Research Article

HOW GENERATIVE AI AND THE INTELLIGENT INDUSTRIAL INTERNET OF THINGS COMPLEMENT EACH OTHER

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DOI: 10.15598/aeee.v23i2.250310

Article history: Received Mar 17, 2025; Revised Apr 22, 2025; Accepted Apr 26, 2025; Published Jun 30, 2025.

Abstract. *Generative modeling is an artificial intelligence (AI) technique to generate synthetic artifacts from analyzing training examples and from learning their patterns and distribution. Generative AI (GenAI) uses generative modeling and advances in Deep Learning to produce diverse content at scale by utilizing existing data. Whereas traditionally GenAI is mostly using media contents, such as text, graphics, audio, and video, it can additionally be used also for data from the (Industrial) Internet of Things. This article provides a systematic overview on the manifold different practical opportunities and challenges GenAI brings for the IIoT. It also presents selected examples from the author's research with his teams. In doing so, it covers the relevance of GenAI for the complete lifecycle of IIoT, from design and development, over testing to deployment. This paper summarizes a keynote presentation from the 13th International Conference on Green and Human Information Technology (ICGHIT) in January 2025 held in Nha Trang, Vietnam.*

Keywords

Generative Artificial Intelligence, Internet of Things, Industrial Internet of Things, Generative Internet of Things.

1. Introduction

It goes back to Schumpeter's idea that innovations can be described as new combinations of pre-existing ideas and technologies [1]. Artificial Intelligence (AI) and the Internet of Things (IoT) can be seen as one successful example of such "Innovation by Combination" of two megatrends, which are fueling each other and are leading to an accelerating pace of innovation. The IoT connects anything, anywhere, anytime [2]. Thus, it provides a platform for a truly pervasive and intelligent environment. Since a couple of years, AI and most notably Edge AI simultaneously make use of and enhance the Industrial IoT (IIoT) [3].

Generative modeling is an artificial intelligence (AI) technique to generate synthetic artifacts from analyzing training examples and from learning their patterns and distribution. Generative AI (GenAI) uses generative modeling and advances in Deep Learning (DL) to produce diverse content at scale by utilizing existing data. These models often generate output in response to specific prompts. Generative AI systems learn the underlying patterns and structures of their training data, enabling them to create new data. Whereas GenAI is mostly using media contents, such as text, graphics, audio, and video, it can additionally be used also for data from the (Industrial) IoT. Thus, the Generative Internet of Things (GIoT) is emerging and holds immense potential to revolutionize various aspects of society, enabling more efficient and intelligent IoT applications.

This article provides a systematic overview on the different practical opportunities and challenges GenAI brings for the IIoT. It is structured as follows: section 2 gives a short overview of the different GenAI technologies, being relevant for the IIoT, where section 3 lists possible use cases from the IIoT. After that, section 4 explains a few examples from the author's research at his institutions, before concluding with a selection of current research directions in section 5 and a short summary in section 6.

2. Generative AI Technologies

GenAI is defined, and commonly distinguished from other types of AI, by its capability to "generate new content" [4]. In the typical case of Generator Adversarial Network (GANs), GenAI uses two neural networks: a generator and a discriminator (cf. Fig. 1). Thus, it generates synthetic artifacts by analyzing training examples (be it cats, dogs, or IIoT data), learning their patterns and distribution and then creating realistic facsimiles. The discriminator then takes the real examples from the dataset and the fake ones generated by the generator and tries to classify them as either real or fake. Based on this classification, it learns to get better at discriminating images in the next round. At the same time, the generator learns how well the generated facsimiles fooled the discriminator and improves the creation of facsimiles in the next round.

GenAI is not new, it is only until recently that large-scale generative models exemplified by Large Language Models (LLMs) (e.g., GPT, LLaMA, and Gemini) and Multimodal Generative Models (e.g., GPT-4V, DALL-E, and Stable Diffusion) have made the breakthrough [6]. There is a selection of several GenAI methods being used, i.e. for GIoT applications [5, 7]:

- Generative Adversarial Networks (GANs) are maybe the most prevalent GenAI technique being used today in IoT data synthesis, consisting of generator and discriminator networks [5, 7]. The generator network aims to generate new data by learning real data distribution, while the discriminator network aims to distinguish synthetic data from real data. The two networks are trained together in interactive and competitive manners, resulting in continuous enhancement of synthesis performance.

