KI - Künstliche Intelligenz
https://doi.org/10.1007/s13218-024-00868-3

PROJECT REPORTS

EASY: Energy-Efficient Analysis and Control Processes in the Dynamic Edge-Cloud Continuum for Industrial Manufacturing

Alexander Schultheis[1,2] · Benjamin Alt[3] · Sebastian Bast[4] · Achim Guldner[4] · David Jilg[1] · Darko Katic[3] · Johannes Mundorf[5] · Tobias Schlagenhauf[6] · Sebastian Weber[4] · Ralph Bergmann[1,2] · Simon Bergweiler[5,7] · Lars Creutz[4] · Guido Dartmann[4] · Lukas Malburg[1,2] · Stefan Naumann[4] · Mahdi Rezapour[5] · Martin Ruskowski[5,7,8]

Received: 31 October 2023 / Accepted: 27 July 2024

Abstract
According to the guiding principles of Industry 4.0, edge computing enables the data-sovereign and near-real-time processing of data directly at the point of origin. Using these edge devices in manufacturing organization will drive the use of industrial analysis, control, and Artificial Intelligence (AI) applications close to production. The goal of the *EASY* project is to make the added value of edge computing available by providing an easily usable Edge-Cloud Continuum with a runtime environment and services for the execution of AI-based Analysis and Control processes. Within this continuum, a dynamic, distributed, and optimized execution of services is automated across the entire spectrum from centralized cloud to decentralized edge instances to increase productivity and resource efficiency.

Keywords Edge-Cloud Continuum · Energy- and Resource-Efficiency · Analysis and Control Processes

1 Introduction

Industry 4.0 (I4.0) [13] denotes the technological change towards intelligent production in which *Artificial Intelligence* (AI) methods, data analysis techniques, the *Internet of Things* (IoT) and distributed systems are integrated into industrial processes. In this context, optimization and efficiency-increase of production processes is investigated [20, 22, 38]. The growing automation and interconnection of factories offers new opportunities, such as the promising use of edge nodes [46]. These are miniaturized computing devices located directly in the production environment. The exploration of the industrial potential of these edge nodes is addressed by the *EASY* project[1] running from 2022 until the end of 2025. The acronym stands for "Energy-Efficient Analysis and Control Processes in the Dynamic Edge-Cloud Continuum for Industrial Manufacturing" and is the name of a German consortium funded by the Federal Ministry for Economic Affairs and Climate Action. In addition, an affiliated project financed by the Austrian Research Promotion Agency contributes toward this research. Namely, the consortium consists of the following partners: Empolis Information Management GmbH (consortia leader), German Research Center for Artificial Intelligence (DFKI), Robert Bosch GmbH, Fraunhofer IOSB-INA, Trier University of Applied Sciences—Environmental Campus Birkenfeld, ArtiMinds Robotics GmbH, coboworx GmbH, and Salzburg Research.

Within *EASY*, this consortium aims to overcome technical barriers in industrial manufacturing by creating an open and standardized *Edge-Cloud Continuum* (ECC) that should enable the optimized execution of Analysis and Control Processes. This continuum is a distributed infrastructure that includes the described edge devices as well as a central cloud, and enables dynamic distribution of computations across all contained devices [35, 39]. AI methods are used to plan and execute both types of processes in the ECC. These methods can run both, centralized on the cloud and decentralized on the edge. The inclusion of the edge nodes allows analyzing the high-frequency data in near real-time, and also enables data protection for companies through non-sharing. This standardized, freely available ECC should lower the entry barriers for small- and medium-sized enterprises to these technologies. To demonstrate and evaluate the described aspects, various prototypes are developed.

In the remainder of this paper, an overview of the architecture of the *EASY* project and the considered processes is

Extended author information available on the last page of the article

[1] Website of the *EASY* project: https://easy-edge-cloud.de/.

given in Sect. 2. In Sect. 3, the AI methods applied to these processes are presented. The use cases to demonstrate the project's results are described in Sect. 4. Afterward, Sect. 5 provides a summary and an outlook for future research in the context of our work.

