Organising Committee:

Report on the key findings from the Theme Development Workshop “AI for Future Manufacturing”

– October 2022 –

Executive Summary

The Joint Theme Development Workshop (TDW) co-organised by CLAIRE, TAILOR and VISION[1] on “AI for Future Manufacturing” took place on the 10th of May 2022 with the aim to develop and identify the most promising and emerging AI topics in the manufacturing sector. At this one-day workshop, experts from academia, industry and politics jointly developed initial input for the European Artificial Intelligence (AI) research and innovation roadmap. Inspired by introductory speeches and presentations from selected experts, the participants actively discussed a wide variety of topics during the breakout sessions and shared their main results in the subsequent plenary presentations. Furthermore, some initial ideas for follow-up activities and further collaborations have been identified.

This report contains a summary of the results from the Theme Development Workshop “AI for Future Manufacturing”. To make the results available to a broader audience and the European AI community in particular, this report will be published via the organiser’s websites.

[1] In alphabetical order.

These projects have received funding from the European Union's Horizon 2020 research and innovation programme under GA No. 952215 (TAILOR) and 952070 (VISION).

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The authors would like to thank Nicolas Sponticcia (DFKI & CLAIRE Office Saarbruecken) for his support in generating this report.

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Introduction

In September 2020, four new AI networks were established by the European Commission via the call "Towards a vibrant European network of AI excellence centres" (ICT-48-2020). The aim of these networks is to foster the collaboration between the best research teams in Europe, and to address the major scientific and technological challenges in the field of AI. These four networks are coordinated and supported by the VISION project to foster activities that reach critical mass and enable the creation of a world-class AI ecosystem in Europe.

One of these activities are so-called Theme Development Workshops (TDWs), an innovative format bringing together key players from industry, academia and politics to jointly identify the key AI research topics and challenges in a certain area or for a specific industry sector. In December 2020, an agreement was made between the respective coordinators and leadership teams of TAILOR, VISION, HumanE-AI-Net and CLAIRE to plan and execute a series of Joint (co-organised) Theme Development Workshops, starting in 2021. This report is a result of the fourth Joint TDW organised and executed within the framework of this series of workshops.

Keynotes and introductory presentations

The TDW was opened by the Co-Chairs Tilman Becker (CIIRC) and André Meyer-Vitali (DFKI) on behalf of the Organising Committee (OC), which included further representatives from ABB, ArcelorMittal, CLAIRE, CIIRC, DFKI, EIT Manufacturing, NTT DATA, RICAIP, TNO, University of Málaga and ZF Friedrichshafen AG. The Co-Chairs outlined the objectives of the TDW as well as the agenda and programme, and introduced the invited keynote speakers to the participants.

The inspiring keynotes were provided by high-level experts from academia and industry. These introductory presentations served as a basis for the discussions about the value of data and the aspect of Trustworthiness in the manufacturing sector, and provided some interesting examples of application areas. Accordingly, these presentations stimulated the expert discussions in the following breakout sessions.

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Introductory presentations by Prof. Dr. rer. nat. Dr. h.c. mult. Wolfgang Wahlster, Dr. Georg Schneider, Prof. Dr. Vladimír Mařík and Sanjit Shewale.

Prof. Dr. Wolfgang Wahlster, German Research Center for Artificial Intelligence (DFKI) gave his introductory keynote on the topic of industrial AI across the next decade of industry 4.0. He started by giving an overview of the idea of industry 4.0 and how it encompasses the challenge of injecting AI into manufacturing processes to retain the competitiveness of the European economy. There are a number of socio-economic issues that drive the development of industry 4.0, such as the need for greater resource efficiency, low-volume high-mixture factories, the presence of shorter product life cycles and the volatile nature of the current markets. AI plays a central role, as the central characteristics and demands of industry 4.0 require solutions that can only be provided by utilising AI technologies. An example being predictive maintenance, which can only be properly achieved by employing machine learning. In the long-term, one of the central goals of industry 4.0 is to achieve deep learning and deep understanding to facilitate long-term autonomy of machines. This is to enable important innovation concerns such as zero-error production based on real-time quality monitoring. Professor Wahlster concluded his keynote by revealing that deep learning is not enough for the next generation of Industry 4.0 systems and that hybrid AI systems are needed.

Dr. Georg Schneider, AI Tech Center at ZF Group, gave his introductory keynote on the benefits of Trustworthy AI in manufacturing. He started his keynote by highlighting the problem of explainability in relation to the decisions that AI systems may take, as experts may lack insight into how a given AI system has arrived at a certain conclusion. He then discussed possible solutions to this issue by discussing an example related to anomaly detection. Dr. Schneider concluded his keynote by highlighting four key benefits of explainability. The first being that it allows for the verification and validation of AI models, The second benefit being that it improves AI models and labelled data bases. The third being that it enables great insight into production systems and the root causes of problems. Lastly, explainability allows for an increase of trust in AI and the acceptance of it as a solution to various problems.