- Variational Autoencoders (VAEs) consist of the encoder and decoder networks, where the encoder network compresses the input data to a latent representation and the decoder network learns to reconstruct synthetic data that closely aligns with the original distribution [7].

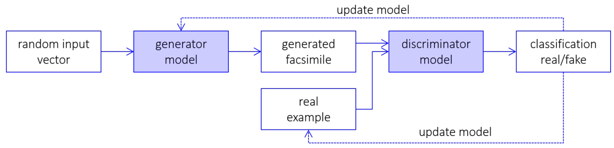

Fig. 1: Generalized Process Flow for Generative AI.

- Generative Diffusion Models (GDMs) are generative models emerging with the state-of-the-art performance of image synthesis. They consist of forward diffusion and denoising processes inspired by non-equilibrium thermodynamics theory [7].

- Geometric DL (GDL) tries to understand, interpret, and describe AI models in terms of geometric principles [7].

- Flow-based Generative Models (FGM) can transform input data distributions from simple to complex through a series of differentiable and invertible transformations that are implemented as neural networks [5].

3. Use Cases for GenAI in the IIoT

GenAI is a game-changer for the IIoT, offering capabilities that enhance efficiency, reduce costs, and drive innovation. By extending available methods for predictive analytics, real-time simulations, and intelligent automation, GenAI is shaping the future of industrial operations in profound ways. As industries increasingly adopt IIoT, GenAI will likely be pivotal in ensuring smarter, safer, and more sustainable practices.

There is a multitude of different uses cases for the GenAI in the IIoT. In the following, a short overview is given together with some abstract examples bringing pivotal benefits across the entire IoT pipeline, encompassing data generation, data processing, interfacing with IIoT devices, and IIoT system development and evaluation. These benefits are relevant for all different IIoT application domains, e.g. autonomous vehicles, robotics, health care, and many more [6].

3.1. Enhanced Data Analytics and Insights

IIoT devices generate vast amounts of data. GenAI can

A.1 synthesize complex data and create meaningful summaries or patterns from raw sensor data, making it easier to derive actionable insights.

A.2 analyze trends and anomalies by generating simulations or predictions, helping to anticipate system behaviors or detect issues early.

A.3 create new data representations and fill gaps in incomplete datasets to improve data quality.

A.4 generate digital twins and high-fidelity virtual models of industrial processes, providing detailed insights and predictions.

3.2. Autonomous and Adaptive Decision-Making

GenAI can enable IIoT devices to:

B.1 generate dynamic architectures, where generative models create on-the-fly solutions for unexpected challenges, e.g. supply chain disruptions or production bottlenecks.

B.2 simulate scenarios, so that virtual environments can be generated to test different IoT responses under various conditions, enhancing real-world deployment reliability.

3.3. Enhanced Predictive Maintenance

GenAI models excel at analysing complex, multivariate data from IIoT sensors to:

C.1 predict equipment failures by generating simulated failure patterns to provice early warnings about machinery needing maintenance and deliver substantial cost savings by preventing unplanned downtime.

C.2 optimize maintenance schedules and generate efficient maintenance plans, minimizing downtime.

C.3 simulate what-if scenarios by predictive simulations to help organizations understand the long-term impact of various operational strategies.

In this sense, category "C. Enhanced Predictive Maintenance" can be understood as a special case of category "A. Enhanced Data Analytics and Insights" and as an outcome of category "B. Autonomous and Adaptive Decision-Making".

3.4. Enhanced Security

Cybersecurity is paramount for IIoT. GenAI can contribute by:

D.1 creating synthetic data to train AI models (e.g. for anomaly detection) without exposing sensitive real-world data, preserving privacy.

D.2 simulating cyberattack scenarios and potential vulnerabilities, as well as testing IoT defenses against potential threats.

D.3 generating adaptive security protocols and proposing real-time, custom solutions to mitigate threats and to safeguard against vulnerabilities.

3.5. Efficient Resource Management

For IIoT systems managing resources, GenAI can:

E.1 model the influence of different resource allocation strategies on system performance.

E.2 optimize operations and generate efficient schedules or routes for resource use.

E.3 simulate future demands and predict and generate plans to balance supply and demand dynamically.

The managed resources can be resources like energy, traffic, or water, but also the IIoT networks itself.

