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Toward AI-based Complex Self-Adaptive Systems

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Abstract

Cloud computing has become an essential pillar of modern IT infrastructures, offering storage and computing capacity on an unprecedented scale. Using this technology, businesses can benefit from great flexibility, almost infinite scalability, and global accessibility, while significantly reducing infrastructure costs. In parallel, the emergence of microservice architectures [1, 2] is revolutionizing the implementation of large-scale software infrastructures and architectures. Although microservice architectures offer modularity, scalability and flexibility, they also pose challenges in deployment, management, latency optimization, and testing. It is crucial to implement strategies to understand user intentions, simplify tasks, detect issues proactively, analyze error causes and maintain system reliability.

To achieve this, each microservice is closely monitored and corrective actions are regularly implemented. This process can be framed by the MAPE-K loop (Monitor, Analyze, Plan, Execute, Knowledge) proposed by Kephart et al. (2003) [3], which provides a methodological framework for autonomous service management. By monitoring services, analyzing the collected data, planning actions, executing these plans and using the knowledge acquired to continually improve the process, the MAPE-K loop helps to maintain the alignment and coherence of the microservice architecture.

Self-adaptive systems (SAS) are engineered to modify their operations dynamically in response to environmental variations. The integration of AI, especially machine learning, into these systems not only facilitates real-time responses to such changes but also helps in predicting and meeting future requirements through optimized solutions. Previous studies have highlighted the significant enhancements in adaptability when machine learning models are incorporated into the MAPE-K feedback loop of these systems.

For example, Araújo et al. (2021) [4] have developed a tool called Finch, which integrates machine learning into the MAPE-K loop to automate the configuration and optimisation of REST systems, thus reducing the manual efforts. Similarly, Weyns et al. (2021) [5] explored the combination of MAPE-K approaches, control theory principles, and machine learning techniques, demonstrating that this integration can produce more robust and efficient adaptive systems. Ouareth et al. (2022) [6] used reinforcement learning to enable dynamic adjustments in the structure and behaviour of MAPE-K loops, which is particularly effective for complex systems requiring decentralised coordination. Lecheheb et al. (2022) [7] have proposed a hybrid approach combining machine learning and Deep Learning to improve the accuracy of the Analyzer component in the MAPE-K loop, thereby reducing the time and resources required to adapt large-scale systems.

Nowadays, with the rise of Generative Artificial Intelligence (GenAI), which in certain ways offers a better alternative to machine learning, research into self-adaptive systems has continued. For example, Nakagawa et al. (2023) [8] explore the use of GenAI to automate goal model generation based on the use of the MAPE-K adaptation loop. This approach aims to improve the efficiency and accuracy of self-adaptive systems by exploiting the capabilities of GenAI to create more robust and context-sensitive adaptation strategies. More specifically, Donakanti et al. (2024) [9] study how LLMs can improve software system adaptation at the architecture level by autonomously generating context-sensitive adaptation strategies, just as humans would. On the other hand, Li et al. (2024) [10, 11] discuss the specific benefits and challenges of employing GenAI, and in particular Large Language Models (LLMs), in self-adaptive systems. Despite the technological diversity and rapid evolution of GenAI, these papers highlight that there are still gaps in understanding the practical benefits of integrating these technologies into self-adaptive systems. Similarly, Nunes et al. (2024) [12] propose MS-RA, a self-adaptive, requirements-driven solution for microservices autoscaling. This approach adjusts resource consumption to meet changing workload demands, ensuring system performance and cost-effectiveness while using fewer resources.

As several directions emerge with the use of GenAI in the context of self-adaptive systems, we would like to focus on improving GenAI and in particular LLMs, by exploring advanced techniques such as diffusion models, Mixture of Experts, and RLHF (Reinforcement Learned via Human Feedback). These methods aim to increase the efficiency of LLMs in complex contexts, enabling them to interact more effectively with dynamic data in real time, particularly during the monitoring and analysis phases. We will also study how the optimisation of the prompts used by GenAI can be aligned with the objectives of each stage of the MAPE-K loop. By refining the prompts for each phase, we hope not only to improve anomaly detection during monitoring, but also to refine the analysis capabilities of GenAI to support all stages of adaptation. Finally, we would like to analyze how different ways of structuring and visualizing data, particularly in the monitoring phase, can facilitate the integration of GenAI into the self-adaptation process, while improving system capacity.

Keywords

Large Languages Models, Generative AI, Artificial Intelligence, Machine Learning, Self-Adaptative Systems, Autonomous Systems

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