

Many-Objective Centralized Adaptation Planning: Towards Hybrid Self-Adaptive and Self-Organizing Systems

Pia Schweizer

Supervisor: Christian Krupitzer

Department of Food Informatics and Computational Science Hub, University of Hohenheim
Stuttgart, Germany

pia.schweizer@uni-hohenheim.de

Abstract—Driving semi-automated vehicles at close distances, called platooning, emerges as a promising strategy to address conflicts associated with the ever-increasing traffic volumes on German highways by optimizing fuel consumption and road utilization. Mapping the architecture of a self-adaptive system to platooning, a fully central coordination of vehicles would introduce a potential bottleneck, while fully decentralized decision-making might lead to conflicting adaptations. Therefore, this project aims to establish a hybrid self-adaptive and self-organizing system that is robust with micro-level autonomic adaptation decisions while centrally optimizing the decision-making.

Index Terms—autonomous systems, optimization, coordination, adaptation.

I. MOTIVATION AND CHALLENGES

Germany faced a staggering 427,000 hours of traffic congestion in 2023 [1], highlighting not only the substantial loss of time drivers spent on the road but also the resultant increased fuel consumption, which directly points to its environmental impact. In the ever-evolving landscape of automotive technology, platooning, the coordinated driving of (semi-)automated vehicles in convoys, depicts a promising approach to address several issues associated with high traffic volumes [2]–[4]. The concept of platooning coordination can be implemented by applying the architecture of a Self-Adaptive and Self-Organizing (SASO) system [5]. A SASO system's ability of a runtime adaptation as a response to changes in its environment and the system itself is the outcome of a coordinated interaction between an adaptation manager (AM), with its collection of software modules, and its managed resources (MR), being hardware or software [6]. A general SASO architecture, as shown in Fig. 1, is constituted of an adaptation manager AM_{SASO} with a set of goals G_{SASO} . Depending on the level of control, the AM_{SASO} can be separated into multiple $AM_{ext,i}$ implemented with a structured functionality, e.g., a MAPE-K model (Monitor-Analyze-Plan-Execute-Knowledge) [7]. The managed resources MR_j are grouped into subsystems S_j . If the subsystem follows its own

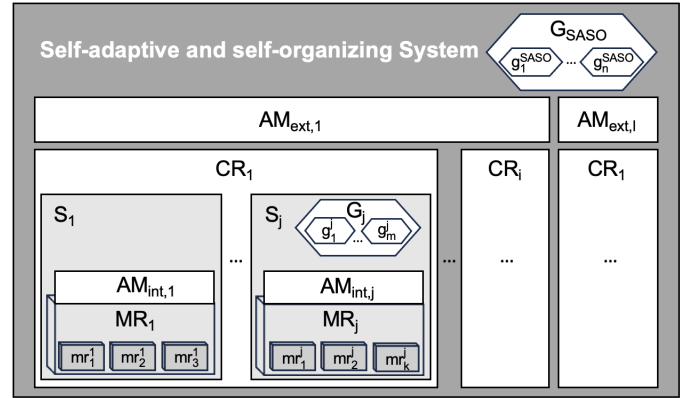


Fig. 1. Architecture for a coordinated SASO system; adapted from [5].

goals G_j , an internal adaptation manager $AM_{int,j}$ takes control of the respective managed resource MR_j . The subsystems can, in turn, be combined into coordinated resource groups CR_i , where the position of the subsystem and the properties of the group directly influence the goal achievement. In the case of fully centralized control of the MR_j by the AM_{ext} , the intercalated AM_{int} forwards the respective signals of control. The focus is on global optimization, with local interests of the MR being ignored [8]. On the contrary, the AM_{int} will act as the sole decision maker in a decentralized approach, with the AM_{ext} being non-existent. While this approach considers local goals, the internal AM is not aware of global optima [9]. By combining both techniques in a hybrid approach, AM_{ext} and AM_{int} collaboratively coordinate the SASO system. By transferring the concept of the coordinated SASO system to the platooning example, a single platoon depicts a Coordinated Resource CR_i , composed of numerous subsystems S_j . The subsystems represent the individual vehicles assigned to adequate platoons by the platooning coordination system (PCS), constituting the AM_{ext} . The PCS aims at optimizing global goals, e.g., energy efficiency, global safety, road capacity, and traffic flow [10]. As autonomous vehicles have their own goals, like improving user comfort and balancing their cost, they might not be interested in following the commands

of the PCS. Instead, the $AM_{int,j}$ provides them with their own adaptation commands. The InHOSaS project ('Integrated Hybrid Optimization of Autonomous Self-adaptive Systems') aims to tackle potentially conflicting adaptations by establishing a hybrid system that combines centralized adaptation planning, which is robust with local decision-making, and decentralized decision-making, optimized by central coordination. For a deeper dive into the approach, Section II outlines the anticipated research objectives, followed by the evaluation methodologies in Section III. Finally, this paper closes with a forecast of the next steps in Section IV.

