder requirements [2].

In this context, Multi-Agent Systems (MAS) have emerged as a transformative paradigm for decentralized coordination. By representing project entities – such as human resources, tasks, and risk factors – as autonomous, intelligent agents, MAS

enables a bottom-up approach to problem-solving. Unlike monolithic systems, agents can perceive changes in their environment, interact through negotiation protocols, and reach a consensus that optimizes the project's global utility while respecting local constraints. This flexibility is particularly crucial for IT projects where the rapid pace of change requires immediate reassessment of priorities and resource reallocation [3].Despite the theoretical advantages of MAS, a critical challenge remains in the effective coordination of these autonomous entities. Current literature often overlooks the synchronization between micro-level agent actions and macro-level project objectives, which frequently leads to potential conflicts in resource allocation and strategic misalignment. Furthermore, the lack of integrated frameworks that combine real-time risk mitigation with multi-agent negotiation remains a significant barrier to the widespread adoption of intelligent DSS in the software development industry [4]. Existing models often fail to provide a balance between the autonomy of individual agents and the overarching constraints imposed by project deadlines and budgets [5].

The aim of this study is to develop and evaluate a coordinated decision support framework for dynamic information technology project management based on a risk-aware multi-agent architecture.The research objectives are:

1) analysis of the limitations of centralized scheduling and predictive decision support approaches under stochastic project uncertainty;

2) formalization of the proposed multi-agent framework, including Project Manager, Task, Resource and Risk agents;

3) development of a risk-aware coordination mechanism based on the modified Contract Net Protocol and auction-based negotiation;

4) definition of a multi-factor utility function for task-resource assignment, considering competence matching, execution cost, fatigue level and risk probability;

5) implementation of a simulation environment for adaptive task allocation and dynamic re-scheduling under disruption scenarios;

6) comparative evaluation of RA-MAS against static, heuristic and learning-based scheduling baselines;

7) assessment of the scalability of the proposed coordination protocol with respect to the number of tasks and active agents.

The remainder of this paper is organized as follows: Section 2 reviews traditional, predictive and

agent-based approaches to project scheduling and resource allocation; Section 3 details the proposed multi-agent architecture and the formal mathematical model of coordination; Section 4 presents the simulation environment and experimental setup; Section 5 discusses the results in comparison with static, heuristic and learning-based scheduling baselines; and Section 6 concludes with a summary of findings and limitations.

2. BACKGROUND AND RELATED WORK

The application of Artificial Intelligence (AI) in project management has evolved significantly in recent years, moving from static heuristic algorithms to dynamic, data-driven decision support systems. Modern research increasingly focuses on the ability of systems to adapt to uncertainty, a critical requirement for IT projects characterized by volatile requirements and complex dependencies [6].

2.1. Traditional and Predictive Methods in Project Scheduling

Traditional project management methods, such as the Critical Path Method (CPM), Program Evaluation and Review Technique (PERT), and resource-constrained project scheduling models, are primarily based on centralized planning. These approaches assume that the project manager or planning system has a global view of tasks, dependencies, resource constraints and deadlines. Their main advantage is interpretability: the resulting schedule can be analyzed, justified and communicated to stakeholders. However, in dynamic information technology projects, centralized schedules often become fragile when local disruptions occur, such as resource unavailability, changing priorities or scope creep.

Heuristic and greedy scheduling methods partially address this limitation by enabling faster reallocation of tasks [7]. Nevertheless, they usually optimize short-term availability rather than global project utility. As a result, such methods may reduce idle time but can also overload key specialists, ignore fatigue accumulation and produce unstable schedules under uncertainty.

The relevance of resource reallocation is also emphasized in Agile multi-project environments, where methodological support is required to redistribute resources dynamically under changing project conditions [8].

Recent research has also explored predictive decision support based on artificial intelligence and machine learning. For instance, neural network models can estimate project success, duration or cost by analyzing historical project data. Such predictive tools are useful for risk assessment and early warning, but they usually do not provide an autonomous mechanism for negotiating task reassignment or resolving conflicts between competing resources. Therefore, traditional and predictive approaches remain limited when the project environment requires continuous adaptation and decentralized decision-making.

2.2. Multi-Agent Systems (MAS) in Scheduling and Resource Allocation

In contrast to centralized and predictive approaches, agent-based methods model project execution as a distributed coordination process. In multi-agent systems, project entities such as tasks, resources, risks and managerial constraints can be represented as autonomous agents. Each agent has local knowledge, individual objectives and the ability to communicate with other agents through negotiation or auction-based protocols.

This direction is also supported by studies on multi-agent management of distributed computing environments, where autonomous entities are used to coordinate resource allocation and execution processes in hybrid infrastructures [9].

This paradigm is particularly relevant for dynamic scheduling and resource allocation because it allows the system to react to local events without rebuilding the entire project plan from scratch. Task agents can request proposals, resource agents can evaluate their availability and competence, and risk agents can adjust the expected utility of assignments according to uncertainty.

Pal et al. [10] explored the use of MAS for complex scheduling problems, utilizing negotiation protocols to resolve resource conflicts dynamically. Their work highlights the efficiency of decentralized coordination but notes that communication overhead can increase exponentially with the number of agents.

More recently, the integration of Multi-Agent Reinforcement Learning (MARL) has gained traction. Pu et al. [11] proposed a MARL-based framework for job-shop scheduling, where agents learn optimal policies through interaction with the environment.