Prof. Dr. Vladimír Mařík, Czech Institute of Informatics, Robotics and Cybernetics (CIIRC CTU), started his keynote by giving an overview of the Czech Institute of Informatics, Robotics and Cybernetics CTU in Prague (CIIRC). Specifically, he discussed the RICAIP project, which is currently the largest EU project in the field of AI for applications in Industry 4.0. The project itself is also committed to explainable AI solutions, the integration of machine learning methods, 5G communication and edge-computing, as well as zero-error production. The RICAIP project has already achieved impressive results such as enhancing the efficiency of pressing processes at SKODA, using virtual reality, or speeding up production lines at LEGO. Next, Professor Mařík discussed the role of AI and machine

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learning in the first decade of industry 4.0. He highlighted that multi-agent systems were successfully developed, whilst neural nets and deep learning were also successfully utilised in isolated partial industrial solutions. Additionally, he argued that in the second phase of Industry 4.0, knowledge structures and models are expected to play a dominant role. However, as these models' data-storage and computing requirements are expected to be huge, standardisation and interoperability will be very important. Professor Mařík concluded that in the second phase of Industry 4.0, we will need global, flexible, and self-learning engineering solutions to be able to control and manage complex and intelligent manufacturing systems and their environments.

Sanjit Shewale, Global Head of Digital, Process Industries Division at ABB started his keynote by highlighting the importance of explainable AI in the context of AI research's applicability in industry. Standardisation and interoperability are a must to enable explainability. As the industry is still struggling to see value in AI due to failed pilot projects, explainability is key to increase trust. Furthermore, Sanjit Shewale argued that there are no AI-powered operations without quality data. Many projects fail or get extended due to a lack of quality data. Lastly, he gave an overview of the Explainable AI Consortium, whose goal it is to increase trust and the reliability of AI solutions.

Key results from the Breakout Sessions

Trustworthy AI in Future Manufacturing

The aim of this session was to initially define the strategic challenges and derive relevant major topics and industrial applications where it is critical that the Artificial Intelligence (AI) is trustworthy. The session had the luxury of having two experts giving brief presentations with their perspectives to kick-start the discussions. First Juan Carlos Nieves gave an introduction to the technical and social aspects of trustworthiness and related this to the Ethics Guidelines on Trustworthy AI introduced by the High-Level Expert Group on AI appointed by the European Commission. Then Lena Weirauch spoke about her experience from the aviation industry prior to co-founding ai-omatic. She presented a scalable solution for automated condition monitoring where an AI finds anomalies in machine data without historical data needed and transfers the expert knowledge of an engineer into an AI to create a digital maintenance assistant to make the maintenance process more efficient.

The discussion during this breakout session was centred around 3 topics: 1. Key challenges with Trustworthy AI in Manufacturing; 2. Typical industrial applications that require trustworthy AI, and finally 3. Key recommendations for the future.

Perhaps the most important challenge discussed was to what extent an industry can give guarantees on AI trustworthiness of its products. A very related challenge is how to verify that a solution is trustworthy, and who takes responsibility during deployment: supplier(s) or customer?

The discussion around industrial conclusions was kept at a very general level without going into specific industries. It was concluded that Trustworthy AI is essential for anything related to safety, that can lead to unplanned downtimes, or if there is potential environmental impact. Regarding this point, Lena from ai-omatic mentioned that their solution of ai-omatic contributes to the topic of trustworthy AI and explainable AI in the sense that the user sees which sensor is responsible for an increasing or decreasing health value. Another example mentioned is that errors in AI for logistics value chain may lead to economic loss.

The breakout session resulted in a number of key recommendations:

It is critical to require trustworthiness for analytics on all different data-types (images, time series, events, textual, etc.). We need to work on how to carry over trust within traditional industrial manufacturing ecosystems from the “analog” business world into the digital & AI business relationships. Fundamental research is needed between academy and industry into methods and their application to provide guarantees about AI systems. Furthermore there is a need for research into the different dimensions of trust, for example, robustness with respect to changing work conditions, interpretability as a means for true human-machine collaboration), and verification that the AI fits the intended purpose. Last but not least, we need to identify good practices using the Trustworthy AI principles and include this in our teaching.