II. CONTRIBUTION AND OBJECTIVES

While the implementation of a fully central coordination is computation-intensive, time-consuming, and introduces a potential single point of failure, the decentralized decision-making might result in conflicting adaptations with autonomous entities incapable of identifying globally optimal solutions. Therefore, the InHOSaS research project aims to develop a hybrid collaborating SASO system. For its realization, this project is divided into two branches. The first branch, addressed by the Intelligent Systems Group at the University of Kiel, employs a bottom-up approach with local decision-making based on autonomous learning. The second branch, the focus of this PhD project, pursues the top-down perspective for which the following central research question emerges: **How should the central planner be constructed to allow for a many-objective, self-aware optimization at runtime while robustly handling the introduction of local decisions that possibly interfere with its global plan?** The development of a central planner and the subsequent integration of local preferences can be structured into several steps with individual research objectives (RO).

RO 1 - Development of a central planner with a situation-aware, single-objective optimization. With a top-down perspective, the managed resources receive adaptation instructions from the central planner and act accordingly. To achieve coordination optimization at runtime, designing a modular architecture that involves planning as optimization [11] is required. The modularity ensures flexibility and eliminates the planner's dependence on a specific optimization technique. According to the 'No Free Lunch' theorem [12] and previous studies on the situation-dependence of various optimization algorithms [13], no technique performs best for every objective function or in every scenario. Therefore, a taxonomy needs to be empirically created on when to apply which optimization technique with a focus on single-objectives, considering stochastic, evolutionary, and mathematical approaches as such optimization techniques are commonly present in SASO systems [14]. Furthermore, the highly dynamic nature of traffic requires an automated runtime selection of the most appropriate optimization technique. Building on the modularity, the planner will be further supplied with a meta-adaptation logic that can autonomously select the most suitable optimization algorithm from a pool of many, depending on the underlying circumstances.

RO 2 - Expanding the central planner's focus to multiple differing goals. A central planner focusing on global optimization and considering individual constraints might provoke an unfair distribution of investments among coordinated subsystems. For instance, in platooning, a platoon leader exhibits a proportionally higher fuel consumption than a vehicle with an inner-platoon position. Therefore, it is necessary to establish a compensation scheme to counteract the unfair distribution of contributions. Furthermore, the single-objective optimization is shifted to multi-objective, enabling the focus on multiple differing goals.

RO 3 - Shift from strict adaptation instructions to recommendations through degrees of freedom. In parallel with establishing a situation-aware central planner, the subsystems of the decentralized setup learn to act autonomously and pursue their interests through reinforcement learning. To ensure the consideration of both the global optimization as well as the local decision-making, upon a merge of the two perspectives, the adaptation plan generated by the AM_{ext} will be further equipped with degrees of freedom, i.e., compiling a set of recommendations rather than strict adaptation instructions. The local AM_{int} then chooses its adaptation action by optimizing the fit to its goals within the pre-set boundaries, which causes a further shift from multi- to many-objective optimization. In contrast to multi-objective optimization, in which the system tries to optimize a compromise of objectives (e.g., using a weighted function), in many-objective optimization several goals are targeted individually.

III. METHODOLOGY

Platooning is the first example of evaluating and comparing the fully centralized, fully decentralized, and hybrid SASO system setups. To build on the simulation environment employed by Lesch et al. [13], the open-source traffic simulation SUMO (Simulation of Urban MObility, [15]) serves to simulate basic traffic situations. Since SUMO does not provide a platooning functionality, Plexe [16], with the available Plexe API for Python, is used as an extension. To cover the variability of the proposed SASO system, various traffic scenarios need to be simulated to reflect traffic's versatility. The systems' performance is evaluated based on different metrics, such as the energy efficiency and the fuel consumption.

IV. FUTURE WORK AND RESEARCH PLAN

The InHOSaS project seeks to create a hybrid SASO system that combines centralized adaptation planning and decentralized decision-making. This system would address challenges resulting from the increasing complexity of today's software systems through top-down optimization and bottom-up learning methods. As a distributed multi-agent system, platooning serves as the initial evaluation domain. Therefore, the first steps will comprise designing appropriate traffic scenarios and defining metrics. Subsequently, a classification will be developed that outlines the suitability of different metrics depending on the underlying scenario while applying a static central planner and static local decision-makers, respectively.