2 EASY Architecture and Processes

In this part, the overall *EASY* framework targeting the project's goals is presented. First, the basic architecture is introduced in Sect. 2.1. Then, the processes within this are described in Sect. 2.2 and classified in the *Business Process Management* (BPM) [12] research state.

2.1 Architectural Overview

The ECC is a distributed environment composed of computing and network infrastructure [24, 35, 39]. Here, edge devices offer local data processing and storage as well as service execution, whereas the cloud provides the same functions on a server network with higher capabilities. These edge nodes can be run by individual members (i.e., industrial companies) while a separate entity provides a central cloud platform. In the ECC, data and computations can be flexibly moved between such edge devices and the cloud. This allows the transfer of data to the cloud to be minimized, as the compute resources available on the edge can be used to at least partially process the data. Therefore, the significant cost involved with large data transfers can be reduced. However, the cloud orchestrates the ECC and determines where analysis or control processes should be computed within the continuum. In addition, this architecture can address the issue of data privacy by allowing companies to avoid moving specific data to a cross-enterprise cloud solution. Therefore, certain assumptions such as the integrity of the cloud platform provider have to be made.

We will develop such a continuum for the *EASY* project in the form shown in Fig. 1. The lowest level is formed by individual assets on the production floor, such as manufacturing robots or IoT control components [21, 45]. These assets are usually constrained in terms of computing power. However, they can still be used to perform small computational tasks. To enhance the compute power at these positions, the assets are connected to edge nodes, which form the second-lowest layer. At these nodes and along the continuum, services can be run to process, aggregate, or simply pass data to other entities. Specialized computing infrastructure at the edge, such as compute clusters or big data storage, could also be employed before moving to the cloud. In this architecture, the path between the edge and the cloud is paved with different layers of nodes providing increasing computational capabilities. This enables a dynamic and optimized execution of

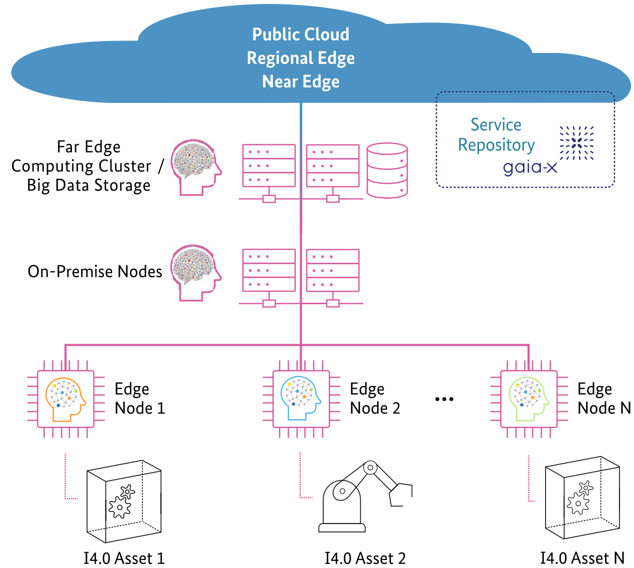

Fig. 1 An overview of the *EASY* architecture

AI services, in terms of metrics, e.g., the project's namesake energy efficiency, but also other Green AI and Sustainable Software Engineering criteria [49], such as resource and data efficiency [23]. To identify and optimize such metrics required for measuring these values in the ECC, a reference model and an exemplary measurement method [17] are used as basis. Within the ECC, the AI services are stored in a central repository based on the Gaia-X architecture [47]. By using these services on the edge nodes, the data only requires transmission to the nearest one with sufficient resources and, in most cases, not all the way to the cloud.