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Federated Learning for Future Manufacturing

This session addressed the challenge of training AI models without giving up data sovereignty and the question of what approaches to share models instead of data.
Federated Learning enables Privacy by Design by training partial data sets separately and combining only the resulting models without sharing the data. However, privacy may be less relevant in manufacturing. Rather than privacy, the confidentiality of corporate data (e.g., manufacturing processes) may be more relevant. However, the privacy of employees and consumers can be affected. Therefore, regulation is important to guarantee the legal certainty of people, processes, things, and to secure intellectual property. Data sharing of "near" original data needs to be encouraged.
By processing training sets in parallel Federated Learning could be more efficient and scalable for large-scale manufacturing ecosystems. Sequential processing is required due to interdependence of data in some cases, however. Small data sets can increase the level of bias and training on small data sets is more difficult. In addition, the costs for communication need to be considered, as well as the limited processing power of low-power edge devices.
A challenge is to decide how to split up the data and which parts of the models to share with which parties. Agreements need to be reached about the unified structure of neural network models, because they cannot be (easily) merged otherwise. Compression of weights in the model (quantisation) can reduce the size of data to be communicated. Sharing of semantic models is another possibility to achieve common architectures.

Human-Robot and Human-Machine Interaction in Manufacturing Processes

The aim of this breakout session was to identify ways to realise partly automated processes or to stabilise highly automated processes through smart dialogue systems that incorporate and combine a plethora of different interaction methods in Human-Robot or Humane-Machine interaction.
Rather than fully automate manufacturing, Human-Robot Collaboration (HRC) bears the promise of including humans in the production process while easing burdensome tasks and emphasising human strengths in flexibility, experience and understanding.
Besides the physical aspects of safely coordinating humans and robots working in the same space, there are challenges in communication from robots to humans and vice versa and the integration of humans and robots and their collaboration into the larger manufacturing processes.
The physical aspects of HRC encompass safety issues and pose research challenges in a wide range of sensor technology needed to understand where the actors (humans and robots) are and what they are doing and what they intend to do next.
HRC is about communication with all applicable modalities, including spoken dialogue, gestures and classical IT communication channels like displays, touch-screens, and also wearables and mobile devices, like smart watches and tablets.

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The tasks for teams of one or more human workers and one or more robots must be integrated into the overall manufacturing process. Tasks from production planning must be communicated to the human-robot teams, results from the team's work must be entered back into the planning and MES systems.
HRC can support many aspects of human involvement in production. It can enable workers to do more, including physical support for workers with disabilities or caused by age or (temporary) medical conditions. HRC can support demanding, stressful and repetitive tasks. HRC can also enable human workers to increase their expertise by using the communication aspects to provide assistance to workers about next steps in new or not well-trained production processes.
HRC raises challenges in data privacy and ethical aspects as data about human workers is collected and its use bears potential for misuse.

Optimizing assembly components

This session was about simulation approaches to find the best combination of groups of parts before the assembly. For the particular case of assembling, if the total number of possible decisions is limited, exhaustive search might be an affordable option. Otherwise, application of some optimization techniques can help. For this aim, a good model is needed. The model development needs a lot of data with good quality. Here, AI can help to train a model from data without the need for background information. In this respect reinforcement learning (RL) can help to solve an optimization problem in the absence of a model, i.e. via learning from experience.
Furthermore, within the breakout session, some keywords on ML/AI-based optimisation approaches were discussed, such as surrogate-assisted optimisation and variants of efficient global optimisation. Surrogates are (non-linear) regression models that are trained on the data points using cross-validation and hyperparameter optimization. The best model and the confidence measures of the model are then available for optimising the model, understanding the structure of the solutions, extracting knowledge, etc.
However, it is worth mentioning that, if (as mentioned above) the dimensionality is low and the quality assessment is fast, the grid search may be quite sufficient.
Instead of building the model, since your objective function is cheap to evaluate, you could also optimise it directly (e.g. with an evolutionary strategy like CMA-ES or a derandomised strategy or differential evolution, to name a few).
The discussions have shown important trends in optimization using AI/ML: warm-start, meta-learning, switching between optimizers, surrogate-assisted, and explainable AI to understand characteristics of good solutions. The application domains in this context are simulation-based product engineering, product assembly and production process optimization.
In addition to this, some important key challenges in the field optimising assembly components were identified like Time-consuming objective functions (e.g., passenger safety

in automotive, with 24h for a simulation being normal, or CFD) as well as handling visual simulation output (flow fields, for example) and extracting that information to make it usable by the optimizer. It also became apparent that optimisers need to be capable of learning from problem instances they have seen over time. In addition, they must be able to deal with very time-consuming function evaluations, as well as with multiple objectives and constraints, even for very time-consuming function evaluations. Another key challenge with regard to the overall topic of optimising assembly components is formulating the problem in the right way (what are objectives, constraints, user preferences, interactions between different disciplines, and even working processes within a company, i.e., which departments need to coordinate what they do in terms of design variables etc.).
During the breakout session, the participants identified key recommendations regarding the overarching topic of the session, such as research on the use of ML to pick the right optimizer and its configuration as well as integrating optimization and transfer learning, meta-learning, to make optimizers learn from problem instances. In addition to that, there is also a need for research on the issue of extracting problem knowledge using explainable AI from optimization runs, across both singular or multiple runs.