REFERENCES

- [1] “ADAC Staubilanz 2023: Deutschland-Ticket reduziert Staus nicht,” Feb. 2024. [Online]. Available: <https://www.adac.de/news/staubilanz-2023/>
- [2] T. Sturm, C. Krupitzer, M. Segata, and C. Becker, “A taxonomy of optimization factors for platooning,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 10, pp. 6097–6114, 2021.
- [3] A. Mushtaq, I. u. Haq, W. u. Nabi, A. Khan, and O. Shafiq, “Traffic flow management of autonomous vehicles using platooning and collision avoidance strategies,” *Electronics*, vol. 10, no. 10, 2021.
- [4] M. Zabat, N. Stabile, S. Frascaroli, and F. Browand, “Drag forces experienced by 2, 3 and 4-vehicle platoons at close spacings,” *SAE Transactions*, vol. 104, pp. 1173–1181, 1995.
- [5] V. Lesch, C. Krupitzer, and S. Tomforde, “Multi-objective optimisation in hybrid collaborating adaptive systems,” in *ARCS Workshop 2019; 32nd International Conference on Architecture of Computing Systems*. VDE, 2019, pp. 1–8.
- [6] C. Krupitzer, F. M. Roth, S. VanSyckel, G. Schiele, and C. Becker, “A survey on engineering approaches for self-adaptive systems,” *Pervasive Mob. Comput.*, vol. 17, no. PB, pp. 184–206, Feb. 2015. [Online]. Available: <http://dx.doi.org/10.1016/j.pmcj.2014.09.009>
- [7] J. Kephart and D. Chess, “The vision of autonomic computing,” *Computer*, vol. 36, no. 1, pp. 41–50, 2003.
- [8] A. Diaconescu, K. L. Bellman, L. Esterle, H. Giese, S. Götz, P. Lewis, and A. Zisman, “Architectures for collective self-aware computing systems,” *Self-Aware Computing Systems*, pp. 191–235, 2017.
- [9] D. Weyns, B. Schmerl, V. Grassi, S. Malek, R. Mirandola, C. Prehofer, J. Wuttke, J. Andersson, H. Giese, and K. M. Göschka, “On patterns for decentralized control in self-adaptive systems,” in *Software Engineering for Self-Adaptive Systems II: International Seminar, Dagstuhl Castle, Germany, October 24-29, 2010 Revised Selected and Invited Papers*. Springer, 2013, pp. 76–107.
- [10] C. Krupitzer, M. Segata, M. Breitbach, S. El-Tawab, S. Tomforde, and C. Becker, “Towards infrastructure-aided self-organized hybrid platooning,” in *2018 IEEE Global Conference on Internet of Things (GCIoT)*, 2018, pp. 1–6.
- [11] E. M. Fredericks, I. Gerostathopoulos, C. Krupitzer, and T. Vogel, “Planning as optimization: Dynamically discovering optimal configurations for runtime situations,” in *2019 IEEE 13th International Conference on Self-Adaptive and Self-Organizing Systems (SASO)*, 2019, pp. 1–10.
- [12] D. Wolpert and W. Macready, “No free lunch theorems for optimization,” *IEEE Transactions on Evolutionary Computation*, vol. 1, no. 1, pp. 67–82, 1997.
- [13] V. Lesch, T. Noack, J. Hefter, S. Kounev, and C. Krupitzer, “Towards situation-aware meta-optimization of adaptation planning strategies,” in *2021 IEEE International Conference on Autonomic Computing and Self-Organizing Systems (ACSOS)*, 2021, pp. 177–187.
- [14] E. Henrichs, V. Lesch, M. Straesser, S. Kounev, and C. Krupitzer, “A literature review on optimization techniques for adaptation planning in adaptive systems: State of the art and research directions,” *Information and Software Technology*, vol. 149, 2022.
- [15] P. A. Lopez, M. Behrisch, L. Bieker-Walz, J. Erdmann, Y.-P. Flötteröd, R. Hilbrich, L. Lücken, J. Rummel, P. Wagner, and E. Wießner, “Microscopic traffic simulation using sumo,” in *The 21st IEEE International Conference on Intelligent Transportation Systems*. IEEE, 2018.
- [16] M. Segata, R. Lo Cigno, T. Hardes, J. Heinovski, M. Schettler, B. Bloessl, C. Sommer, and F. Dressler, “Multi-Technology Cooperative Driving: An Analysis Based on PLEXE,” *IEEE Transactions on Mobile Computing*, vol. 22, no. 8, pp. 4792–4806, 2023.