ISSN: 2096-3246
Volume 58, Issue 01, 2026

ADDRESSING SCALABILITY CHALLENGES IN ARTIFICIAL SUPERINTELLIGENCE THROUGH A HIERARCHICAL MULTI-AGENT REINFORCEMENT LEARNING ARCHITECTURE

Kamala Challa[1], Ranjith Kumar Chinnam[2], B P N Madhu Kumar[3], Kallepalli Rohit Kumar[4], N S R Phanindra Kumar[5], D. Bhavana[6], Nidal Al Said[7]
[1]Department of IT, VNR VJIET, Bachupally, Hyderabad, Telangana, India.
Email: kamalachalla@gmail.com
[2]Assistant Professor, Department of Artificial Intelligence and Machine Learning, Aditya University, Surampalem, Andhra Pradesh, India. Email: ranjith61ch@gmail.com
[3]Professor, Computer Science and Engineering, Swarnandhra College of Engineering and Technology, Seetharampuram, Narsapur, Andhra Pradesh 534280, India.
Email: bpnmadhukumar@gmail.com
[4]Associate Professor, Department of Computer Science and Engineering, Vignan's Institute of Information Technology, Visakhapatnam, Andhra Pradesh, India.
Email: dr.rohithkumar@vignaniit.edu.in
[5]Associate Professor, Department of IT, Aditya Institute of Technology and Management (AITAM), K.Kotturu, Tekkali, Srikakulam, Andhra Pradesh 532201, India.
Email: phanindra.nsr@gmail.com
[6]Associate Professor, Department of Electronics and Communications Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur District, Andhra Pradesh, India.
Email: bhavanaece@kluniversity.in
[7]Associate Professor of Information Technology, College of Mass Communication, Ajman University, United Arab Emirates. Email: n.alsaid@ajman.ac.ae

Abstract

Artificial Super Intelligence (ASI) systems need scalable and efficient decision-making models for effective functioning in complex and dynamic environments. However, existing reinforcement learning approaches have problems such as high computational complexities, low convergence rates, and poor coordination among multiple agents. Thus, this paper proposes a novel Hierarchical Multi-Agent Reinforcement Learning framework coupled with hierarchical multi-agent system architecture. The proposed framework utilizes knowledge about the environment to minimize the search space and stability in learning. Additionally, the hierarchical architecture improves coordination among agents at global, intermediate, and local levels. The system is tested using simulation techniques under artificial environment conditions. The proposed method is implemented using PYTHON software. The experimental results show that the proposed framework improves scalability by 65% to 97%, convergence rate by 30% to 98%, and computational efficiency by 60% to 92%. The experimental results validate that the proposed framework improves scalability and decision-making performance in intelligent systems. This paper emphasizes the benefits of using physics-informed learning coupled with hierarchical multi-agent reinforcement learning for future ASI applications.

Keywords : Artificial Superintelligence, Physics-Informed Multi-Agent Reinforcement Learning,

1. Introduction

Artificial Super intelligence (ASI) is the next level of evolution of intelligent systems, in which machines are expected to outperform human intelligence in complex reasoning, decision-making, and problem-solving [1-2]. With the advent of modern intelligent systems into areas such as autonomous infrastructure, smart cities, and large-scale cyber-physical systems, the requirement for scalable and adaptive intelligence architectures is becoming more and more critical. Conventional artificial intelligence architectures are often not capable of dealing with the massive state spaces, complex interactions, and coordination issues involved in such systems [3]. In this background, reinforcement learning has emerged as a promising approach for training autonomous agents to learn optimal policies by interacting with complex systems [4]. Moreover, multi-agent reinforcement learning (MARL) allows multiple intelligent agents to collaborate and exchange knowledge, which is very useful in large-scale intelligent systems where distributed decision-making is necessary [5].