3.6. Enabling Creativity in IIoT Applications

GenAI can open doors to innovative applications by:

F.1 creating new device functionalities and features based on specific environments.

F.2 enhancing sustainability initiatives by generating solutions for reducing emissions and waste in industrial processes.

F.3 generating synthetic environments for testing, so that IIoT developers can simulate diverse scenarios to enhance robustness before deployment.

3.7. Personalized User Experiences

GenAI can use IIoT data to:

G.1 generate customized interactions, so that devices can learn user preferences and create personalized responses or settings.

G.2 improve decision support and generate actionable insights and recommendations for complex industrial operations.

G.3 design new services and suggest lifestyle enhancements based on usage patterns.

3.8. Natural Language Interfaces

Integrating GenAI can allows IIoT systems to:

H.1 improve voice and text interaction. so that devices can provide smart, nuanced and conversational

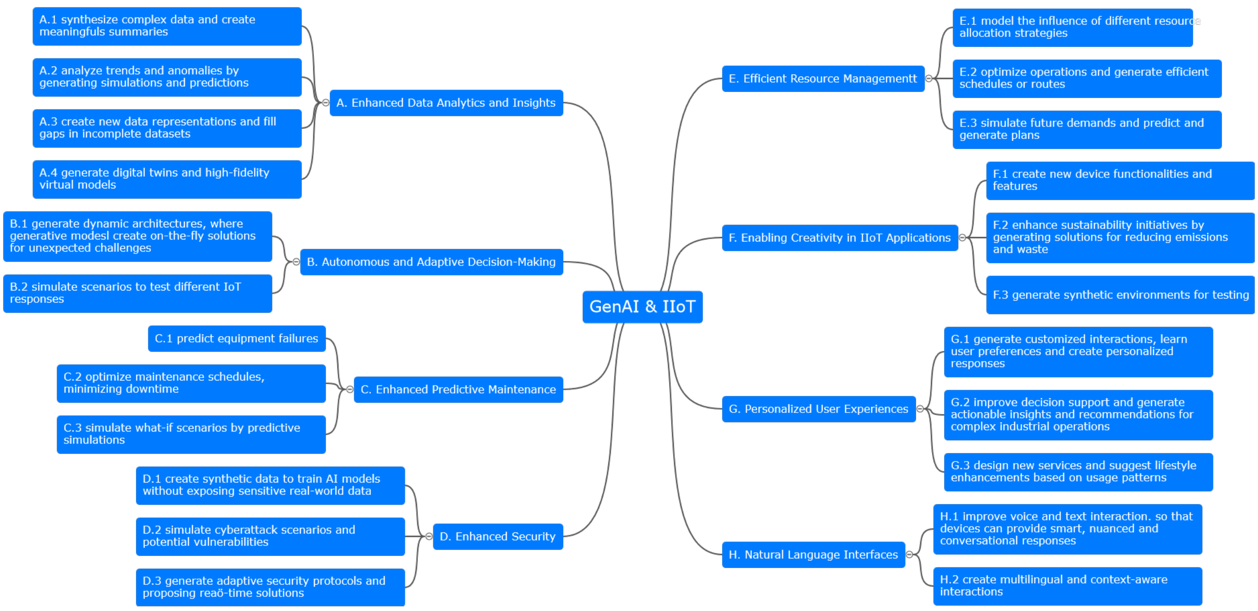

Fig. 2: Systematic Overview of Use Cases and Applications for GenAI & IoT.

responses.

H.2 create multilingual and context-aware interactions and enhance accessibility and user satisfaction.

4. Use Cases for GenAI in the IIoT

This chapter shows some examples from selected projects from the author's teams at Offenburg University* and at Hahn-Schickard Association of Applied Research†.

4.1. Sensor Design

As described in category A.4, deep learning and GenAI can be used to generate digital twins and high-fidelity virtual models of industrial processes, providing detailed insights and predictions.

In [8] and [9], a novel indirect photoacoustic sensor (PAS) has been developed that uses deep learning techniques (Fig. 2). Studies were carried out in controlled settings. As a result, the sensor's repeatability and the influence of temperature and humidity on the microphone output voltage proves that deep learning models along the pipeline shown in Fig. 3 can efficiently be used to accurately describe the sensor's behaviour. The findings demonstrate the sensor's consistent characteristics after the post-processing stage.

