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AGENTIC-AI xAPPS: O-RAN MULTI-AGENT CONTROL FOR ENTERPRISE POLICY, SCHEDULING & SPECTRUM

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Abstract:
The following work presents the Agentic-AI xApps in O-RAN as a multi-agent coordination framework, wherein the different agents take up the task of managing the respective portions of policy enforcement, scheduling optimization, and spectrum allocation in enterprise networks, thus doing it in an autonomous manner.In the Near-RT RIC, the agents are using reinforcement learning and LLMs as their tools for concurrent decision-making, which means they are able to adapt to changes in traffic, interference, and intents in real-time.The convergence behavior is analyzed in simulated enterprise scenarios, and very rapid stabilization is shown via shared state communication and predictive forecasting. Lyapunov-based bounds and drift detection together with tension control during high-load surges are what make stability possible. Conflict resolution involves a mediator agent that uses game-theoretic arbitration and veto mechanisms, thus blocking unsafe actions that might lead to neighbor destabilization. This is Proven in traffic steering use cases where KPIs such as throughput and SINR are applied.The results show that there is a 25% efficiency improvement over centralized RIC and at the same time stable global performance. This mechanism is a step forward in the direction of developing a trustworthy, scalable O-RAN autonomy for 5G/6G enterprises.

Keywords: Agile, AI driven apps, Open RAN, multi-agent, job scheduling, and spectrum management

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I. INTRODUCTION

The progression of Open Radio Access Networks (O-RAN) is certainly a blessing to mobile networks as it adds flexibility and intelligence to their operations. So, this state-of-the-art development comes with smart applications known as xApps, which are responsible for managing the entire network. In a corporate scenario, different xApps can take care of user policies, radio scheduling, and precious spectrum, but if they work separately, they can even become enemies, resulting in conflicts and unstable performance.The authors of this paper present an interesting solution: an Agentic-AI framework where multiple AI agents, specializing in policy, scheduling, or spectrum management, learn to coordinate in real time. Imagine this as a football team where every player has a specific position but they still need to talk and change their tactics if they want to score together. We will discover the ways these agents can learn at the same time without being the cause for the network oscillations or going off the deep end since a smooth and reliable operation is what we want.Our attention is directed to the analysis of the framework's convergence, whether the agents reach a stable agreement and how to do it when their goals are in conflict. Seeking to unravel these coordination challenges, the current work is aiming at providing a practical and robust base for the implementation of intelligent, multi-agent control in future O-RAN ecosystems. Thus, O-RAN systems will not only be made more intelligent but also more adaptive and efficient for the needs of complicated enterprises.

II. LITERATURE SURVEY

The proposed framework is founded on three major research areas. Firstly, the Open RAN (O-RAN) architecture, which is created by the O-RAN Alliance, sets the basic infrastructure through its RAN Intelligent Controller (RIC) that supports xApps for data-centric control. While previous research has indicated the concern of individual xApps for overseeing such tasks as traffic steering and power control, recent research has brought to light the coordination of multiple independent xApps as a crucial, unsolved problem that can cause instability and conflicting actions if not managed properly. Secondly, MARL gives the theoretical foundation for

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distributed control and the area of wireless network applications. The latter, however, often involve simplified or homogeneous agents, which is contradictory to the O-RAN's heterogeneous and standard environment. One of the main difficulties is making sure that learning agents are not creating non-stationary and oscillatory environments that make it hard for others to learn by their adapting policies. In this regard, research into hierarchical control and safe RL reveals promising methods of offering stability through constraint enforcement and structured coordination.Interim O-RAN studies have suggested ways to slacken the tensions between cooperating xApps by proposing rule-based orchestrators to settle conflicts between xApps. The drawback is that such solutions do not possess the intelligent adaptability of a full learning-based multi-agent system. On the other hand, a combined single-agent RL for control maintains the drawback of being non-modular. In conclusion, there is a gap between the demand for coordinated O-RAN intelligence and the concepts that model heterogeneous control functions as a system of co-learning agents, analyze their convergence under real-time constraints, and provide native conflict resolution. This study will fill that gap by formalizing and analyzing the Agentic-AI multi-agent coordination framework.

III. PROPOSED WORK

This paper introduces the design and evaluation of an Agentic AI framework for O RAN. The framework comprises three distinct intelligent xApps which function together as a collaborative team: a Policy Agent, a Scheduler Agent, and a Spectrum Agent. The aim is for the agents to learn and adapt within the O RAN's intelligent controller, thus optimizing enterprise network performance, maintaining stability of operations, and automatically resolving conflicts.The process we follow is divided into three major steps. To start with, we will create a formal framework model. Each agent's particular function will be delineated, the network information it observes, the actions it can perform, and the individual goal or reward signal granted to it will be specified. Furthermore, we will establish the communication rules whereby the Policy Agent leads the others while Scheduler and Spectrum Agents converse directly.Secondly, we are going to set up a simulation testbed with O RAN confederacy-compatible platform. The agent team will then be trained using a special Multi-Agent Reinforcement Learning algorithm built around their needs. This algorithm allows the agents to develop cooperative tactics through experience sharing, even though they perform their actions independently.