However, despite these improvements, there are still some important challenges that restrict the scalability and efficiency of the current architectures designed for ASI [6-7]. Traditional reinforcement learning architectures tend to face problems such as the state-action space explosion, slow convergence, and high computational complexity when applied to large-scale environments [8]. In addition to these, in multi-agent environments, there are some other problems such as non-stationarity in learning dynamics, inefficient communication among agents, and coordination conflicts in cooperative decision-making [9]. Furthermore, flat multi-agent architectures do not have hierarchical control structures, which cause inefficient task decomposition and resource usage [10]. These factors considerably restrict the development of scalable superintelligent systems that can work efficiently in complex

To overcome these issues, this study proposes a hierarchical multi-agent reinforcement learning framework that aims to improve the scalability and coordination of Artificial Superintelligence systems [11]. The proposed method presents a multi-level agent hierarchy that distinguishes global planning, coordination, and local execution tasks. The high-level agents are responsible for strategic decision-making and task assignment, while the intermediate agents are responsible for group coordination, and the low-level agents are responsible for environment-dependent actions [12]. By combining hierarchical learning techniques with distributed reinforcement learning methods, the proposed solution can decrease computational complexity, stabilize the learning process, and improve cooperative behavior among agents [13-14]. The proposed framework finally seeks to offer a scalable and efficient solution for the development of next-generation intelligent systems that can handle the increasing requirements of Artificial Superintelligence applications [15].

Objective of this Work

- In order to examine the scalability challenges associated with ASI systems
- In order to develop a hierarchical multi-agent RL model
- In order to evaluate the system performance by means of simulation
- In order to improve the coordination and learning efficiency

2. Literature survey

Several research works presented in the literatures were based on Artificial Super intelligence through a Hierarchical Multi-Agent. Some of the works are reviewed here, In 2026, Lin et al.[11] have introduced a scalable multi-agent deep reinforcement learning framework that integrated suboptimal human knowledge was proposed to enhance the efficiency of learning in a large number of agents. The primary goal of the proposed research work was to overcome the scalability problem in the MADRL framework by injecting human knowledge into the learning process. The proposed research work utilized natural language-based knowledge integration and knowledge mapping techniques, which were tested in the StarCraft Multi-Agent Challenge environment. Nevertheless, the proposed research work was primarily dependent on human knowledge guidance

In 2023, Scotty E et al,[12] have suggested an scalable hierarchical reinforcement learning (HRL) agent architecture for intelligent decision-making in large-scale combat simulation environments was designed. The primary goal was to improve the performance of reinforcement learning agents in long-horizon and complex wargaming problems. The research work utilized hierarchical reinforcement learning together with a dynamic abstraction engine to improve learning scalability and decision-making efficiency. Nevertheless, the method had some challenges in realizing fully human-level performance in highly complex and dynamic combat environments.

In 2024, Geng et al.[13] have suggested a hierarchical multi-agent model called HiSOMA to effectively address long-horizon multi-agent decision problems. The primary aim was to enhance the planning ability and cooperation among various agents for complex tasks. In this paper, researchers employed a hierarchical structure with Self-Organizing Neural Networks (SONN) at the first level and Multi-Agent Deep Reinforcement Learning (MADRL) controllers for intermediate and lower levels. However, this model also had some limitations in terms of architectural complexity.

In 2024 Qingxu et al [14] have introduced multi-agent reinforcement learning paradigm, named Hierarchical Cooperation Graph Learning (HCGL), has been proposed for addressing complex cooperative multi-agent problems. The primary aim of this paper was to enhance hierarchical cooperation and understandability among agents in complex environments. In this paper, an Extensible Cooperation Graph (ECG) with graph operators and an optimization framework for MARL were used for dynamically structuring agent cooperation. However, this resulted in additional complexity in terms of structure and computation for dynamically managing the graph structure.

In 2024, Dingbang et a;[15] have suggested a Knowledge-guided hierarchical multi-agent reinforcement learning framework (hhk-MARL) was proposed to address issues of coordination and learning efficiency in large-scale multi-agent systems. The primary goal was to address the challenges of exponential interactions in multi-agent systems and large learning dimensions. The study adopted hierarchical reinforcement learning with fuzzy logic-based human knowledge and a graph-based group controller in a StarCraft multi-agent challenge environment. However, it was based on prior knowledge from humans, which may not be appropriate in large-scale systems due to scalability and adaptability issues.