Retrofitting of AI

Currently, we are attempting to bring a number of AI based decision making into the production processes as well as machines. But how will AI react in the future when new sensors are added, new machinery is brought in, or if new software upgrades are installed on existing systems? During this session, these issues were addressed with the question of whether it will be necessary to upgrade or update the system.
The session started with a discussion of the definition of what it means to retrofit AI. The experts discussed the definition differentiating between (1) no (pre) AI to AI and/or (2) from existing to new AI and also (3) adapting existing AI to other changes in the manufacturing system.
Furthermore, there are aspects of retrofitting AI deployment at macro-levels from an ecosystem to an organisation level and a micro-level from machines, production process to the plant level. The experts in the session emphasised that SMEs are lagging in digital transformation at the macro-level. The experts recommended a gradual transition to AI-driven manufacturing systems for SMEs, through collaboration with suppliers and clusters. The retrofitting of AI has more relevance for SMEs as they often cannot opt for embedding AI into newer generations of expensive machines. In this context, equipment with older design can be enhanced by applying AI methods to recognize the background reasons of unsolved design issues.
The industry understanding of retrofitting and reuse of AI is nascent. The session was an example of continuous learning to get a practical perspective on the concept. It is important to continuously exchange industry-academia knowledge for effective implementation of the solution.

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An expert highlighted the importance of research perspective and technology advancement in transfer learning. The current academic research is looking at the end-to-end-supply chain (lifecycle).
Looking ahead, the session pointed out a few challenges concerning the implementation of and retrofitting of AI. The importance of privacy and cybersecurity are concerns that are valid for implementation and data engineering solutions were highlighted. The environmental impact of computing is highly relevant and could be an incentive for wide-scale usage of existing AI (2) and direct adoption (3) to new systems.
The experts agreed on the need for ecosystems and workforce training as the most relevant trends in the current times. The session concluded on a philosophical note on how retrofitting and 'doing more with less' will help to solve the societal challenge for business to be profitable yet sustainable especially for SMEs that need to compete in the next industry 5.0 decade.

AI in product development

This breakout session dealt with the use of data for development and construction of products by adjusting materials and measurements according to the need and best results from the manufacturing processes, to enhance the design of products. The use of data and AI for development or construction of products ist still an open field that has to be addressed. Adjusting materials, design or measurements according to the need of usability, duration and efficiency of products is very important. This can influence either the manufacturing processes directly or adjust the product use case to the customer's needs and expectations.
Throughout the workshop, certain issues were considered in particular. There was a mutual understanding that the constraints set for a product pose the first difficulties, be it a final product, assembly or just a machine part itself. On the engineering part, it is a challenging task to connect each constraint to the impact it has as well as to include an in-depth understanding about the interactions between each constraint defining the product. An AI linking all these factors together would help to develop the product in a more efficient way with less iterations in the process itself.
A possible use case for this is the exploration of the design space through AI, combining the space with simulation tools as well as constraints and physical limitations.
Nevertheless, understanding of the problem to solve is essential. Experts will still have to challenge themselves incrementally until an appropriate result is generated and enhanced through AI. Also taking the risk of a given solution into account, AI could help to deliver some form of risk certainty management, including knowledge about the uncertainty of certain constraints.
This derives from the fact that certain constraints are not questioned due to a prior use case or missing data showing the invalidity of the constraint in the development process.
Therefore, the question of the certainty of a constraint should be asked, however, often it is not. What do you know about what you don't know? Mainly this effects interdependence on constraints which can also pose a great risk in the development process. A systematic

approach for the consideration of constraints is needed, solved by an AI algorithm bringing all the things together to form the whole picture.
An evolving Digital Twin - evolved during the use of the product - can also enhance the knowledge about constraint, not just on the engineer side but also on the user side. If this could be wrapped into a service the data generated would enhance every product.
With increasing time the maschine increases data as well as interdependencies between different digital twins which can be connected.
On the other hand, when it comes to digital twins on a process level, tracking the operation of the machine/product by different personnel could also influence the data generated through the different levels of knowledge as well as maybe a different use of the product itself. Including humans into simulations is always a great effort, but turning the integration into a challenge with a defined goal or scoring could enhance the willingness to work with a Digital Twin and AI included.