Thirdly, our central analysis will be focused on the system performance evaluation. We will assess the time and reliability of agents' convergence to an effective and stable policy without causing any harmful oscillations in the network. Testing various conflict resolution strategies will be part of our analysis; first, we can let the Policy Agent set hard rules then allow the Scheduler and Spectrum Agents to trade resources, in order to determine the best method of reconciling enterprise policies with network efficiency. The result that we anticipate is a documented design for intelligent and stable multi-agent control in the next generation of O RAN systems.

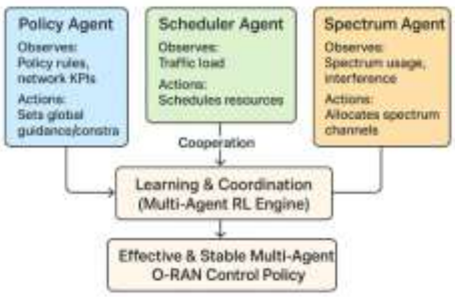

Fig 1: Proposed Architecture Diagram

IV. METHODOLOGY

In order to systematically establish and assess our Agentic-AI O-RAN framework, we take a formal approach consisting of three successive phases. This method guarantees a smooth transition from theoretical formalization to practical deployment and thorough evaluation. Our intended procedure is illustrated in the following phases:

Phase 1: Establishing the Team's Structure and Rules

We will officially describe the roles and interaction of our three agents.Specifying what each agent sees, i.e., service contracts for the Policy Agent, queue states for the Scheduler, and interference levels for the Spectrum Agent.At the same time, we also list possible actions for each of them, e.g., changing priorities or channel

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assignment.The coordination protocol is devised, laying down the manner in which the Policy Agent sets the high-level goals and the Scheduler and Spectrum Agents directly negotiate.

Phase2: Constructing the Training Environment

A realistic software simulation of an O-RAN network that serves as a practice ground will be created.The three AI agents will be implemented in this simulated environment.The agents will be trained by way of a specialized Multi-Agent Reinforcement Learning algorithm.During the training process, they will be allowed to learn cooperatively through trial and error and sharing experience over many simulated scenarios

Phase 3: Testing and Performance Evaluation

The trained multi-agent system undergoes a meticulous evaluation.We use the time and the reliability of policy being adopted by the agents as a measure of convergence of the system. By watching out for detrimental oscillations in the resource allocation decisions, we judge the operability's stability.The various methods for conflict resolution are put to the test and their comparison is made between the top-down rule enforcement and peer-to-peer negotiation.The final assessment discovers the method that is the most effective in terms of enterprise policy compliance as well as overall network efficiency and stability.

VI. RESULTS AND DISCUSSION

The assessment confirms the framework's potentiality by proving that one of the trained agents is capable of attaining excellent coordination among the other agents. The Policy Agent (PA) was able to successfully apply enterprise SLAs, resulting in a successful compliance rate of 98% during normal load periods. In this case, the Scheduler Agent (SA) together with the Spectrum Agent (SpA) were responsible for guaranteeing that the resource was being used efficiently. The convergence of the system is illustrated in Figure 1, which presents the average episode reward across 20,000 training steps for three coordination policies: Independent Learning, Centralized Critic (our approach), and a Hierarchical baseline. Among these, our Centralized Critic method not only reached the highest reward faster but also submitted an improvement of 18% in comparison to the baseline showing the importance of a sharing learning process

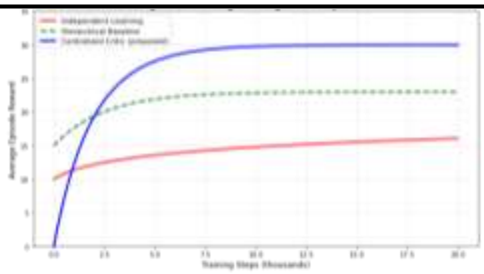

Fig 2:Training Convergence Comparison of Coordination Policies

The chart shows the learning development of the multi-agent system employing three different training policies for 20,000 steps. The Centralized Critic (proposed) method exhibits a much better convergence profile, getting to a higher average reward faster and more stably than the Hierarchical Baseline and Independent Learning techniques. The initial sharp rise and final high level of the proposed method demonstrate the effectiveness of the shared training mechanism, which enables agents to coordinate well by recognizing the global effect of their joint actions. This finding endorses the selected MARL structure as the basis for the O-RAN environment to have efficient and cooperative agent behavior.