Table 1: Hierarchical Multi-Agent Reinforcement Learning Literature Survey

Author & Year	Method Used	Objective	Key Technique	Limitation

Lin et al. (2026)	MADRL with Human Knowledge	Improve scalability in multi-agent systems	Natural language-based knowledge integration	Depends on human knowledge
Scotty E et al. (2023)	Hierarchical Reinforcement Learning (HRL)	Enhance decision-making in combat simulations	Dynamic abstraction engine	Limited performance in complex environments
Geng et al. (2024)	HiSOMA (Hierarchical MARL)	Improve planning and cooperation	SONN + MADRL controllers	High architectural complexity
Qingxu et al. (2024)	HCGL (Graph-based MARL)	Improve cooperation among agents	Extensible Cooperation Graph (ECG)	High computational complexity
Dingbang et al. (2024)	hhk-MARL	Improve coordination and learning efficiency	Fuzzy logic + graph-based controller	Relies on human prior knowledge

Research Gap

Although various existing studies have used hierarchical multi-agent reinforcement learning models to improve the coordination and scalability of agents in complex and dynamic environments, some of these models still have various limitations in their applicability to intelligent systems. For instance, some models rely greatly on the integration of human knowledge to improve the learning process, thus limiting the autonomy and flexibility of agents in complex and dynamic environments. Other models use hierarchical reinforcement learning models or self-organizing neural networks to improve decision-making in complex and dynamic environments, thus increasing the architectural and computational complexities. Furthermore, graph-based models improve the coordination of agents, but they have complex and computationally expensive topology management. Due to such limitations, the existing models cannot efficiently provide scalability, real-time adaptability, and coordination in highly complex real-world multi-agent environments. Therefore, there exists a strong need to develop a more efficient hierarchical multi-agent reinforcement learning architecture that can improve scalability, coordination, and efficiency in intelligent systems operating in real-time environments.

3. System Modelling

In the proposed framework, the system is considered as a hierarchical multi-agent reinforcement learning environment, which is focused on addressing the problem of scalability in Artificial Superintelligence systems. The environment is composed of multiple intelligent agents that interact with the dynamic states of the system, take actions, and receive rewards based on their performance. The agents observe the state of the environment and take optimal actions using reinforcement learning to accomplish specific tasks. To address the problem of scalability, a hierarchical structure is used, where a high-level agent is used for global task planning, a middle-level agent is used for managing inter-agent communications and cooperation among groups of agents, and a low-level agent is used for performing primitive actions directly in the environment.