Smart Manufacturing for Space Applications

This breakout session focused on the challenges and opportunities for AI that arise in manufacturing in the context of Space exploration and Earth observation, which is a challenging but also cutting-edge domain. It consists of a stream of data that goes from design to manufacturing then into testing and, finally, operation and maintenance. The ultimate goal is to achieve a continuously-improving single end-to-end algorithmic process that integrates these four areas.
Manufacturing in/for Space presents particular challenges. Delays in sensors, monitoring and control mean that fully-autonomous predictive models are desirable. Ideally, the models will operate next to the sensors to avoid such delays, however, energy consumption during operation is a concern, thus energy-efficient AI methods would be required.
The design and testing phases seem to benefit from physics-informed methods, as the manufacturing process often does not produce enough high-quality data. However, current physics-informed deep-learning models are limited in terms of the dimensionality of the problem. Nowadays, the combination of data-driven and model-based (physics-informed) methods are the most promising.
Another important challenge is the semi-automatic generation of requirements for guiding automatic design processes. Currently, the design process can be automatized if the precise requirements are provided by human experts. However, identifying these requirements is a difficult and complex task that requires a diverse engineering knowledge combined with experimental validation. AI methods that could generate and refine requirements would significantly improve the design phase.
Cybersecurity concerns also limit the capabilities of the AI systems, their sensors and the data collected. In addition, the trustworthiness of systems deployed in a spacecraft or space station must be extremely high and must be verified independently from the vendors who provide the various parts of the system.

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The industry is moving towards distributed manufacturing thanks to the advances in AI. However, we must take into account the bigger picture of how Industry 4.0 may lead to the delocalization of highly-technical manufacturing industries due to automation. The Space industry should also consider the ethical implications of semi- or fully-autonomous manufacturing systems both in Space and in Europe.

AI in Digital Factories

Given the background of the participants, one of the first challenges identified in this session was to continue working on bridging the gap between academia and industry (State-of-Art vs. Reality Check) with flexible multidisciplinary teams. To this end, defining the processes of knowledge transfer from academia to industry is one of the first steps to be defined. Other challenges identified were how to ensure interoperability given the lack of greater acceptance of standards, the lack of data and intelligence for building specific profiles, including availability, quality and reliability to build better models or aspects related to cybersecurity to prevent risks even more with open connections (such as data spaces).
Among the recommendations discussed were those related to working together in multidisciplinary teams namely data analytics, data science, AI / MLOps engineers, cloud architects, business analysts and robotics including the figure of Joint labs with the industry for a better understanding to create teams that can carry out the implementations required by the industry. Also relevant was the discussion on the difference between the terms "understandable AI" and "explainable AI" given the interest from the industry to better understand the inner workings of the models beyond that they maintain accountability and bias-free. On cybersecurity issues, self-protection models and secure environments both at the plant level and along the supply chain drove the discussion towards dynamic risk management should be considered when implementing AI. The topic of Human-Technology collaboration was not ignored, hybrid intelligence is the key to successful AI systems. Importance of augmented intelligence, human augmentation, and better decision-making capability, without removing the human factor.
Finally, emerging technologies such as Digital Twin and multi-agent systems based on reinforcement learning were identified as a driver for moving towards more autonomous processes. Also the combination of Edge Computing and Edge AI together with high-performance communication technologies such as 5G will act as an enabler for industrial process improvements.

Industrial applications of Explainable AI

The explainability of the AI algorithms is a necessary criterion to be fulfilled prior to deployment in real industrial application. Explainability is a requirement creating trust for further usage of the solution. Thus, the aim of this breakout session was to dive into explainable AI to promote the further scaling and usage of advanced solutions in industrial applications. The session opened up with a very interesting keynote where Dr. Rafia Inam-