2.2 Processes in EASY

In *EASY*, we focus both on Analysis and Control Processes and address these dynamically in the ECC using AI techniques:

1. *Analysis Processes*: These processes are geared towards examination and analysis of data, e.g., based on IoT sensor streams [45]. Considering this, local analyses such as visual quality control [32] or error detection [15] are to be carried out. Regarding the ECC, the analysis will identify the use of resources such as computing capacity and energy consumption. In addition, aspects of the decentralized architecture that can increase data security are explored [10, 11].
2. *Control Processes*: These processes concern the management of the value creation processes, meaning the manufacturing facilities and their resources. This includes the dynamic allocation of these resources throughout the ECC, as well as the automated planning

of production processes and their flexible and correct execution [6, 27]. In addition to the sustainability criteria, the processes should be robust and flexible so that in cases of deviations they can still be executed or adapted accordingly, even in cases of deviations [16] or changed metrics [6].

In the BPM research field, flexible analysis and production processes have already been addressed [29]. Both processes should focus on their resource efficiency, as criterion [9] already specified above for each type. To consider this and other sustainability metrics accordingly, semantic information about the processes must be available [25] and provided in a suitable semantic structure [30]. This must be an appropriate digital representation of the devices in the ECC or the production resources, e.g., like a semantic Asset Administration Shell [4, 41]. The approaches mentioned so far rarely use extensive AI methods. However, these offer great potential for optimizing adaptive process management and go beyond manually performed adaptations [27, 33]. Therefore, the *EASY* project targets this issue in the ECC and in physical smart factories. The AI methods used to manage these processes are presented next.

3 AI Methods in EASY

In the *EASY* project, various established AI methods address processes in the ECC and are investigated for optimizing resource usage. In the following, we present the techniques of AI Planning (Sect. 3.1), Case-Based Reasoning (Sect. 3.2) and Distributed Learning (Sect. 3.3) in this context.

3.1 AI Planning

AI Planning aims at solving a state transformation problem, where the goal consists of finding a sequence of steps to transform a discrete world model from an initial state to a desired goal state [14, 19]. This technique is already applied in the BPM area to increase automation and support [33]. In *EASY*, we investigate this technique to facilitate flexible Analysis and Control Processes dynamically in the ECC. The relevant analysis process mainly consists of service orchestrations regarding computation resources in the ECC. Here, the goal state is achieving an optimal distribution of computation and data across the individual instances, e.g., for data aggregation. As the result, this is federated among the participated edge nodes and the cloud. For the control processes, the manufacturing environment is considered, where the goal state is a desired product with specific characteristics. The planning problem thereby consists of finding a sequence of executable manufacturing actions which lead to the desired products. Both, the generated analysis and the control processes, can be executed automatically. A drawback of solving complex planning problems is the high computational complexity needed, especially when used on edge devices. To mitigate this, we will combine AI Planning with other AI techniques [18].

3.2 Case-Based Reasoning

Case-Based Reasoning (CBR) is an AI method for experience-based problem-solving [1, 7]. Problems and their corresponding solutions are stored as cases that form the basis of addressing new problems. Using similarity as a criterion, suitable cases are identified, and their solution is adapted. In the context of the *EASY* project, both analysis and production processes are created using CBR. In the manufacturing domain, CBR can be used to perform analysis processes such as predictive maintenance or identifying data quality issues based on IoT time series data [31, 42, 44]. The advantage of using CBR in this context is that in comparison to other AI methods only a few error cases are required. To optimize production processes, a case is represented as a workflow in the sub-field of *Process-Oriented Case-Based Reasoning* (POCBR) [36]. In the context of planning of processes, POCBR is used to reduce computational complexity and increase flexibility by reusing already solved problems [28]. Thus, existing plans are retrieved and, if necessitated, adapted for the new requirements by AI Planning. In *EASY*, we use this for flexible planning and execution of the processes. These CBR applications for analysis and control are to take place on the edge as well as in the cloud dynamically.