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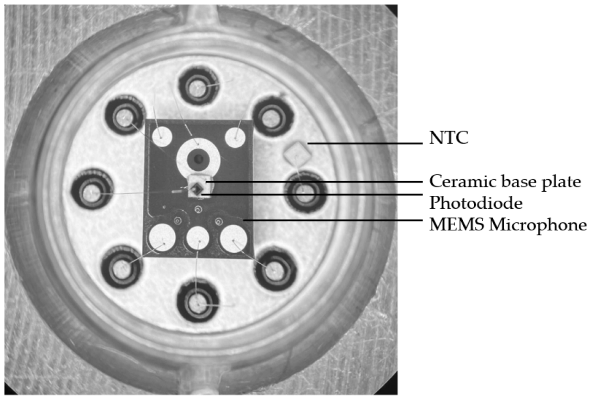

Fig. 3: Photo of PAS sensor [9].

4.2. System Optimization

In [10], an enhanced Angle of Arrival (AoA) prediction method is presented, which uses neural networks and the Primary and Adjacent Antennas Representation (PAAR) transformation. PAAR leverages rotational symmetry in segmented antenna data, to transform the data into a rotation-invariant form. Thus, PAAR improves predictive accuracy and stability, especially with limited training data. Experiments with two Digital Video Broadcasting - Terrestrial (DVB-T) datasets were conducted and evaluated four different neural network models, each varying in parameter size.

The results demonstrate that the PAAR method clearly outperforms the traditional unprocessed approach, which we refer to as the plain approach, in

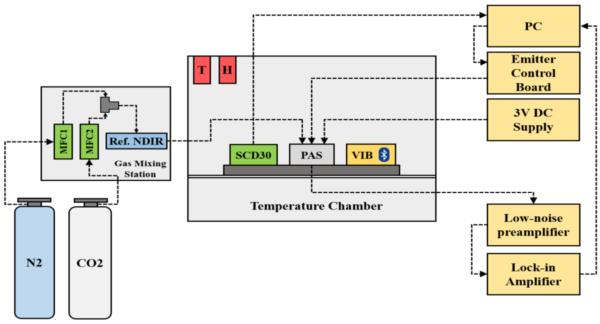

Fig. 4: Block diagram of the instrumentation and control workflow for a novel indirect PAS sensor [8].

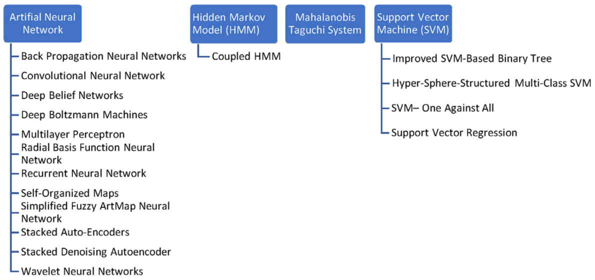

Fig. 5: Machine learning concepts used for predictive maintenance of bearings [11].

data-limited scenarios, reducing the mean absolute angular error (MAAE) by up to 40%.

However, with extensive training data, the plain approach can surpass PAAR due to error propagation. The study demonstrates that the PAAR method effectively enhances AoA prediction, especially with sparse training data.

4.3. Predictive Maintenance

GenAI models can analyse complex, multivariate data from IIoT sensors to optimize maintenance schedules and generate the efficient maintenance plans, minimizing unscheduled downtimes of machines caused by outages of machine components in highly automated production lines, as listed in category C.2.

Considering machine tools such as grinding machines, the bearing inside of spindles is one of the most critical components. Fig. 5 provides an overview of Machine learning concepts used for predictive maintenance of bearings.

The paper also presents the prediction of remaining useful life, which is important for estimating the productive use of a component before a potential failure, optimizing the replacement costs and minimizing downtime. The architecture is depicted in Fig. 4, results are shown in [12–14].