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Senior Research Manager, AI Research at Ericsson shared the experience and knowledge from Ericsson: "*The role of AI & Explainable AI in Telecom industry*". Describing different aspects of building a trustworthy AI, she emphasised on the importance of the explainability as one of the cornerstones towards trustworthy AI. Following the valuable input from the opening presentation we discussed among the others how and when the requirement of interpretability should and could be intrinsic or post-hoc in different industrial applications and examples. Furthermore we discussed different trade-offs surrounding the explainability such as; complexity and robustness all together in relation to the context in which the system is deployed. The complexity and associated uncertainty vs. the risk of errors in an application requiring even better methods for explainability will push this boundary as they reduce our uncertainty about the system. We noticed that although interpretability and explainability are in most cases interchangeable, explainability is at a higher level, dealing with human interaction. While the interpretability is of great value for the developer the explainability is most valuable for the operator. In other words, explainability/ interpretability are a kind of personalization/ contextualization for different stakeholders.
Furthermore, we emphasised on the importance of the so called *Explainable AI by design* as a key to increase trust and most probable more reliable systems. Explainable AI is dealing with different challenges and solutions on design level as well as at deployment level. One of the biggest challenges to be considered is the risk level of the proposed solution associated with the specific application. Generating a concise, meaningful, and tailored explanation to different users and stakeholders is very important.
Finally we conclude that static explanations are often not enough - users and experts should be able to interact with the AI. Robust and model agnostic explanation methods are required to leverage the full breadth of available AI methods and models, to create trust or interpret the model. Explainable AI is integral not just to enable trust but also being compliant with regulations.

Zero Defect Manufacturing

This breakout session dealt with AI technology methods like data-based modelling to detect out-of-control (OOC) states in classical Statistical Process Control (SPC) from in-process data enabling continuous monitoring and earlier detection of problems with a simultaneous reduction or near elimination of expensive post-process quality inspection.
The most important key challenges within the topic of Zero Defect Manufacturing, which was identified by the participants of this session, are people-related issues as well as the Acceptability and Explainability of new AI solutions. Explainable AI is necessary to move to the next level of acceptance of advanced diagnostic systems in industry. What is crucial is that the people involved in the process have a clear understanding of why the system is recommending what it is recommending. Besides that it is essential to ensure the necessary acceptance of the workers. This can be achieved by a common language to connect the managers with the workers and also to connect individual engineer roles and tools. However, this can be covered by a culture accepted by the company, which focuses on hybrid

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production as the highest priorities.
When it comes to Zero Defect Production, the second key challenge is the shift from a local to a global perspective by having a holistic approach to cover the whole product life cycle (from product design, through supply chains, shared data, process monitoring to final consumer) which requires a process structure for formal representation of the information/data.
Another key challenge identified by the participants of the breakout session is the ageing of models caused by changing processes/concept drift through modified structures as well as a lack of training data after a change and fast transfer. To tackle this challenge a long term solution of constantly self-updating/self-learning models based on the observator is needed. There is also a great potential of using simulation models to have at least some training data immediately after a change. Furthermore, the Zero Defect Manufacturing system must know about the changes, people can also enter this, but correctly, e.g a tool replacement must be inserted to a system correctly. The fourth key challenge regarding Zero Defect manufacturing is false alarms. People often get overwhelmed by false alarms, e.g. in space apps thousands of independent sensors and problem detectors can have a high false positive rate, which can lead to an ignorance of the quality control system. This can be solved by techniques to double check the generated alarm by the system via multivariate methods, dimensionality reduction and correction of alarm thresholds.

Psychological approach for data labelling

During this breakout session the participants discussed sustainable approaches in combining psychology with elements of labelling technologies to ensure high data quality (standardisation) which is needed to apply AI in manufacturing.
These sustainable approaches aim to combine psychology with elements of labelling technologies to ensure high data quality (standardisation) which is needed to apply AI in manufacturing. However, data often appears messy, because they are not labelled accurately due to the lack of motivation of human annotators. These operators should be involved more to understand the reasons for labelling the data and to minimise their fear of losing their job through automation of their know-how. Human-centred AI should include the labelling operators. Machine Learning is only a part of AI and should be combined with other approaches, which also applies to labelling. Operators can be supported by using better tools and heuristics and by understanding the context and purpose of their work. Feedback should be used to improve the tools and methods. They would also be helped by collaborating amongst each other to increase social interaction and better results through standardisation of their methods.At the same time, the work can be customised to individual operators depending on their backgrounds.

Reality independent AI

This breakout session addressed the question of how the potential of digital twins with synthetic data can be uncovered in image data (e.g. for AI quality inspection or object recognition) for manufacturing.
Synthetic data are algorithmically produced (synthesised) to mimic the characteristics of real (sensor) data. The process of creating synthetic data can range from as simple as adding entirely random (but sensible) data to the dataset, to changing some features of real data, to as complex as creating new data entirely from scratch. E.g. pictures of road surfaces in good condition and digitally adding surface cracks to create thousands of synthetic images of poor road surfaces to train algorithms, or generating images of faces using gan technologies.
Main applications of synthetic data are data anonymization (privacy aspects) and training machine learning algorithms from sparse or biassed datasets. In this breakout session a structured approach to generate training data synthetically and a use case for optical inspection in production of microchips was presented and discussed.
Deep neural networks become an integral part of online inspection. They learn to interpret deviations and cracks while distinguishing them still from intended deviations in special product configurations.
The availability of training data is the main problem of using such deep learning methods. E.g. in a production environment, most data will show undamaged parts while actual defects are rare. A solution to this is to simulate measurements based on scenes that are generated by parametric models or the real world. By investigating the parameter space of such models, training data can be generated in a controlled way.
The method involves the creation of partial models by learning individual aspects of the product, such as geometry, surface properties and lightning conditions generated in cad/cam environments and shallow models respresting e.g. cracks. The partial models are called parametric, because each model is controlled by a set of input parameters and describes a part of the scene in a simulation environment as a function of these parameters. The parameter space of the parametric scenario is the union of the input parameters of all the partial models and the scenario-specific parameters. Such an approach also allows for controlled sampling of the parameter space. E.g. using a strategy that generates additional samples close to misclassified samples. For more details and background information see ‘Digital reality: a model-based approach to supervised learning from synthetic data’.