This approach allows the system to adapt to unseen scenarios, such as machine breakdowns or sudden task priority changes. Similarly, Shyam et al. [12] developed a decision support mechanism where agents autonomously reallocate resources in real-time, demonstrating superior performance over static algorithms in dynamic environments.

The reviewed studies show that traditional and predictive methods and agent-based methods address different aspects of the scheduling problem. Traditional methods provide a clear global plan but have limited adaptability under stochastic uncertainty. Predictive artificial intelligence models improve estimation and risk forecasting but do not directly perform decentralized resource negotiation. Agent-based methods, in contrast, support autonomous coordination and dynamic reallocation, but many existing solutions are developed for manufacturing, cloud computing or generic scheduling environments rather than for information technology projects with human-centered constraints.

2.3. Research Gap

The comparison of traditional, predictive and agent-based approaches reveals a specific research gap in the context of information technology project management. Centralized scheduling methods, including CPM, PERT and resource-constrained project scheduling models, provide structured planning but insufficiently support real-time adaptation when project conditions change [13]. Predictive artificial intelligence models improve the estimation of duration, cost or risk, but they do not solve the coordination problem itself, since they usually do not determine how tasks should be renegotiated among available resources.

Decision support under incomplete certainty is particularly important for project environments where alternatives must be ranked despite uncertainty in constraints, risks and expected outcomes [14].

Existing multi-agent approaches provide stronger support for decentralized coordination, but most of them focus on generic industrial scheduling, manufacturing systems, cloud computing or job-shop environments. They rarely account for the specific soft constraints of information technology projects, such as developer expertise matching, fatigue accumulation, team workload balance, context switching and the risk of overloading key specialists.

Therefore, the research gap addressed in this study is the lack of a coordinated decision support framework that combines decentralized multi-agent negotiation with risk-aware and fatigue-aware resource allocation for dynamic information technology project environments. The proposed approach aims to bridge this gap by integrating competence matching, risk probability and human workload factors into a unified agent utility function.

3. METHODOLOGY AND SYSTEM ARCHITECTURE

This study proposes a decentralized, multi-agent framework designed to address the dynamic nature of IT project management. Unlike traditional centralized scheduling systems (e.g., RCPSP solvers), the proposed architecture models the project environment as a stochastic ecosystem where autonomous agents negotiate to optimize resource allocation under uncertainty [15].

3.1. Architectural Design

The system architecture is built upon the FIPA (Foundation for Intelligent Physical Agents) standards, ensuring interoperability and scalability [16]. The system comprises four distinct agent types, each possessing specific ontological knowledge and behavioral goals:

– Project Manager Agent A_{PM} – the global optimizer responsible for high-level milestone tracking and conflict resolution. It decomposes the Work Breakdown Structure (WBS) into auctionable tasks;

– Task Agents A_{Task} – represent individual units of work (e.g., «Develop API Endpoint»). Their goal is to be completed as quickly as possible within budget;

– Resource Agents A_{Res} – epresent team members (Developers, QA, DevOps). Their goal is to maximize utility (work on suitable tasks) while minimizing «burnout» (overload) and context switching;

– Risk Agents A_{Risk} – specialized monitoring agents that calculate the probability of failure for specific tasks based on historical data and current system metrics.

Fig. 1 illustrates the «Risk-Aware Contract Net Protocol» designed for this study.

3.2. Mathematical Formalization

To ensure the scientific validity of the proposed method, we define the coordination problem formally.

Let $\mathcal{T} = \{t_1, t_2, \ldots, t_n\}$ be the set of tasks, and $\mathcal{R} = \{r_1, r_2, \ldots, r_m\}$ be the set of available resources. Each task t_i requires a specific skill vector $S_t \in \mathbb{R}^k$. Each resource r_j possesses a competency vector $C_r \in \mathbb{R}^k$ [17].

3.2.1. The Competency Matching Function

The suitability of a resource r_j for a task t_i is defined by the cosine similarity between the required skill vector and the resource's competency vector:

$$Match(t_i, r_j) = \frac{S_{t_i} \cdot C_{r_j}}{\|S_{t_i}\| \|C_{r_i}\|}. \qquad (1)$$

3.2.2. The Agent Utility Function

A critical innovation of this framework is the inclusion of a Fatigue Factor ϕ and a Risk Factor ρ in the utility function [18]. A Resource Agent r_j calculates the bid utility U_{ij} for task t_i as follows:

$$U_{ij} = \alpha \cdot Match(t_i, r_j) - \beta \cdot Cost(t_i) - \gamma \cdot \phi_j(t) - \delta \cdot \rho_{ij}, \qquad (2)$$

where α, β, γ and δ are non-negative weighting coefficients that determine the relative importance of competence matching, execution cost, fatigue and risk, respectively. In the proposed framework, these coefficients are not learned automatically by a machine-learning algorithm. They are selected before the simulation by the project manager or an expert group using an Analytic Hierarchy Process (AHP)-based pairwise comparison procedure, which is a common multi-criteria decision-making approach for deriving weights from expert judgments [19].