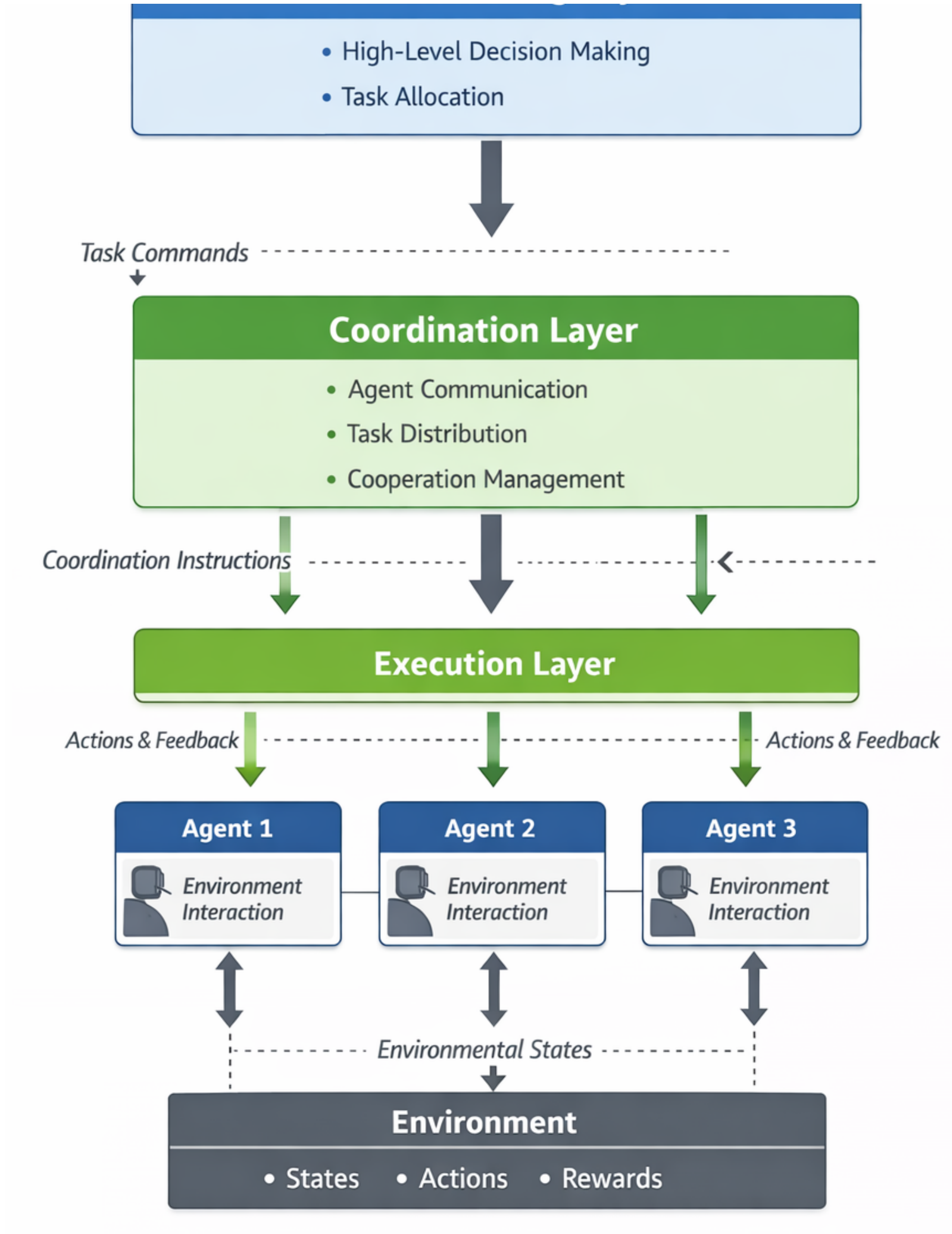

Fig 1: Proposed Overall system workflow Flowchart

The states used in the system include environmental conditions, interactions among agents, and task-related states, which play an important role in the decision-making process. The system uses a reward mechanism that promotes the completion of tasks efficiently and encourages agents to cooperate with each other. The proposed system, through interactions with the environment, enables the agents to learn and make decisions efficiently. Proposed Overall system workflow Flowchart is shown in fig 1.

Hierarchical System Layers

Global Planning Layer (Top Level) – Responsible for strategic decisions, monitors the global environment, defines overall goals, and decomposes tasks into sub-tasks for the coordination layee

Coordination Layer (Middle Level) – Responsible for communication and cooperation between groups of agents, task allocation, conflict resolution, and tracking progress to achieve efficient cooperation.

Execution Layer (Bottom Level) – Composed of individual agents that carry out tasks, interact with the environment, and supply feedback to agents for learning.

The proposed system workflow begins with environment initialization, followed by agents observing the current states of the environment. The hierarchical controller then allocates tasks to different agent groups, after which the agents interact directly with the environment. Based on their actions, agents receive reward feedback and update their policies accordingly. The coordination layer manages communication and cooperation among agents to ensure efficient task execution. Through repeated interaction, feedback, and collaboration, the system undergoes continuous learning, gradually improving overall performance and scalability.