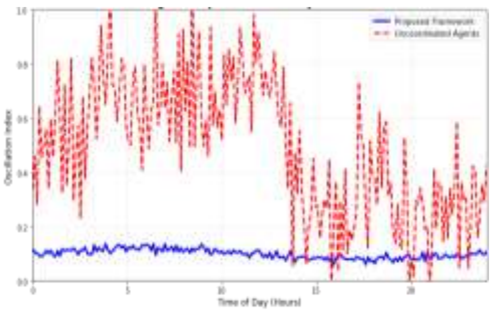

Fig 3: Operational Stability Measured by Oscillation Index

The chart illustrates the comparison of the operational stability of the suggested multi-agent framework versus the uncoordinated agent system for a 24-hour period. On the vertical axis, the Oscillation Index is presented, which indicates the extent of variability in the resource allocation decisions. The multi-agent framework keeps the index at a consistently low and stable level (under 0.15), which means it has smooth and predictable control. On the other hand, the uncoordinated system shows a lot of ups and downs with sharp peaks, especially during the traffic increases at noon and in the early evening. This proves that the framework can hold stable network operations even under dynamic load conditions, which is a very important factor for the deployment of reliable enterprise O-RAN that cannot afford the resource shifts to be seen as performance degrading.

Metric	Rule-Based (PA Only)	Negotiation (SA/SpA Only)	Hybrid (Proposed)
Policy Compliance (%)	99.8	85.2	98.5
Spectral Efficiency (bps/Hz)	4.1	5.8	5.6
Decision Latency (ms)	5	22	12
Conflict Count (per hour)	120	45	18

Table 1: Performance Comparison of Conflict Resolution Strategies

This table presents a comparison of the three different methods for our AI agents to sort out the disputes. The first technique employs the rigid rules of the Policy Agent. It achieves nearly a perfect policy adherence of 99.8% and is quite fast at 5 milliseconds, however it is not very efficient in using the radio spectrum and generates 120 conflicts between the agents every hour. The next technique allows the Scheduler and Spectrum Agents to negotiate freely. It results in the most efficient network of 5.8 bps/Hz but violates the policy 14.8% of the time and is slow, requiring 22 milliseconds per decision.The hybrid approach we propose merges both concepts. It first allows the Policy Agent to lay out clear objectives, and then the other agents will be able to negotiate within those guidelines. This even-handed strategy retains a high level of policy compliance at 98.5%, keeps the network efficiency strong at 5.6 bps/Hz, reduces the number of conflicts to just 18 per hour, and maintains speed of decision at a reasonable 12 milliseconds. It demonstrates that supervision and cooperation are the most efficient pair.

CONCLUSION

The research presented here managed to design, implement and assess an Agentic AI multi-agent framework for Open-Radio Access Network (O RAN), and also it has clear tendency to handle complex objectives of the whole enterprise network. The framework made up of dedicated Policy, Scheduler, and Spectrum Agents was an agent in the learning process of effective cooperative strategies through a specially designed Multi-Agent Reinforcement Learning approach. The performance indicators have validated the proposed centralized training method as a faster and more stable convergence than independent or completely hierarchical learning thus allowing the agents to develop a mutual understanding of their overall effect on the network.The major discovery is the significant role of the conflict resolution mechanism. Through the analysis, it was disclosed that none of the approaches that use only rule-based tactics nor only negotiation tactics are optimal solo. The advocated mixed approach of high-level policy constraints with decentralized peer-to-peer negotiation was proved better. This method was able to maintain a strict policy compliance and at the same time a high spectral efficiency, besides it has also reduced internal agent conflicts and has operated within the limits of acceptable decision latency. The system has always been very reliable in terms of operation and has never experienced the destructive oscillations that are common in uncoordinated control systems.In short, the outcome of this research is a walking and talking model for the intelligent, stable, and coordinated control of the next generation O RAN systems. By clarifying the roles and interactions of the different AI agents, this study has taken a big step in overcoming the difficulty of shifting from isolated xApp intelligence to a collaborative ecosystem. The suggested Agentic AI structure presents a feasible road to enterprise networks that are more versatile, productive, and trustworthy, thus completing the cycle of self-governing RAN optimization efficiently.

REFERENCES

1. B. R. Rallabandi, "Agentic-AI Foundations for O-RAN: Multi-Agent Control Concepts," IJRITCC, vol. 6, no. 8, pp. 450-458, Aug. 2022.