The selection procedure includes three steps. First, the expert group defines the priority profile of a concrete information technology project, for example time-to-market, quality-oriented delivery, risk-critical execution or sustainable workload distribution. Second, the relative importance of the four criteria – competence matching, cost, fatigue and risk – is evaluated through pairwise comparisons. Third, the obtained priority vector is normalized so that $\alpha + \beta + \gamma + \delta = 1$ and then used in the utility function. If the expert judgments are inconsistent, the pairwise comparison matrix is revised before the coefficients are accepted.

Thus, α, β, γ and δ are configurable decision-support parameters rather than trainable model parameters. This design preserves the interpretability of the proposed multi-agent coordination mechanism: the project manager can explicitly control whether the system should prioritize faster task completion, lower execution cost, reduced

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fatigue of key specialists or lower assignment risk. The fatigue factor $\phi_j(t)$ denotes the current accumulated fatigue of resource r_j normalized to the interval [0; 1], while ρ_{ij} denotes the risk probability for assigning task t_i to resource r_j as provided by the Risk Agent.

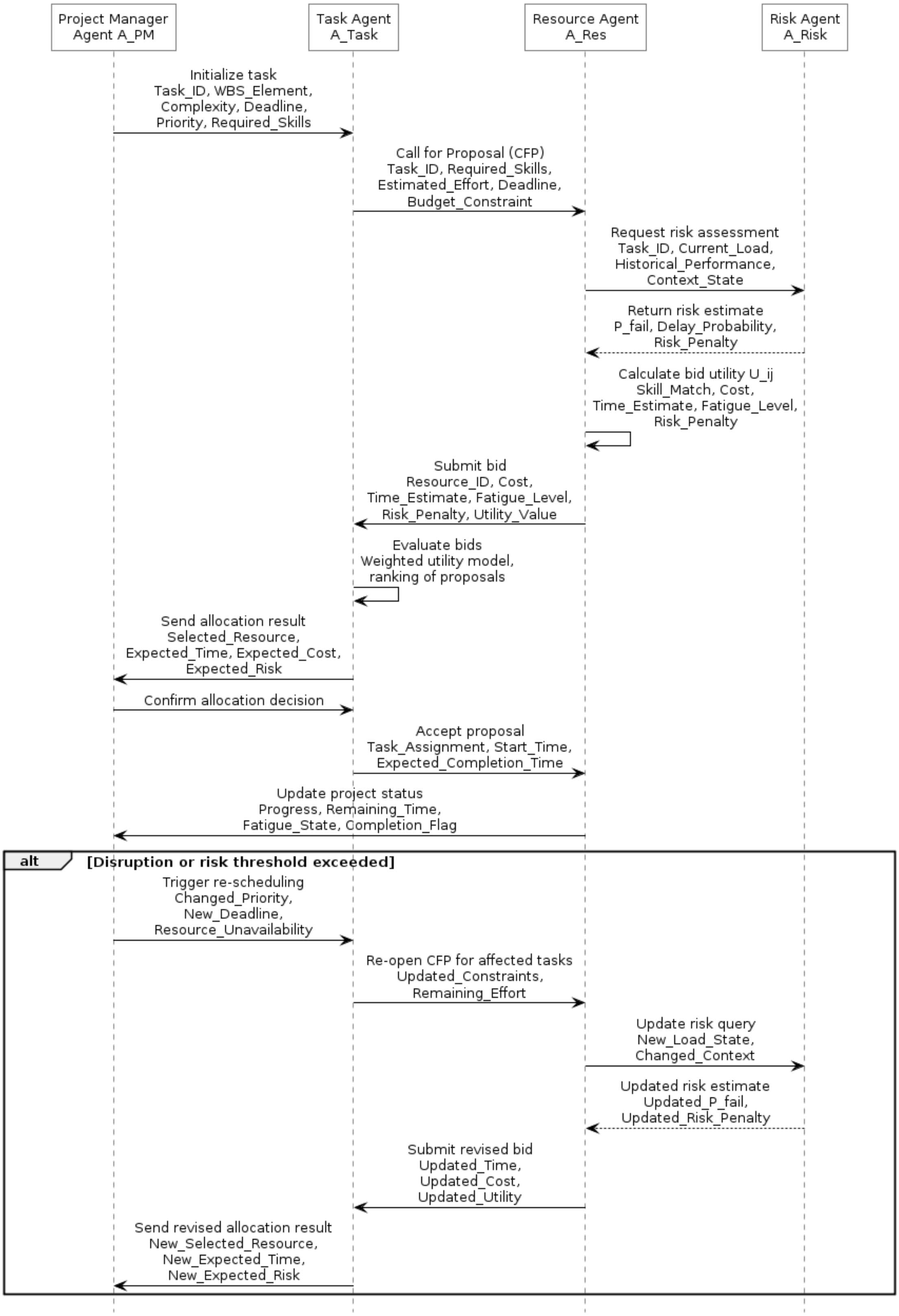

Fig. 1. **Illustration of the Risk-Aware Contract Net Protocol**

Source: **compiled by the authors**

3.2.3. The Global Optimization Objective

The system aims to maximize the collective utility of the project execution E:

$$Maximize\ E = \sum_{i=1}^{n}\sum_{j=1}^{m} x_{ij} \cdot U_{ij}. \tag{3}$$

Subject to:

$\sum_{j=1}^{m} x_{ij} = 1,\ \ \forall i \in \{1 \dots n\}$ – each task is assigned to exactly one resource. (4)

$\sum_{j=1}^{m} x_{ij} \cdot Dur(t_i) \leq Capacity(y_j)$ – no resource is allocated beyond physical time. (5)

3.3. Dynamic Re-Scheduling Algorithm

Unlike static PERT charts, the MAS utilizes a dynamic trigger mechanism [20]. Re-negotiation is initiated if:

– $\Delta\rho_{ij} > \epsilon$ (risk probability increases beyond threshold);

– a new high-priority task t_{new} enters the backlog.