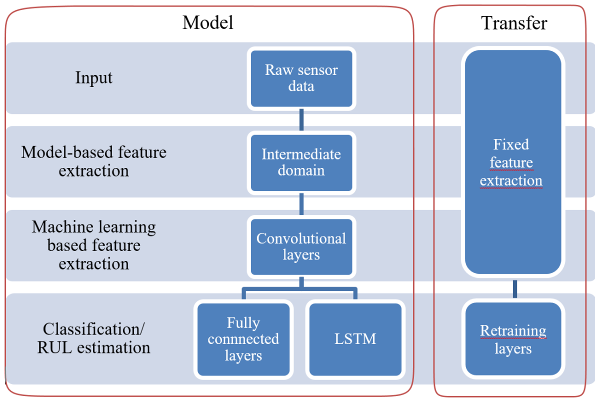

Fig. 6: The model and the transfer learning approach for the classification and RUL part of the proposed predictive maintenance solution [12].

4.4. IIoT Security

Two use cases show the potential efficiency of GenAI for the security of IIoT systems, as anticipated in category D.

(1) Recently, the number of connected devices rapidly grows, thus adversaries have more opportunities to gain access to IoT devices and use them to launch what is called large-scale attacks. With the rapid proliferation of Internet of Things (IoT) devices, the need for efficient and effective Intrusion Detection System (IDS) tailored for IoT environments has become increasingly paramount. For some years now, complete Security Information and Event Management (SIEM) systems have also been in use, which comprehensively combine as many suitable technologies (such as intrusion detection and prevention, asset management, log analysis) as possible.

Security Information and Event Management (SIEM) systems are a combination of different categories: Security Information Management (SIM) and Security Event Management (SEM). SIEM technology enables the real-time analysis of security alarms generated by network components or applications. By analyzing log information, coherent reports can be generated that can also be used for compliance purposes.

[15] explores various techniques employed in contemporary IoT IDS, including traditional signature-based approaches like Snort and Bro/Zeek, as well as emerging deep learning-based methods.

[16] provides an overview on techniques and datasets used in the studied works, discuss the challenges of using ML, DL and Federated Learning (FL) for IoT cyber security.

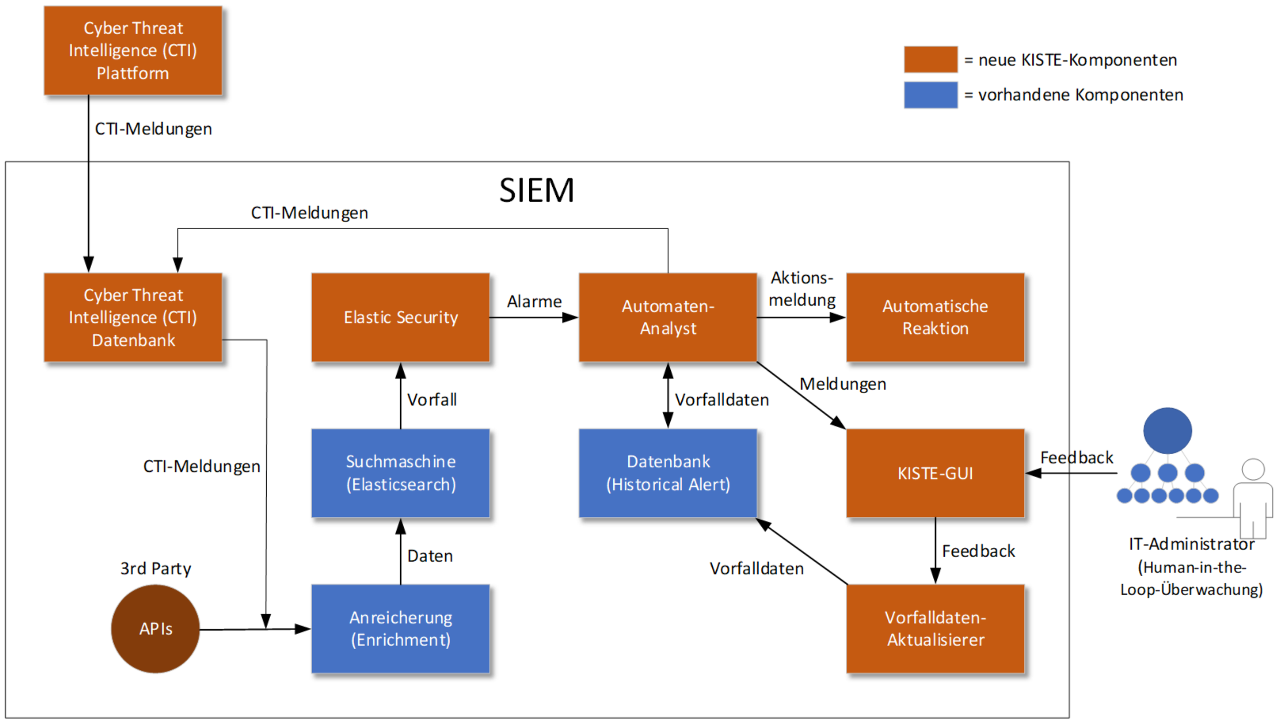

Fig. 7: Architecture of the proposed SIEM system from Kiste project. It features an automated analyst for simplified and cost-efficient operations also for small and medium size enterprises [17].