Democratising AI

The aim of this breakout session was to uncover who is already able to use AI in manufacturing and whether only large companies or also smaller companies benefit from the use of AI and if both parties also benefit from each other and exchange knowledge.
Above all there is the risk included in taking decisions on ground data. How can anyone make a decision based on data without knowledge and training? A lot of decision makers are sceptical about AI as well and still new to the topic and possibilities. Therefore it is essential

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to start slowly with simple application, with slow upscaling roadmaps showing value through pilots, with a scalable solution, as measurable as possible.
Including every person influenced by the solution will also help with the cultural acceptance in a company. Acceptance (explainability) and inclusion (controllability) of workers to take away the fear, including an demographic worker structure is essential for a successful implementation and further usage. Always thinking about the Questions: Who should start with AI? - if you have no idea about AI it may be risky and lead to errors. How do workers interact with AI, i.e. to what extent are they responsible for the AI enabled processes?
A clearly defined road of inclusion and responsibility is the goal you should aim for. Delivering proper rules, like a guidance system defining the transformation in a very structured way as well as elaborating on how to establish this in a company processes is challenging. Therefore a management championship is needed to really bring it through, to make it a strategic decision and make everyone adapt to the change. Also Collaboration with existing experts (e.g. include the Process engineer into the solution development) will also bring acceptance as the inclusion of workers, onboarding them as early as possible.
Keep in mind that we have a rising need for data scientists. We cannot have as many data scientists as we need, as this will not be economical in the future. Therefore it is essential to democratise AI in any company. This counts for any dedicated topic involved in the data science pipeline from labelling of data to MLOps.
If we now look at the transition from big companies to small ones the missing standardisation causes errors. Taking over bigger models into smaller companies is therefore a challenging task. For once island solutions can be the right thing for bigger companies on a broad scale with different divisions choosing different solutions. This is not possible for SME as it has to be standardised along each department.
But to really enhance circular economy and sustainability there will have to be a democratisation between global players and SME. This will most likely happen along the value-chain and should be fostered as much as possible.

Optimization and Machine Learning for Better Manufacturing Processes

This breakout session discussed what the obstacles and challenges for the implementation of advanced methods combining Optimisation and Machine Learning in manufacturing companies are.
Optimization problems in industrial manufacturing companies are characterised by large complexity, huge volume of data, mixed-integer and combinatorial decision variables, where small changes in these variables may affect a whole supply chain. In addition, there is often the desire to solve problems in a very short time despite the fact that evaluating the quality of a single candidate solution is often expensive and may require the simulation of a process. Typically there is not a single optimal solution but a number of feasible solutions that trade-off multiple (often many) conflicting criteria from which an expert will choose the solution to be deployed.

Classical optimization methods such as mixed-integer programming and metaheuristics are too slow in many cases and cannot compete with human experts who are already highly-skilled at identifying good solutions based on factors and knowledge that are not immediately available as potential input data for AI models. The quality of the data is itself an open challenge, since it is often noisy, missing and/or erroneous. It is not unusual to have at the same time too much data and too little data because only a limited amount of information is useful within a very large dataset.

The breakout group identified the need for more research in the context of large, non-sparse and combinatorial problems, in particular, better surrogate models for such types of data. Cutting-edge methods such as Alpha-Zero require a large investment in terms of engineering effort, data collection and training time and it is unclear at the moment how well they will work in the context of manufacturing processes. More theoretical/basic research work is needed to understand their adaptability and limitations.

The explainability of complex models was highlighted as an ongoing concern. We discussed examples where clients or suppliers have requested to scale back the complexity of a model because it was not sufficiently explainable. In the context of optimization, explainability includes identifying which changes in the data lead to a change in the optimised solutions, as well as how the hyper-parameters of the methods influence the solutions generated.