The algorithm uses a Vickrey-Clarke-Groves (VCG) mechanism to ensure truthful bidding, preventing agents from «gaming» the system to avoid difficult tasks.

3.4. Simulation & Visualization Logic

To validate the methodology, we simulated a scenario with tasks and developers with heterogeneous skill sets [21]. The simulation compares three approaches:

– Greedy Allocation – assigns tasks to the first available resource without global workload balancing or risk-aware evaluation;

– DRL-based Scheduler – uses a learned scheduling policy to assign tasks according to the current project state, resource availability and disruption conditions;

– MAS-Coordinated Allocation (Proposed RA-MAS) – uses the explicit utility function defined in Eq. (2), which considers competence matching, execution cost, fatigue level and risk probability.

Fig. 2 contrasts the resource load distribution of the Greedy baseline, the DRL-based Scheduler and the proposed RA-MAS approach. The comparison shows that the DRL-based Scheduler improves load distribution compared with the greedy heuristic, while RA-MAS provides the most balanced allocation due to explicit fatigue-aware and risk-aware negotiation.

3.5. Interpretation of Methodology

The graphical results (Fig. 2) demonstrate that the mathematical model defined in Section 3.2 successfully reduces workload imbalance. The minimization of load variance directly correlates with reduced overload risk and confirms the effectiveness of the proposed agent-based negotiation protocol.

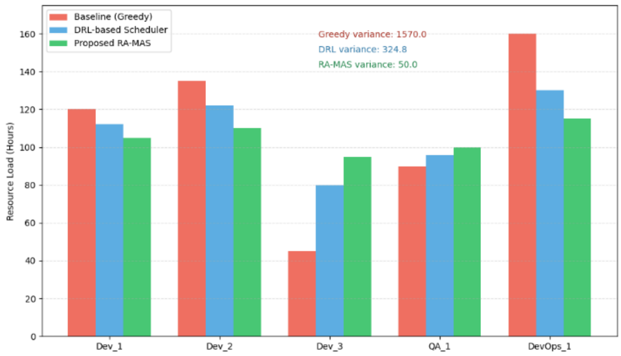

Fig. 2. **Comparison of Resource Load Balancing: Greedy vs DRL vs RA-MAS**

***Source:* compiled by the authors**

4. IMPLEMENTATION AND SIMULATION

To validate the efficiency of the proposed Coordinated Decision Support Framework, we developed a multi-agent simulation environment representing a typical software development lifecycle (SDLC) [22]. The simulation focuses on measuring the system's adaptability to stochastic perturbations, such as resource unavailability and dynamic scope changes.

4.1. Simulation Environment

The experimental prototype was implemented using Python 3.9 leveraging the Mesa framework for agent-based modeling (ABM). The choice of Mesa allows for a modular representation of the interaction between Task Agents and Resource Agents within a discrete-time space, where each step t represents 4 hours of real-world project time [23].

The computing environment consisted of a high-performance cluster (AWS EC2 t3.2xlarge instance) to run Monte Carlo simulations (N = 1000 iterations per scenario) to ensure statistical significance of the results.

4.2. Experimental Setup and Dataset

The simulation models a «Virtual IT Department» consisting of heterogeneous resources. We utilized a modified version of the PSPLIB (Project Scheduling Problem Library) J30 and J60 datasets, adapted for IT specifics by adding «Skill

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Requirements» (Backend, Frontend, DevOps) to the tasks [24-26].

The Risk Agent was configured to inject probabilistic delays based on a Poisson distribution λ = 0.2 for task completion, simulating the uncertainty inherent in debugging and integration phases.

Table 1. **Agent Configuration Parameters**

Agent Type	Quantity	Skill Vector S	Fatigue Threshold ϕ_{max}	Cost Rate
Senior Dev	2	[0.9, 0.8, 0.5]	0.85 (Resilient)	$80
Middle Dev	4	[0.6, 0.6, 0.3]	0.70 (Standard)	$45
Junior Dev	3	[0.3, 0.4, 0.1]	0.50 (Fragile)	$25
QA Engineer	2	[0.1, 0.1, 0.9]	0.75	$35

Source: **compiled by the authors**

The Risk Agent was configured to inject probabilistic delays based on a Poisson distribution $\lambda = 0.2$ for task completion, simulating the uncertainty inherent in debugging and integration phases.

4.3. Simulation Scenarios

We designed three distinct scenarios to stress-test the coordination protocol [27]:

– baseline (Static Environment) – no external disruptions. Tasks are processed based on the initial plan generated by the Critical Path Method (CPM);

– scenario A (Resource Disruption) – a «Bus Factor» event where a Senior Developer agent becomes unavailable at t = 30 % of project completion;

– scenario B (Scope Creep) – injection of 15 % new high-priority tasks at t = 50 %, requiring immediate re-negotiation of the backlog.