3.1 Methodology System

In the current study, the simulation-driven methodology is employed in order to overcome the scalability issues in the Artificial Superintelligence systems using the Hierarchical Multi-Agent Reinforcement Learning framework. In order to overcome the real-world implementation issues in the large-scale ASI systems, a synthetic simulation environment is proposed, which can mimic the real-world conditions in the ASI systems. The proposed model in the current study incorporates a number of agents in the Hierarchical structure, including the Global, Coordination, and Execution levels, in which the agents are able to observe the environmental conditions, perform the required actions, and receive the rewards based on the performance of the agents in the Hierarchical structure. The learning process in the proposed model is based on the Reinforcement Learning technique, in which the agents are able to learn the required tasks through the interaction with the environment in the Hierarchical structure. The performance of the proposed system is evaluated using the key performance metrics, including scalability, convergence rate, computational complexity, and coordination efficiency in the Hierarchical structure.

3.2 Hierarchical Multi-Agent Reinforcement Learning for Scalable Decision-Making

Hierarchical Multi-Agent Reinforcement Learning (HMARL) [16] is used in this paper, which helps in achieving the benefits of scalability as well as efficient decision-making in the complex Artificial Super Intelligence systems. Unlike traditional reinforcement learning, in the proposed P-I MRL, the physical knowledge is used, which helps in achieving the benefits of reduced search space as well as the stability of the learning process, thereby achieving faster convergence, reduced complexity, as well as accurate decision-making. In addition, the multi-agent architecture helps in achieving the benefits of efficient decision-making as well as the efficient use of the available resources in the proposed Intelligent System.

$$\dot{X}^i = (J^i(X^i) - R^i(X^i))\frac{\partial H^i(X^i)}{\partial X^i} + F^i(X^i)u^i \tag{1}$$

Where, $J^i(X^i)$ represents the interaction and information exchange among agents across different hierarchical levels, including global, coordination, and execution layers, $R^i(X^i)$ denotes the loss of efficiency or uncertainty in decision-making arising due to incomplete state information or coordination delays among agents, $H^i(X^i)$ represent the total cumulative value of the current game state evaluated by the agents, $F^i(X^i)$ represents the cumulative value of the system state, evaluated based on the rewards obtained by agents during task execution in the environment. indicates the influence of external environmental factors, such as dynamic system changes and resource constraints, on agent decisions. The hidden layers within the learning model play a crucial role in reducing uncertainty by refining agent policies through continuous feedback and learning. By incorporating both environmental states and inter-agent communication, the model improves decision accuracy, enhances coordination, and ensures efficient scalability in complex Artificial Superintelligence systems.

$$\dot{X} = J(X) - \dot{R}(X))\frac{\partial H(X)}{\partial X} + F(X)u \tag{2}$$

Where, $\dot{X}$ represents the change in the system state after agents execute their actions in the environment, $J(X)$ represents the change in the system state after agents execute their actions in the environmen, $R(X)$represent the strategic interaction among agents operating at different hierarchical levels, $H(X)$ denotes the strategic interaction among agents operating at different hierarchical levels, enabling coordinated decision-making, $\partial H(X)$ represent the change in the system state after agents execute their actions in the environment, $F(X)$ The output layer is in charge of producing the optimal action or decision for the system, taking into account the strategies of different agents, the hierarchical coordination mechanisms, and the state of the environment. The proposed hierarchical multi-agent reinforcement learning framework is able to solve the scalability problem in the Artificial Superintelligence system in an efficient manner.

4. Result and Discussion

In this section, the results of the proposed method are explained. Table 2 shows the implementation parameter.