3.3 Distributed Learning

Distributed Learning is a *Machine Learning* (ML) [37] approach performed across multiple computing resources [40]. Traditional ML and Deep Learning [8] systems rely on large amounts of centrally stored data, so that most (locally stored) data cannot be used due to computational complexity. The classical approach in ML or DL would be to send the (small) data sets of the single machines to a central server. There, a model is trained based on the data. In practice though, data often cannot be transported over a network due to privacy or bandwidth issues [26, 48]. To address this in *EASY*, we use *Federated Learning* (FL) [34] as a distributed ML approach to keep the data local at each machine as an edge-node and learn for local analysis processes there. Instead of explicit data, the local model weights are shared in the ECC. Besides the advantage that no real data is sent, all nodes share their knowledge within the continuum. The respective edge devices can adapt the globally merged analysis model for their data without directly influencing the performance of the other local models. In addition to traditional manufacturing data analysis using FL, robotic learning and optimization is also contained in *EASY* based on this technique. For this purpose, existing previous work [3] is built upon to first pre-train predictive robot foundation models on large data sets in the cloud and then achieve model-based parameter optimization on the edge devices [2]. Additional to the described communication reduction in these applications, energy consumption should be reduced by the distributed FL methodology.

4 Use Cases and Demonstration

To showcase the approaches developed in the *EASY* project, six demonstrators are built based on different use cases, briefly described in the following. The participating and associated industrial partners aim to ensure that the demonstrators represent real-world use cases. In addition to qualitative aspects, quantitative parameters based on the metrics to be developed, such as energy or resource efficiency, are examined for each demonstrator.

Together with SmartFactory^{KL} and SmartFactoryOWL as associated partners, DFKI and Fraunhofer are creating two similar setups at the respective, cooperating locations. These are used to demonstrate the concept of shared production across multiple sites. This use case demonstrates the flexible and resilient control processes as well as analysis processes for quality control. To apply the POCBR approach, the CBR framework ProCAKE [5, 43] is used and extended for the application in the ECC.

Bosch realizes a demonstrator which is especially suited to invest analysis processes using FL. The demonstrator consists of several standardized, interconnected edge devices whose behavior is monitored and controlled using a graphical interface. In this setup, the data of several milling machines connected to edge devices are processed and models are learned federated on this basis.

FL approaches in the ECC are also being explored by ArtiMinds in a demonstrator that focuses on robot learning and optimization. Among others, force-control and vision-based handling are investigated. The implementation of the FL methods will also be integrated into the industrial robot data platform ArtiMinds LAR.[2]

In another demonstrator, Coboworx and Salzburg Research, present analysis processes by monitoring the condition of an industrial robot in a distributed palletizing application. The reliable communication within the ECC is visualized and measured regarding anomaly detection, to prevent possible economic downtimes.

Furthermore, the Environmental Campus explores analysis processes with focus on the resource, data, and energy efficiency of distributed learning and applies these in demonstrators for analyzing multi-modal sensor data.

5 Summary and Outlook

In this paper, we present the idea of the *EASY* project, which aims at realizing a dynamic ECC for industrial manufacturing. Our focus is on the application of AI methods to BPM processes, namely to the presented Analysis and Control Processes. In this context, we describe various research areas for future work, addressed within the *EASY* project. We will demonstrate the project results in an industrial context and evaluate them regarding their energy and resource efficiency.

Acknowledgements This work is funded by the German Federal Ministry for Economic Affairs and Climate Action under Grant No. 01MD22002C *EASY* and co-funded by the Austrian Research Promotion Agency under Grant No. FO999897905.

Funding Open Access funding enabled and organized by Projekt DEAL.