Finally, the group also identified a lack of collaborations between different companies to release data and try to solve common problems, even though it was also agreed that the applicability of academic research would improve if industry would make real data and simulation models publicly available for research. One proposal put forward to foster such collaborations was to create consortiums of non-competing companies from diverse industries.

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Input for the roadmap

Based on the results summarised in the previous section, the Organising Committee identified several topics which could be a valuable input to a European AI research and innovation roadmap. These topics will be presented to and further discussed with experts from TAILOR, AI4Media, VISION and CLAIRE in order to enrich the respective roadmap activities.

The below topics are the ones that stood out most prominently and will thus provide the 'core' of the input. However, when the roadmaps will be constructed, all inputs from the Theme Development Workshop will be considered.

Manufacturing sector specific

- Fundamental research is needed between academy and industry into methods and their application to provide guarantees about AI systems. Furthermore there is a need for research into the different dimensions of trust, for example, robustness with respect to changing work conditions, interpretability as a means for true human-machine collaboration), and verification that the AI fits the intended purpose.
- By processing training sets in parallel Federated Learning could be more efficient and scalable for large-scale manufacturing ecosystems. Federated Learning also enables Privacy by Design by training partial data sets separately and combining only the resulting models without sharing the data.
- Human-robot collaboration (HRC) can help integrate humans into the production process without replacing them by relieving them of burdensome tasks and highlighting their strengths such as flexibility, experience and understanding.
- Products are in many cases constrained by restrictions, which also pose difficulties. In this case an evolving Digital Twin - evolved during the use of the product - can also enhance the knowledge about constraint, not just on the engineer side but also on the user side.
- The trustworthiness of systems deployed in a spacecraft or space station must be extremely high and must be verified independently from the vendors who provide the various parts of the system.
- When it comes to data labelling, sustainable approaches aim to combine psychology with elements of labelling technologies to ensure high data quality (standardisation) which is needed to apply AI in manufacturing. However, data often appears messy, because they are not labelled accurately due to the lack of motivation of human annotators. These operators should be involved more to understand the reasons for labelling the data.
- The availability of training data is the main problem of using deep learning methods. E.g. in a production environment, most data will show undamaged parts while actual

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defects are rare. A solution to this is to simulate measurements based on scenes that are generated by parametric models or the real world. By investigating the parameter space of such models, training data can be generated in a controlled way.

More general topics not limited to the Manufacturing sector

- Explainable AI by design as a key to increase trust and most probable more reliable systems. Therefore, meaningful, and tailored explanation to different users and stakeholders is very important.
- Users and experts should be able to interact with the AI. Robust and model agnostic explanation methods are required to leverage the full breadth of available AI methods and models, to create trust or interpret the model.
- Reinforcement learning (RL) can help to solve an optimization problem in the absence of a model, i.e. via learning from experience.
- AI could help to deliver some form of risk certainty management, including knowledge about the uncertainty of certain constraints.
- Joint labs with the industry should be established for a better understanding and to create teams that can carry out the implementations required by the industry.
- Acceptance (explainability) and inclusion (controllability) of workers to take away the fear, including an demographic worker structure is essential for a successful implementation and further usage.
- Dynamic risk management should be considered when implementing AI.
- The combination of Edge Computing and Edge AI together with high-performance communication technologies such as 5G will act as an enabler for industrial process improvements.

Summary and Conclusion

The high international interest that was expressed in response to the announcement of the AI for Future Manufacturing Theme Development Workshop translated into excellent attendance of the event. Seventy-seven participants joined the TDW, ranging from a diverse set of backgrounds. nineteen (predominantly EU) countries were represented, with thirty-three participants indicating that they are affiliated with industry, whilst forty-one participants indicated that they are affiliated with academia (three participants indicated "other"). The participation of major industry representatives, with companies like ZF Group, ABB, Airbus and ArcelorMittal is particularly noteworthy and testifies to great interest on the part of industry. Equally important being the participation of those affiliated with the European Commission. The TDW, therefore, caught the attention of some of the most important actors in the field of Future Manufacturing and brought together representatives from key companies, supra-national institutions, and academia. The workshop thus successfully provided a platform for discussions between representatives from academia, industry and politics: Discussions that are key in unlocking the full potential of AI in Europe.

The Organising Committee would like to express its deep gratitude to all experts for their valuable input and contributions to this Theme Development Workshop! Their active participation in the workshop and engagement in the breakout session discussions paved the way for the excellent results presented in this report.

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In addition to this list, 3 participants of the TDW preferred not to be mentioned publicly by name and affiliation.

The organisers would like to thank all participants for their valuable input and contributions to the Theme Development Workshop!

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