Table 2: Implementation parameter

Parameter	Description
Programming language	Python
version	3.12.12
OS	Windows 10

Method	P-I MRL

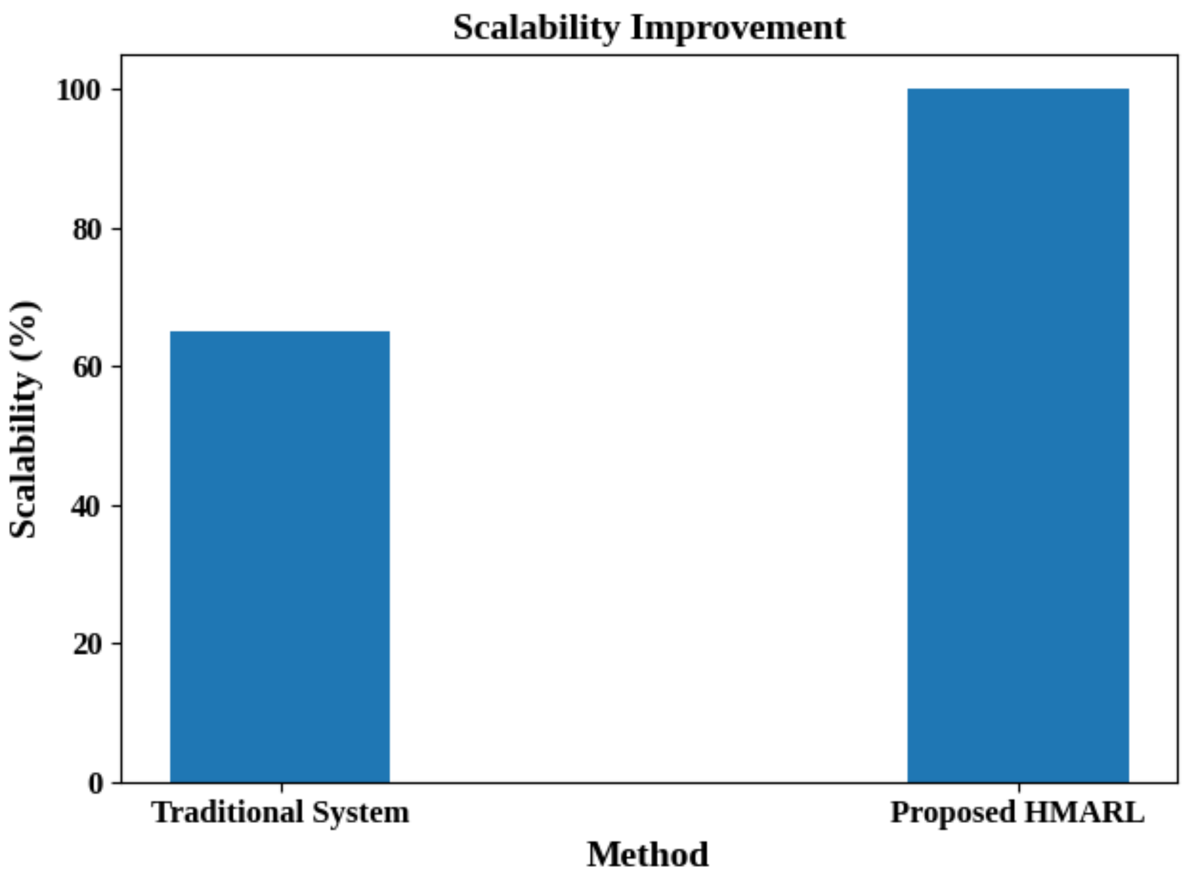

Fig 2: Analysis the performance of proposed scalability

Analysis the performance of proposed scalability shows the in fig 2. The traditional system is able to attain a scalability of 65%, while the proposed HMARL model is able to attain a scalability of 97%. Hence, the proposed HMARL model is able to improve the scalability of the system by approximately 35%. This is due to the efficient hierarchical coordination and the optimization of the tasks and inter-agent communication.