References

1. Aamodt A, Plaza E (1994) Case-based reasoning: foundational issues, methodological variations, and system approaches. AI Commun 7(1):39–59
2. Alt B, Katic D, Jäkel R, Beetz M (2022) Heuristic-free optimization of force-controlled robot search strategies in stochastic environments. In: IROS 2022, pp 8887–8893
3. Alt B, Katic D, Jäkel, R, Beetz, M (2021) Robot program parameter inference via differentiable shadow program inversion. In: 2021 IEEE International Conference on Robotics and Automation (ICRA), Xi'an, China, 2021, pp 4672–4678
4. Bader SR, Maleshkova M (2019) The semantic asset administration shell. In: 15th SEMANTiCS proceedings. Springer, Berlin, pp 159–174
5. Bergmann R, Grumbach L, Malburg L, Zeyen C (2019) ProCAKE: a process-oriented case-based reasoning framework. In: 27th ICCBR workshop proceedings of the CEUR-WS.org
6. Bergmann R, Müller G (2018) Similarity-based retrieval and automatic adaptation of semantic workflows. Syn Btw Know Eng Softw Eng 626:31–54

[2] https://www.artiminds.com/robotics-software-and-services/learning-and-analytics-for-robots/.

7. Bergmann R, Althoff KD, Minor M, Reichle, M, Bach K (2009) Case-based reasoning-introduction and recent developments. KI 1(2009):5–11
8. Buduma N (2017) Fundamentals of deep learning: designing next-generation machine intelligence algorithms, 1st edn. O'Reilly, Sabastopol, CA
9. Chu H, Dong K, Yan J, Li Z, Liu Z, Cheng Q, Zhang C (2023) Flexible process planning based on predictive models for machining time and energy consumption. Int J Adv Manuf Technol 128(3–4):1763–1780
10. Creutz L, Dartmann G (2020) Cypher social contracts a novel protocol specification for cyber physical smart contracts. In: IGCSC 2020, pp 440–447
11. Creutz L, Schneider J, Dartmann G (2021) Fides: distributed cyber-physical contracts. In: 3rd IEEE TPS, pp 51–60
12. Dumas M, Rosa ML, Mendling J, Reijers HA (2018) Fundamentals of BPM, 2nd edn. Springer, Berlin
13. Gilchrist A (2016) Industry 4.0: the IIoT. Springer, Berlin
14. Green C (1969) Application of theorem proving to problem solving. In: 1st IJCAI Proceedings, IJCAI'69. Morgan Kaufmann Publishers Inc., San Francisco, pp 219–239
15. Grüger J, Malburg L, Bergmann R (2023) IoT-enriched event log generation and quality analytics: a case study. IT 65(3):128–138
16. Grumbach L, Bergmann R (2021) SEMAFLEX: a novel approach for implementing workflow flexibility by deviation based on constraint satisfaction problem solving. Expert Syst 38(7):e12385
17. Guldner A, Bender R, Calero C, Fernando GS, Funke M, Gröger J, Hilty LM, Hörnschemeyer J, Hoffmann GD, Juner D, Kennes T, Kreten S, Lago P, Mai F, Malavolta I, Murach J, Obergöker K, Schmidt B, Tarara A, De Veaugh-Geiss JP, Weber S, Westing M, Wohlgmuth V, Naumann S (2024) Development and evaluation of a reference measurement model for assessing the resource and energy efficiency of software products and components–Green Software Measurement Model (GSMM). Future Gener Comput Syst 155:402–418
18. Hammond KJ (1990) Case-based planning: a framework for planning from experience. Cogn Sci 14(3):385–443
19. Haslum P (2006) Admissible heuristics for automated planning. Ph.D. thesis, Institutionen för datavetenskap
20. Hozdić E (2015) Smart factory for industry 4.0: a review. Int J Mod 7(1):28–35
21. Ismail A, Truong H, Kastner W (2019) Manufacturing process data analysis pipelines: a requirements analysis and survey. J Big Data 6:1
22. Jazdi N (2014) Cyber physical systems in the context of Industry 4.0. In: AQTR 2014. IEEE, pp 1–4
23. Kern E, Hilty LM, Guldner A, Maksimov YV, Filler A, Gröger J, Naumann S (2018) Sustainable software products—towards assessment criteria for resource and energy efficiency. FGCS 86:199–210
24. Khalyeyev D, Bures T, Hnetynka P (2022) Towards characterization of edge-cloud continuum. In: ECSA 2022 Proceedings of the LNCS, vol 13928. Springer, Berlin, pp 215–230