The project KISTE[‡] is diving into the direction of FL for anomaly detection in the IIoT by integrating edge processing with SIEM correlation to enable an automated analyst for simplified operations [17]. It proposes a novel framework for detecting anomalies in IIoT networks by combining federated learning (FL) with a customized SIEM solution. The architecture collects telemetry and log data from edge devices, performing local preprocessing and low-level analysis before aggregating anomaly detection models on an FL server hosted within a central security monitoring and incident detection component. Detected anomalies are correlated with alerts generated by the SIEM monitoring the core IT network, providing a unified and comprehensive view of potential threats (cf. Fig. 8).

(2) GANs have earned significant attention in various domains due to their generative model's compelling ability to generate realistic examples probably drawn from sample distribution. Image security includes the protection of digital images from unauthorized access, modification, or distribution. This requires a guarantee of image privacy, integrity, and authenticity to prohibit them from being exploited by malicious attacks. GANs can also be utilized for improving image security by exploiting its generation ability in encryption, steganography, and privacy-preserving techniques.

[‡]https://kiste-project.info/ (project website available in German only)

The survey paper [18] reviews GANs-based image security techniques providing a systematic overview of current literature and comparing the role of GANs in image encryption, image steganography, and privacy preserving from multiple dimensions. Additionally, it outlines future research directions to further explore the potential of GANs in addressing privacy and image security concerns.

4.5. Resource Optimization

Resources can be modeled and optimized by GenAI, as described in category E.1. The efficiency of blockchain networks is one of such examples, as such networks especially suffer from scalability issues which hinders integration with IoT. Consequently, solutions to improve blockchain scalability by minimizing the computational complexity of consensus algorithms or by optimizing blockchain storage requirements, have received attention. I.e, the inefficiencies of its inter-peer communication must also be addressed. In this context, [19] provides a survey on Network Optimization Techniques for Blockchain Systems.

One example [20] proposes to leverage cloud resources for storing blocks within the chain using particle optimization and genetic algorithms. An improved hybrid architecture design uses containerization to create a side chain on a fog node for the devices connected to it and an Advanced Time-variant

Multi-Objective Particle Swarm Optimization Algorithm (AT-MOPSO) to determine the optimal number of blocks to be transferred to the cloud for storage. This algorithm uses time-variant weights for the velocity of the particle swarm optimization and the non-dominated sorting and mutation schemes from Non-dominated Sorting Genetic Algorithm (NSGA-III). The proposed AT-MOPSO showed significantly better results than other state of the art algorithms with regards to cloud storage cost and query probability. Importantly, the approach also improved energy efficiency by 52%.

5. Future Research Directions

From the viewpoint of the author, amongst many other research topics, three are especially relevant and interesting:

- increase the efficiency of GenAI for IIoT especially in combination with EdgeAI, so that operations can be executed locally without the overhead of full data exchange and without compromising privacy,
- identify novel applicability of GenAI for IIoT. This could be done by „generating“ and implementing novel use cases through the GenAI-based Schumpeter-combination of existing technologies, and
- optimize the GenAI approaches and go even further in the system modelling.

6. Summary

This short keynote paper provides a systematic overview of the potential use cases and applications of GenAI for the Industrial Internet of Things. It also showcases some selected research projects from the author's teams with promising and forward-looking results.

It will be interesting to continue this research journey, to identify further use cases and to improve the existing approaches.

Acknowledgment

The author is extremely grateful to collaborate with such great co-authors and personalities with excellent brains in his teams. He is thankful for all the intense discussions, fruitful ideas, and objective-oriented efforts.

The results would not have been possible without the generous funding of the respective ministries, agencies, and donors.

We acknowledge support by the Open Access Publication Fund of the Offenburg University of Applied Sciences.

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