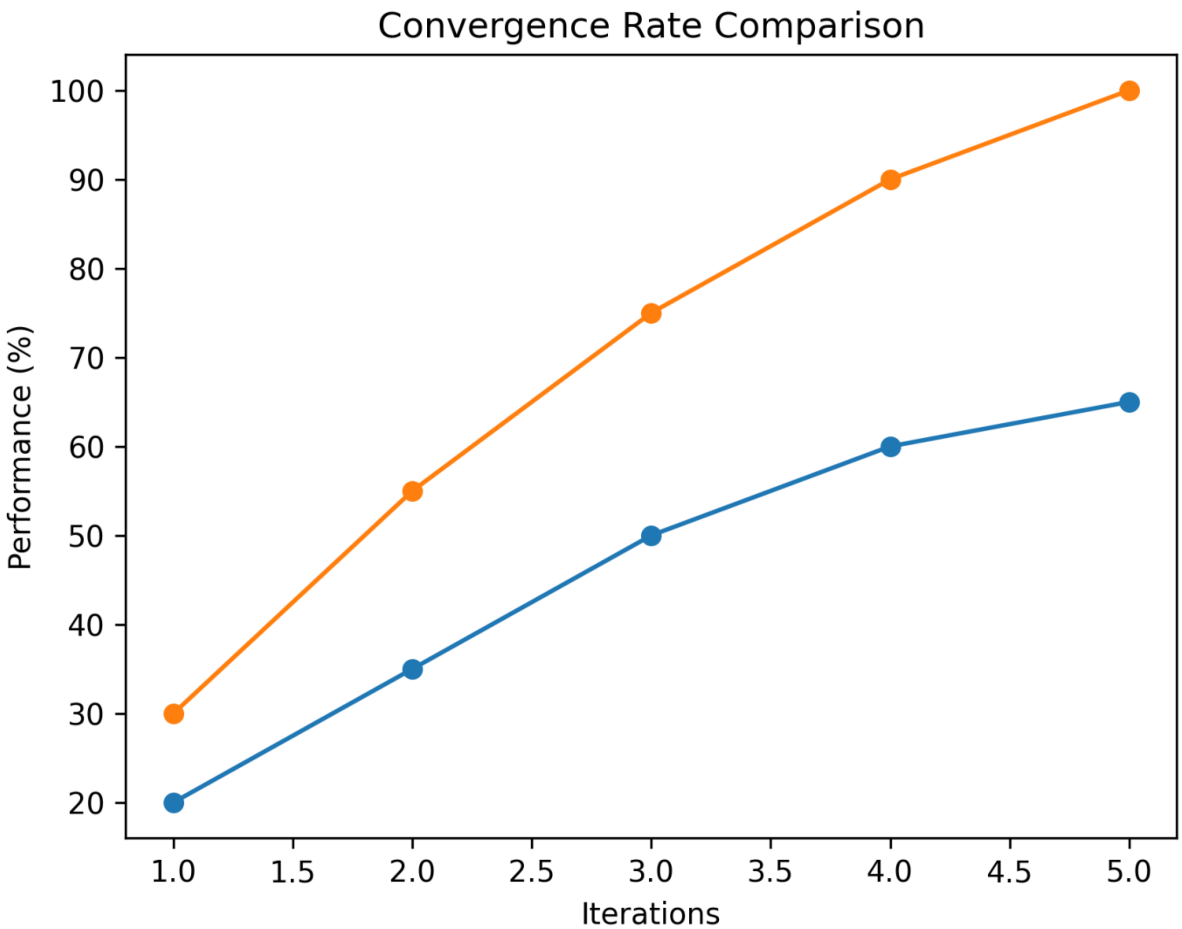

Fig 3: Analysis the performance of Convergence rate

Fig 3 shows the convergence is used to compare the learning performance of the traditional system and the proposed HMARL framework. As shown, the traditional system gradually improves its performance from 20% to 65%, while the proposed model quickly converges from 30% to 98% within less iteration. This indicates that the proposed system greatly enhances learning performance.

Table 3: Analysis of the Computation efficiency

Method	**Efficiency (%)**
Traditional System	60
Proposed HMARL	92

The table 3 shows the comparison for the computational efficiency between the traditional system and the proposed HMARL framework. The traditional system's efficiency is given as 60%, whereas the efficiency for the proposed HMARL model is calculated as 92%. This is an increase in efficiency by 32%. This is an improvement in the system through optimized hierarchical coordination and efficient task allocation in large-scale intelligent environments.