4.4. Implementation Logic (Coordination Algorithm)

The core logic of the agent interaction during the simulation follows the specific Re-negotiation Loop. Below is the pseudocode representing the decision-making process within the simulation step.

Algorithm 1: Multi-Agent Dynamic Re-Scheduling
Input: Set of Pending Tasks T, Set of Resources R
Output: Allocation Matrix X

```
for each simulation_step t do
   Update Risk_Probabilities(T) based on historical_velocity
   Detect Events (Disruption OR New_Task OR Delay > Threshold)
   if Event_Detected then
      Trigger "Auction_Phase"
      for each task t_i in Unassigned_T do
         Broadcast CFP (Call For Proposal) to R
         for each resource r_j in R do
            Calculate Utility U_ij = Skill_Match - Fatigue_Cost - Risk_Penalty
            Submit Bid(U_ij, Time_Est)
         end for
         Winner r_best <- Select Max(Bid) using VCG_Mechanism
         Assign t_i to r_best
         Update r_best.Schedule and r_best.Fatigue
      end for
   else
      Continue execution of current assignments
   end if
end for
```

4.5. Comparative Metrics

To quantify the «success» of the MAS approach, we track the following Key Performance Indicators (KPIs) [22]:

– makespan (project duration) – the total time required to complete all tasks;

– resource utilization variance (σ^2_{util}) – indicates how evenly the work is distributed;

– adaptation latency – the computational time (in seconds) required to stabilize the schedule after a disruption.

4.6. Visual Analysis of Simulation Results

To evaluate resilience, Fig. 3 illustrates the project's burn-down trajectory during a disruption event, highlighting the MAS framework's ability to recover velocity through autonomous re-negotiation compared to the permanent stagnation observed in the static baseline [28], [29], [30].

5. RESULTS AND DISCUSSION

This section presents the empirical results obtained from the simulations described in Section 4.

The performance of the proposed Risk-Aware Multi-Agent System (RA-MAS) was evaluated against three control baselines:

– baseline A (CPM/Static) – a traditional Critical Path Method approach where the schedule is fixed at the initial planning stage and is not dynamically renegotiated after disruptions;

– baseline B (Greedy Heuristic) – a dynamic but non-coordinated approach where available tasks are assigned to the first available free resource without negotiation, risk assessment or fatigue-aware balancing;

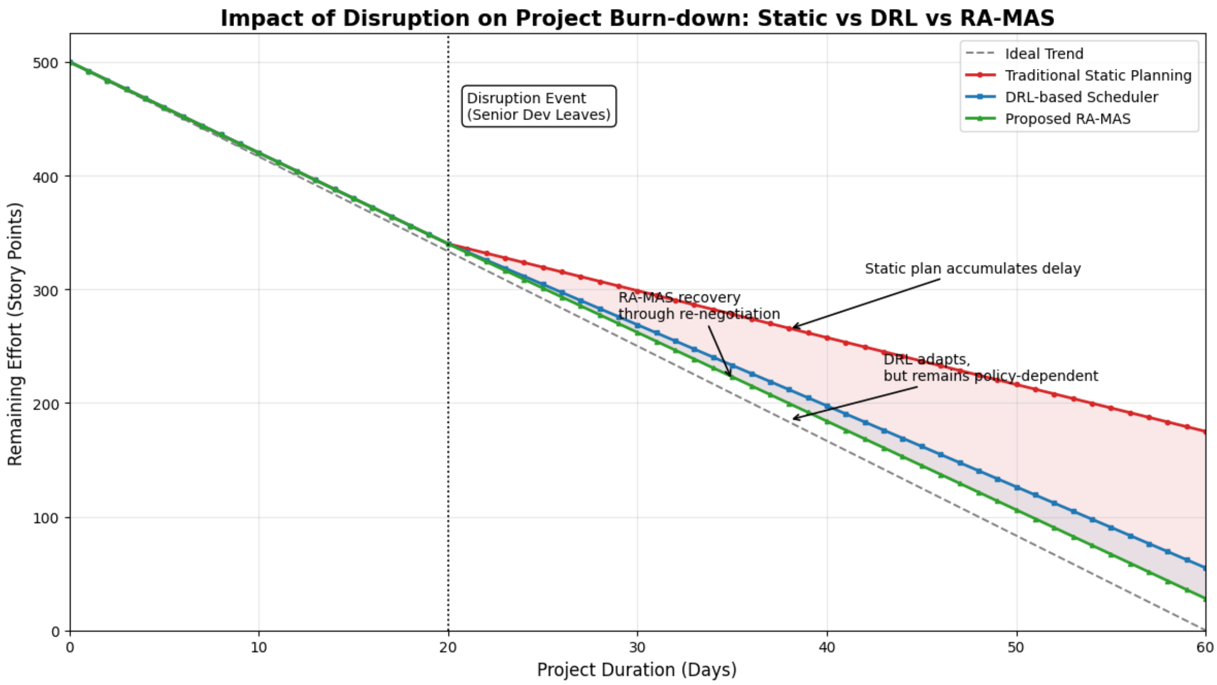

Fig. 3. **Impact of Disruption on Project Burn-down: Static vs DRL vs RA-MAS**
Source: **compiled by the authors**

– baseline C (DRL-based Scheduler) – a deep reinforcement learning scheduler inspired by the approach described in [12], where a learned scheduling policy is used to solve resource-constrained project scheduling problems under resource disruptions. In this baseline, task-resource assignments are selected according to the current project state, including remaining task duration, resource availability, disruption events and risk-related indicators. In contrast to the proposed RA-MAS, the DRL-based approach relies on a trained policy, while RA-MAS uses explicit utility-based negotiation and therefore provides more transparent decision logic for project managers.