25. Klein P, Malburg L, Bergmann R (2019) FTOnto: a domain ontology for a Fischertechnik simulation production factory by reusing existing ontologies. In: LWDA 2019 workshop proceedings, vol 2454. CEUR-WS.org, pp 253–264
26. Lipp R, Schmeink A, Dartmann G, Fazli L, Vollmer T, Winter S, Peine A, Lukas M (2021) Incremental parameter estimation of stochastic state-based models. In: IEEE 19th world symposium on applied machine intelligence and informatics (SAMI), Herl'any, Slovakia, pp 317–322
27. Malburg L, Bergmann R (2022) Towards adaptive workflow management by case-based reasoning and automated planning. In: 30th ICCBR Workshop Proceedings, CEUR Workshop Proceedings, vol 3389. CEUR-WS.org, pp 1–10
28. Malburg L, Brand F, Bergmann R (2023) Adaptive management of cyber-physical workflows by means of case-based reasoning and automated planning. In: EDOC workshops 2022, LNBIP, vol 466. Springer, Berlin, pp 79–95
29. Malburg L, Hoffmann M, Bergmann R (2023) Applying MAPE-K control loops for adaptive workflow management in smart factories. J Intell Inf Syst 61:83–111
30. Malburg L, Klein P, Bergmann R (2023) Converting semantic web services into formal planning domain descriptions to enable manufacturing process planning and scheduling in industry 4.0. Eng Appl Artif Intell 126:106727
31. Malburg L, Schultheis A, Bergmann R (2023) Modeling and using complex IoT time series data in case-based reasoning: from application scenarios to implementations. In: 31st ICCBR Workshop Proceedings, pp 81–96
32. Malburg L, Rider MP, Seiger R, Klein P, Bergmann R (2021) Object detection for smart factory processes by machine learning. Proc Comput Sci 184:581–588
33. Marrella A (2017) What automated planning can do for business process management. In: BPM 2017 Workshop Proceedings, LNBIP, vol 308. Springer, Berlin, pp 7–19
34. McMahan B, Moore E, Ramag D, Hampson S, y Arcas BA (2017) Communication-efficient learning of deep networks from decentralized data. In: 20th AISTATS Proceedings, vol 54. PMLR, pp 1273–1282
35. Milojicic D (2020) The edge-to-cloud continuum. Computer 53(11):16–25
36. Minor M, Montani S, Recio-García JA (2014) Process-oriented case-based reasoning. Inf Syst 40:103–105
37. Mitchell TM (1997) Machine learning. McGraw-Hill, New York
38. Monostori L, Botond K, Bauernhansl T, Kondoh S, Kumara S, Reinhart G, Sauer O, Schuh G, Sihn W, Ueda K (2016) Cyber-physical systems in manufacturing. Cirp Ann 65(2):621–641
39. Moreschini S, Pecorelli F, Li X, Naz S, Hästbacka D, Taibi D (2022) Cloud Continuum: the definition. IEEE Access 10:131876–131886
40. Peteiro-Barral D, Guijarro-Berdiñas B (2013) A survey of methods for distributed machine learning. Prog AI 2(1):1–11
41. Redeker M, Volgmann S, Pethig F, Kalhoff J (2020) Towards data sovereignty of asset administration shells across value added chains. In: 25th ETFA, vol 1. IEEE, pp 1151–1154
42. Schultheis A (2024) Exploring a hybrid case-based reasoning approach for time series adaptation in predictive maintenance. In: 32nd ICCBR Workshop Proceedings, vol 3708. CEUR-WS.org, pp 230–235
43. Schultheis A, Zeyen C, Bergmann R (2023) An overview and comparison of CBR frameworks. In: 31st ICCBR Proceedings of the, LNCS, vol 14141. Springer, Berlin, pp 327–343
44. Schultheis A, Malburg L, Grüger J, Weich J, Bertrand Y, Bergmann R, Serral Asensio E (2024) Identifying missing sensor values in IoT time series data. In: 32nd ICCBR Proceedings of the LNCS, vol 14775. Springer, Berlin, pp 240–257
45. Seiger R, Malburg L, Weber B, Bergmann R (2022) Integrating process management and event processing in smart factories: a systems architecture and use cases. J Manuf Syst 63:575–592
46. Shi W, Dustdar S (2016) The promise of edge computing. Computer 49(5):78–81
47. Tardieu H (2022) Role of Gaia-X in the European data space ecosystem. In: Designing data spaces: the ecosystem approach. Springer, Berlin, pp 41–59
48. Vieting PM, de Lamare RC, Martin L, Dartmann G, Schmeink A (2019) Likelihood-based adaptive learning in stochastic state-based models. IEEE Signal Process Lett 26(7):1031–1035