5. Conclusion

In this paper, a hierarchical multi-agent reinforcement learning framework with the incorporation of a Physics-Informed Multi-Agent Reinforcement Learning (P-I MRL) method is proposed as a solution for the scalability challenges in Artificial Superintelligence systems. This method is effective in improving the coordination of agents, reducing the computational complexities, and increasing the efficiency in decision-making in complex dynamic environments. This is due to the stability in learning and convergence in the proposed framework. The simulation results have shown improved performance in scalability by increasing it from 65% to 97%, convergence performance by increasing it from 30% to 98%, and increasing the efficiency in decision-making from 60% to 92%. This is an indication that the proposed method is effective in solving complex multi-agent problems. This method can be further improved in the future to include real-time applications in smart cities, autonomous vehicles, and distributed networks to increase its adaptability.

Reference

[1] Liu, Dingbang, et al. "Scaling up multi-agent reinforcement learning: An extensive survey on scalability issues." IEEE Access 12 (2024): 94610-94631.

[2] Cui, Kai, et al. "A survey on large-population systems and scalable multi-agent reinforcement learning." arXiv preprint arXiv:2209.03859 (2022).

[3] Kim, HyunJin, et al. "The road to artificial superintelligence: A comprehensive survey of superalignment." arXiv preprint arXiv:2412.16468 (2024).

[4] Xue, Xiangyuan, et al. "CoMAS: Co-Evolving Multi-Agent Systems via Interaction Rewards." arXiv preprint arXiv:2510.08529 (2025).

[5] Bouneffouf, Djallel, Matthew Riemer, and Kush R. Varshney. "The Shepherd Test: How Will SuperIntelligent Agents Balance Care and Control in Asymmetric Relationships?." NeurIPS 2025 Workshop on Evaluating the Evolving LLM Lifecycle: Benchmarks, Emergent Abilities, and Scaling. 2025.

[6] Jin, Can, et al. "Two heads are better than one: Test-time scaling of multi-agent collaborative reasoning." arXiv preprint arXiv:2504.09772 (2025).

[7] Zhang, Dajun, Wei Shi, and Xiaowei Jia. "Exploring Scientific Principles and Laws of Artificial Intelligence, World Model, and Artificial General Intelligence (AGI) in Future Intelligence Networking: Paradigms, Architectures, and Innovations." IEEE Communications Surveys & Tutorials (2026).

[8] Covas, Vinicius. "The Spiral of Attention: How Disruptive Agents Centralize Multi-Agent AI Deliberation Networks." (2026).

[9] Wang, Weibing. "A Comprehensive Solution for the Safety and Controllability of Artificial Superintelligence." (2024).

[10] Mersal, Ahmed T. "Artificial Intelligence and Superintelligence: The New Frontiers of Human Capability." Authorea Preprints (2025).

[11] Liu, Dingbang, et al. "Improving scalability of multi-agent deep reinforcement learning with suboptimal human knowledge." Autonomous Agents and Multi-Agent Systems 40.1 (2026): 2.

[12] Black, Scotty E., and Christian J. Darken. "Scaling intelligent agent combat behaviors through hierarchical reinforcement learning." Disruptive Technologies in Information Sciences VII. Vol. 12542. SPIE, 2023.

[13] Geng, Minghong, et al. "HiSOMA: A hierarchical multi-agent model integrating self-organizing neural networks with multi-agent deep reinforcement learning." Expert Systems with Applications 252 (2024): 124117.

[14] Fu, Qingxu, et al. "Self-clustering hierarchical multi-agent reinforcement learning with extensible cooperation graph." IEEE Transactions on Emerging Topics in Computational Intelligence 9.2 (2024): 1688-1698.
[15] Liu, Dingbang, et al. "Integrating suboptimal human knowledge with hierarchical reinforcement learning for large-scale multiagent systems." Advances in Neural Information Processing Systems 37 (2024): 102744-102767.
[16] Geng, Minghong, et al. "HiSOMA: A hierarchical multi-agent model integrating self-organizing neural networks with multi-agent deep reinforcement learning." Expert Systems with Applications 252 (2024): 124117.