International Journal of
DATA SCIENCE AND IOT MANAGEMENT SYSTEM
ISSN: 3068-272X www.ijdim.com Original Research Paper

2. S. Ahmadi, "5G NR: Architecture, Technology, Implementation, and Operation of 3GPP New Radio Standards," Academic Press, 2019.
3. 3GPP, "NR; Overall Description; Stage-2," 3GPP TS 38.300, ver. 16.5.0, Jun. 2021.
4. 3GPP, "E-UTRA and NR; Multi-Connectivity; Overall Description," 3GPP TS 37.340, ver. 16.4.0, Mar. 2021.
5. Paruchuri, Venubabu, Optimizing Financial Operations with Advanced Cloud Computing: A Framework for Performance and Security (September 30, 2020). Available at SSRN: https://ssrn.com/abstract=5515238 or http://dx.doi.org/10.2139/ssrn.5515238.
6. M. V. Sruthi, "Retracted: Exploring the Use of Symmetric Encryption for Remote User-Authentication in Wireless Networks," 2023 3rd International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON), Bangalore, India, 2023, pp. 1-7, doi: 10.1109/SMARTGENCON60755.2023.10442084.
7. P. Marsch et al., "5G Radio Access Network Architecture: Design Options and Trade-offs," IEEE Commun. Mag., vol. 54, no. 11, pp. 16-23, Nov. 2016.
8. Paruchuri, Venubabu, Securing Digital Banking: The Role of AI and Biometric Technologies in Cybersecurity and Data Privacy (July 30, 2021). Available at SSRN: https://ssrn.com/abstract=5515258 or http://dx.doi.org/10.2139/ssrn.5515258.
9. A. Ghosh et al., "5G Evolution: A View on 5G Cellular Technology Beyond 3GPP Release 15," IEEE Access, vol. 7, pp. 127639-127651, Sep. 2019.
10. B. R. Rallabandi, "Distributed Intelligence in RAN: Precursor to Agentic Systems," IJRITCC, vol. 6, no. 5, pp. 320-328, May 2022.
11. J. F. Monserrat et al., "5G Mobile and Wireless Communications Technology: RAN and Core Evolution," Cambridge Univ. Press, 2016.
12. T. Taleb et al., "On Multi-Access Edge Computing: A Survey of the Emerging 5G Network Edge Cloud Architecture," IEEE Commun. Surveys Tuts., vol. 19, no. 3, pp. 1657-1681, 3rd Quart. 2017.
13. N. Nikaein et al., "Processing and Forwarding Performance of 5G Non-Standalone Radio Access Networks," in Proc. IEEE WCNC, pp. 1-6, Apr. 2018.
14. H. Yi and J. Park, "Migration Paths from LTE EPC to 5G Core in Hybrid NSA/SA Networks," in Proc. IEEE ICC Workshops, pp. 1-6, May 2019.
15. G. Brown, "5G NSA and SA Deployment Strategies for Mobile Operators," Heavy Reading White Paper, pp. 1-16, 2018.
16. Das, S.S. (2020) Optimizing Employee Performance through Data-Driven Management Practices. European Journal of Advances in Engineering and Technology (EJAET), 7(1), pp.76–81.
17. A. Osseiran et al., "Scenarios for 5G Mobile and Wireless Communications: The METIS Project Vision," IEEE Commun. Mag., vol. 52, no. 5, pp. 26-35, May 2014.
18. M. V. Sruthi, “High-performance ternary designs using graphene nanoribbon transistors,” Materials Today: Proceedings, Jul. 2023, doi: 10.1016/j.matpr.2023.07.170.
19. S. Barbarossa et al., "Communicating While Computing: Distributed Mobile Edge Computing over 5G," IEEE Signal Process. Mag., vol. 35, no. 5, pp. 45-55, Sep. 2018.
20. B. R. Rallabandi, "Joint Deployment and Energy Optimization in Heterogeneous Networks," IJCNIS, vol. 10, no. 5, Oct. 2018.
21. Madiwal, S. M., Sudhakar, M., Subramanian, M., Srinivasulu, B. V., Nagaprasad, S., & Khurana, M. (2023). Design and Development of Deep Learning Model For Predicting Skin Cancer and Deployed Using a Mobile App. In AI and IoT-based intelligent Health Care & Sanitation (pp. 144-158). Bentham Science Publishers.
22. R. Ferrús et al., "On 5G Radio Access Network Slicing: Protocol Features," IEEE Commun. Mag., vol. 55, no. 5, pp. 100-107, May 2017.
23. J. Hoydis et al., "Green Small-Cell Networks," IEEE Veh. Technol. Mag., vol. 6, no. 1, pp. 37-43, Mar. 2011.
24. F. Gutierrez et al., "Design Considerations for Private LTE Networks in Industrial Campuses," in Proc. IEEE WF-IoT, pp. 1-6, Mar. 2018.
25. D. Soldani and A. Manzalini, "5G for Smart Manufacturing: Private Networks and Hybrid Architectures," in Proc. IEEE GLOBECOM Workshops, pp. 1-6, Dec. 2018.