The results are analyzed across three key dimensions: Time Efficiency (Makespan), Resource Stability, and Computational Overhead.

5.1. Impact on Project Duration (Makespan)

We ran 1000 Monte Carlo iterations for each scenario. Fig. 4 illustrates the distribution of project completion times under Scenario B, which combines scope creep and resource disruption. The box plot comparison highlights the difference between static, heuristic, learning-based and agent-based coordination approaches in terms of project duration stability.

As observed, Baseline A (CPM) exhibits the widest distribution of completion times, with a mean makespan of 142 days and a standard deviation of 18.4 days. This confirms the fragility of static plans under disruption conditions: when a key resource becomes unavailable or new high-priority tasks are introduced, the original schedule cannot adapt effectively. Baseline B (Greedy) improves the mean duration to 135 days and reduces variance, but its local assignment logic still leads to unstable results because it does not consider global workload balance, risk probability or fatigue accumulation.

Baseline C (DRL-based Scheduler) demonstrates better adaptability than CPM and Greedy baselines. The learned scheduling policy reduces the mean makespan to 128 days and lowers the standard deviation to 8.9 days. This indicates that learning-based scheduling can respond more effectively to dynamic project states when the training scenarios are representative. However, the DRL-based approach still depends on the quality of the training process and provides limited interpretability of individual allocation decisions.

In contrast, the proposed RA-MAS achieved the lowest mean makespan of 124 days, corresponding to a 12.6 % reduction compared to CPM. More importantly, RA-MAS also demonstrated the lowest variance, with a standard deviation of 6.2 days. This result confirms that the proposed risk-aware negotiation protocol not only shortens the expected project duration, but also improves schedule predictability. Compared with the DRL-based scheduler, RA-MAS provides slightly better time performance while preserving explicit decision logic based on competence matching, execution cost, fatigue level and risk probability.

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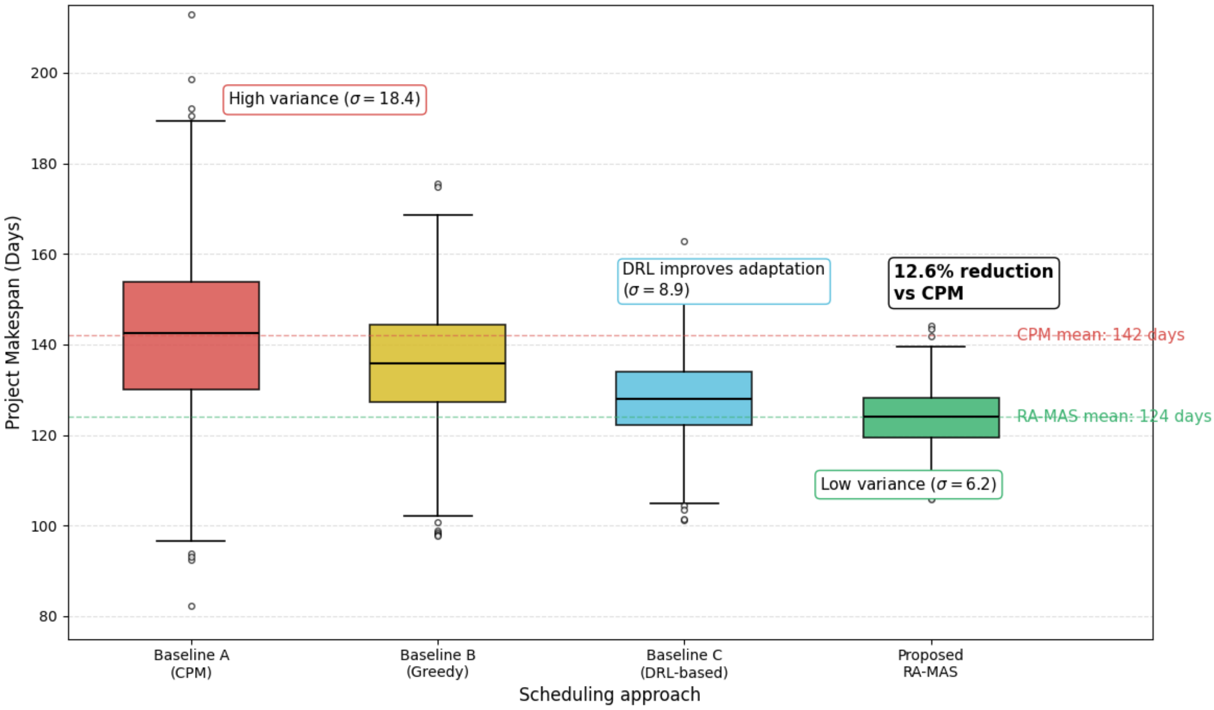

Fig. 4. **Project completion time distribution showing the reduced makespan and variance achieved by RA-MAS compared with CPM, Greedy and DRL-based scheduling baselines**

***Source:* compiled by the authors**

5.2. Resource Utilization and Load Balancing

Efficiency is not solely about speed; it is also about the sustainability of the team's workload. We utilized the Gini Coefficient G to measure the inequality of resource distribution, where $G = 0$ represents perfect equality and $G = 1$ represents maximal inequality (e.g., one developer doing all the work).