49. Weber S, Guldner A, Fazlic LB, Dartmann G, Naumann S (2023) Sustainability in artificial intelligence—towards a green AI reference model. In: Künstliche Intelligenz in der Umweltinformatik, LNI. Gesellschaft für Informatik

Authors and Affiliations

Alexander Schultheis[1,2] · Benjamin Alt[3] · Sebastian Bast[4] · Achim Guldner[4] · David Jilg[1] · Darko Katic[3] · Johannes Mundorf[5] · Tobias Schlagenhauf[6] · Sebastian Weber[4] · Ralph Bergmann[1,2] · Simon Bergweiler[5,7] · Lars Creutz[4] · Guido Dartmann[4] · Lukas Malburg[1,2] · Stefan Naumann[4] · Mahdi Rezapour[5] · Martin Ruskowski[5,7,8]

✉ Alexander Schultheis
alexander.schultheis@dfki.de; schultheis@uni-trier.de

Benjamin Alt
benjamin.alt@artiminds.com

Sebastian Bast
s.bast@umwelt-campus.de

Achim Guldner
a.guldner@umwelt-campus.de

David Jilg
david.jilg@dfki.de

Darko Katic
darko.katic@artiminds.com

Johannes Mundorf
johannes.mundorf@dfki.de

Tobias Schlagenhauf
tobias.schlagenhauf@de.bosch.com

Sebastian Weber
seb.weber@umwelt-campus.de

Ralph Bergmann
ralph.bergmann@dfki.de; bergmann@uni-trier.de

Simon Bergweiler
simon.bergweiler@dfki.de

Lars Creutz
l.creutz@umwelt-campus.de

Guido Dartmann
g.dartmann@umwelt-campus.de

Lukas Malburg
lukas.malburg@dfki.de; malburgl@uni-trier.de

Stefan Naumann
s.naumann@umwelt-campus.de

Mahdi Rezapour
mahdi.rezapour@dfki.de

Martin Ruskowski
martin.ruskowski@dfki.de; martin.ruskowski@rptu.de

1 German Research Center for Artificial Intelligence (DFKI), Experience-Based Learning Systems, Branch Trier University, Behringstraße 21, 54296 Trier, Germany

2 Artificial Intelligence and Intelligent Information Systems, Trier University, 54296 Trier, Germany

3 ArtiMinds Robotics GmbH, Albert-Nestler-Straße 11, 76131 Karlsruhe, Germany

4 Trier University of Applied Sciences, Environmental Campus Birkenfeld, Institute for Software Systems, P.O. Box 1380, 55761 Birkenfeld, Germany

5 German Research Center for Artificial Intelligence (DFKI), Innovative Factory Systems, 67663 Kaiserslautern, Germany

6 Robert Bosch GmbH - Central Research, Robert-Bosch-Campus 1, 71272 Renningen, Germany

7 Technologie-Initiative SmartFactory KL e.V., Trippstadter Straße 122, 67663 Kaiserslautern, Germany

8 Chair of Machine Tools and Control Systems, University of Kaiserslautern-Landau, Gottlieb-Daimler-Straße 47, 67663 Kaiserslautern, Germany