The Gini coefficient is calculated using the following formula:

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left|x_i - x_j\right|}{2n^2\bar{x}}. \quad (6)$$

The data in Table 2 provide a broader comparison of the proposed RA-MAS with static, heuristic and learning-based scheduling approaches. While the Greedy approach keeps resources busy, it leads to a high Gini coefficient of 0.35, indicating that senior developers are often overloaded while juniors remain underutilized. The DRL-based scheduler improves both makespan and workload distribution compared to CPM and Greedy baselines; however, it requires preliminary training and its allocation logic is less transparent for project managers. The proposed RA-MAS, utilizing the utility function defined in Eq. (2), achieves the most balanced workload distribution by explicitly considering fatigue and risk factors, resulting in the lowest Gini coefficient of 0.18 and the lowest overload frequency.

Table 2. **Comparative Analysis of Resource Utilization Metrics**

Metric	Baseline A CPM/Static	Baseline B Greedy	Baseline C DRL-based Scheduler	Proposed
Mean makespan, days	142	135	128	124
Standard deviation of makespan, days	18.4	12.7	8.9	6.2
Mean idle time, %	18.4	12.1	10.2	8.5
Overload frequency	N/A	22 % of tasks	9 % of tasks	4 % of tasks
Gini coefficient of resource utilization	0.42	0.35	0.24	0.18
Adaptation latency after disruption, s	0.8	1.4	3.7	2.1
Critical path failure probability	0.31	0.26	0.19	0.17
Need for preliminary training	No	No	Yes	No

***Source:* compiled by the authors**

The comparison shows that the DRL-based scheduler performs better than the static and greedy baselines under disruption scenarios. However, the proposed RA-MAS demonstrates the best overall results in terms of mean makespan, schedule stability, workload balance and overload reduction. The DRL-based scheduler achieves competitive adaptability, but this result depends on the availability of representative training scenarios and a properly defined reward function. In contrast, RA-MAS does not require a preliminary training stage and keeps the allocation logic explicitly interpretable through competence matching, execution cost, fatigue level and risk probability.

5.3. Discussion: The Cost of Coordination

A common criticism of multi-agent systems is the computational and communication overhead required for agent negotiation. In the proposed RA-MAS architecture, this overhead is mainly caused by Call for Proposal broadcasting, bid calculation, risk estimation requests and winner selection in the auction-based coordination mechanism. Therefore, an additional scalability experiment was conducted to verify whether the proposed system remains practically applicable when the number of tasks and agents increases.

In this experiment, the number of project tasks was gradually increased from 50 to 1000. For each configuration, the number of Resource Agents was scaled proportionally to the task set size, while the Project Manager Agent and Risk Agent remained fixed. The measured value was the adaptation latency, defined as the time required to generate a new task-resource allocation after a disruption event. Each configuration was executed 30 times, and the average value was used for the scalability analysis.

Table 3. **Scalability analysis of RA-MAS rescheduling latency**

Number of project tasks	Number of Resource Agents	Total number of active agents	Mean number of negotiation messages	Mean re-scheduling time, s	Standard deviation, s
50	8	60	1,650	0.31	0.04
100	12	114	4,900	0.72	0.09
200	20	222	16,200	2.15	0.21
500	40	542	80,500	10.84	0.88
1000	80	1082	321,000	42.70	3.95

***Source:* compiled by the authors**

As shown in Table 3, the re-scheduling time increases non-linearly with the number of tasks and active agents. This behavior is expected because the negotiation mechanism requires interaction between Task Agents, Resource Agents and the Risk Agent. However, even for the largest tested configuration with 1000 tasks and 1082 active agents, the mean re-scheduling time remained below one minute. This result confirms that the proposed RA-MAS does not become computationally infeasible at the considered scale and can be used for interactive decision support in large information technology projects.

The communication overhead also remains controlled because the agents do not communicate in a fully connected manner. Instead, the main communication paths are limited to Task Agent – Resource Agent – Risk Agent interactions and the final reporting of allocation results to the Project Manager Agent. Therefore, the number of messages grows primarily with the number of task-resource proposal evaluations rather than with all possible pairwise interactions between agents.

5.4. Strategic Implications for IT Management

The obtained results refine the initial hypothesis of this study: decentralized utility-driven coordination is more resilient than centralized static planning in stochastic project environments and remains competitive with modern learning-based scheduling approaches. The comparison with CPM/Static, Greedy Heuristic and DRL-based Scheduler baselines demonstrates that RA-MAS provides not only shorter project duration, but also better workload balance, lower overload frequency and more transparent decision logic.

The strategic implications for information technology project management can be summarized as follows:

– resilience over static optimality – while CPM produces a clear initial project plan, this plan becomes fragile when resource disruption or scope creep occurs. RA-MAS does not rely on a fixed schedule; instead, it continuously supports task reallocation through agent negotiation and risk-aware utility evaluation;

– interpretability compared with learning-based scheduling – the DRL-based scheduler demonstrates strong adaptability, but its decisions depend on a learned policy and are less transparent for project managers. In contrast, RA-MAS explains each allocation decision through explicit factors: competence matching, execution cost, fatigue level and risk probability;

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– risk mitigation – the inclusion of the Risk Agent allows the system to reduce the probability of critical path failure by considering task-specific and resource-specific risk estimates during negotiation. This transforms risk assessment from a separate monitoring activity into an active component of resource allocation;

– human-centric project management – by explicitly modeling fatigue in the utility function, the system acts not only as a scheduler, but also as a workload balancing mechanism. This is especially important for information technology projects, where overload of key specialists may lead to delays, quality degradation and burnout;

– practical scalability – the scalability experiment confirms that the communication overhead of the proposed coordination protocol remains acceptable when the number of tasks and active agents increases. Therefore, RA-MAS can be considered suitable for interactive decision support in medium and large dynamic project environments.

CONCLUSIONS

This study proposed and evaluated a Risk-Aware Multi-Agent System (RA-MAS) for coordinated decision support in dynamic information technology projects. The framework uses Project Manager, Task, Resource and Risk agents that negotiate task allocation through a modified Contract Net Protocol and auction-based coordination mechanism. Unlike static scheduling methods, the proposed approach explicitly considers competence matching, execution cost, fatigue level and risk probability in the utility function.

The experimental evaluation was conducted through Monte Carlo simulation under disruption scenarios, including resource unavailability and scope creep. RA-MAS was compared with CPM/Static, Greedy Heuristic and DRL-based Scheduler baselines. The proposed approach achieved the lowest mean project makespan of 124 days, compared with 142 days for CPM/Static, 135 days for Greedy Heuristic and 128 days for the DRL-based Scheduler. It also demonstrated the lowest standard deviation of makespan, 6.2 days, which confirms higher schedule stability under uncertainty.

The results also showed improved workload balance. The Gini coefficient of resource utilization decreased from 0.35 in the Greedy baseline to 0.18 in RA-MAS, while overload frequency was reduced to 4 % of tasks. Compared with the DRL-based Scheduler, RA-MAS provides competitive performance without requiring a preliminary training stage and keeps the allocation logic interpretable for project managers.

The scalability analysis confirmed that the coordination protocol remains practically applicable as the number of tasks and active agents increases. Although re-scheduling time grows non-linearly, it remains acceptable for interactive decision support. The main limitation of the study is the use of adapted PSPLIB data and a simplified representation of human communication; therefore, validation on real software project data remains necessary.

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Скоординована підтримка прийняття рішень в ІТ-проєктах із використанням мультиагентних систем штучного інтелекту

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АНОТАЦІЯ

Актуальність: У статті розглядається проблема адаптивного розподілу ресурсів і планування завдань в управлінні проєктами у сфері інформаційних технологій в умовах стохастичної невизначеності. Централізовані методи планування часто втрачають стабільність, коли під час виконання проєкту змінюються доступність ресурсів, пріоритети завдань або обсяг робіт. **Метою статті:** є розроблення та оцінювання скоординованого підходу до підтримки прийняття рішень для динамічних проєктів у сфері інформаційних технологій на основі мультиагентної архітектури з урахуванням ризиків. **Завдання:** Дослідження спрямоване на формалізацію взаємодії агентів керування проєктом, завдань, ресурсів і ризиків; визначення механізму розподілу завдань на основі функції корисності; оцінювання запропонованого підходу в сценаріях порушення доступності ресурсів і неконтрольованого розширення обсягу робіт. **Методи:** Запропонована система використовує децентралізовану архітектуру, у якій автономні агенти узгоджують призначення завдань за допомогою модифікованого протоколу контрактної мережі та аукціонного механізму координації. Функція корисності поєднує відповідність компетенцій, вартість виконання, накопичену втому та ймовірність ризику. Вагові коефіцієнти обираються за допомогою експертної процедури попарного порівняння на основі методу аналізу ієрархій. Експериментальне оцінювання виконано за допомогою однієї тисячі ітерацій імітаційного моделювання Монте-Карло на адаптованому наборі даних календарного планування проєктів. **Наукова новизна:** полягає в поєднанні логіки прийняття рішень з урахуванням ризиків і втоми в межах мультиагентних переговорів для управління проєктами у сфері інформаційних технологій. **Практична значимість:** Запропонований підхід може підтримувати керівників проєктів під час адаптивного перепланування, балансування навантаження та проактивного зниження ризиків. **Результати:** Запропонована система досягла середньої тривалості проєкту сто двадцять чотири дні порівняно зі ста сорока двома днями для статичного базового методу критичного шляху, ста тридцятьма п'ятьма днями для жадібної евристики та ста двадцятьма вісьмома днями для планувальника на основі глибокого навчання з підкріпленням. Стандартне відхилення тривалості проєкту зменшилося до шести цілих двох десятих дня, а коефіцієнт Джині використання ресурсів – до нуля цілих вісімнадцяти сотих. **Висновки:** Отримані результати підтверджують, що децентралізована мультиагентна координація з урахуванням ризиків підвищує стійкість проєкту, передбачуваність розкладу та збалансованість навантаження.

Ключові слова: мультиагентні системи; розподілений штучний інтелект; управління проєктами у сфері інформаційних технологій; системи підтримки прийняття рішень; розподіл ресурсів з урахуванням ризиків; календарне планування проєктів

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