CONTROL IN STEEL

Deliverable 5.1:

Future research roadmap

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1. Introduction

1.1. Aim of this document

ControlInSteel is a dissemination project reviewing 46 conducted research projects of the RFCS. This report summarizes the analysis results with respect to transferability.

The present deliverable is a roadmap for future research – a strategic document outlining topics and activities recommended for enhancing research in automation downstream for the next years.

2. Retrieval of data and information

2.1. Conducted work during the dissemination events

Throughout the years 2021, 2022, the project team contributed to various events and workshops and conducted three self-organised web events for pursuing the dissemination work. We will refer to these events as basis of our analysis. Therefore, we will now list these events and give a short summary on how they have been relevant for this deliverable in general. Later on, we will compile a table with topics, comments and concise steps to proceed and reference the according events:

- **[1] 23.09.-24.09.2021, Aachener Stahlkolloquium** (ASK35)
  - Chance for extracting first-hand information from high level steel managers driving innovation
  - Forum discussion with Dr. Katharina Kortzak-Hojda, Paul Pennerstorfer (Primetals) and Dr. Rosa Peter (HKM) – moderated by Dr. Neuer (coordinator of ControlInSteel)
- **[2] 11.6.2022, BFI Colloquium** (BFI, invited steel producers)
  - On this event, a series of novel ideas were presented to mayor German steel producers participated with the aim of getting feedback. Teams from the steel producers evaluated potential application fields.
- **[3] 16.05.2022, EUROSTEELMASTER 2022** (RINA)
  - Targeted at an audience consisting of researchers and students, as well, as different experts and stakeholders from steel industry
  - The event gave hints towards skill sets required in future for implementing modern automation and control concepts. These skills
- **[4] 22.06.2022, European Steel Technology Platform** (ESTEP) Dissemination Event 2022 – Beyond Steel Research Projects
  - Presentation of ControlInSteel towards members of the ESTEP and an audience of experts
  - Discussion among the members of ESTEP
  - Follow-up individual telecons

- **[5] 28.06.2022, Digitalization as key driver in the Steel Industry** (UPM)
  - Dissemination activity organized by an alliance of EELISA, PLATEA and the consortia of RFCS-WISEST and RFCS-ControlInSteel to join forces in uncovering the current status and prospects of digitalization in steel industry and revealing future chances as well, as challenges.
- **[6] 07.07.2022, Advanced Control Solutions for Sustainability**, ControlInSteel Webinar (BFI, RINA, SSSA, UPM and ESTEP)
  - Dissemination event specialized on solutions regarding sustainability, focusing one of the most important future activity fields for automation
  - Current state of research (2022) was determined and several next steps could be elaborated
- **[7] 13.07.2022, Distributed Autonomous Control Solutions**, ControlInSteel Webinar (BFI, RINA, SSSA, UPM and ESTEP)
  - Presentation of the "past" technologies seen throughout the reviewed projects in ControlInSteel
  - A lot of presentations contained outlooks and perspectives that have been systematically compared with the existing solution taxonomy
- **[8] 14.07.2022, The Future of Control in the Steel Sector**, ControlInSteel Webinar (BFI, RINA, SSSA, UPM and ESTEP)
  - The final workshop organized by the ControlInSteel team was fully devoted to the topic of this deliverable. It compiled bridging and visionary talks that were focusing on future research and how this future work could be broken down in smaller and incremental steps
  - It was also lead-in work for this document and helped to filter out and extract reliable future technology trends for control in automation downstream
- **[9] IFAC COSY2022, Workshop on Control of Complex Systems** (IFAC)
  - This topical workshop from IFAC, fusing latest dissemination and master thesis topics with overarching application examples from different automation fields. The ControlInSteel consortium performed a dedicated session on steel industrial applications, with an active discussion also with experts from other branches and sectors.

- COSY2022 was important to get into touch with a non-steel-centric group of control experts that were investigating various different application fields.

2.2. Questions discussed and elaborated during these events

It can be assumed that technology developments, particularly in the previous ten years, have fundamentally changed how routine and complex activities are carried out.
The fact that virtually all expectations for innovation, regardless of the application domain, are frequently closely associated with the use of developing technologies and the steadily growing amount of available data, is telling.
When it comes to fully utilizing ICT technologies and data to help the steel sector handle the technological, societal, and financial difficulties that are arising, it is quite difficult to claim that "*we are already there.*"
Among the events listed in 2.1. a couple of potential future research could be identified that were recurring on many events, generally summarizing:

- Green steel production
- Quantum computing
- Worker safety
- Cybersecurity
- Artificial intelligence, specifically going beyond pure machine learning applications, enabling autonomous decision support
    - Causal AI, Counterfactual AI

The roadmapping exercise encompasses three main steps:

- Identification of the gaps that hinder the rapid and effective uptake of policy-making and policy-implementation solutions and approaches;
- Elaboration of a set of future research challenges and application scenarios in policy making;
- Definition of a set of practical research directions and recommendations for all stakeholders involved.

Clearly, the core activity of the roadmap lies on the elaboration of the research challenges and policy recommendations. We will discuss such future fields in two dedicated sections, adopting (A) an application centric view and (B) a methodology point of view.

Following assorted questions were driving the dialogue round at the webinars and the forum discussions:

- Has the development in industry and in training not kept up with the technical development of IT? (What are the reasons for this?)

- Where does the steel industry stand in terms of IT and AI use compared to other industries?
- Are steel production processes safe for the involved personnel?
- Where does the steel industry stand in a global comparison within the steel producing companies worldwide?
    - Which technologies can provide a cutting-edge advantage in this comparison?
    - How must the skillset of automation and control engineers be developed to address upcoming needs for keeping up with international competition?
- What are short-term goals (or next steps) for expanding the global process route to artificial intelligences or full automation?
- Where are artificial intelligences already being used today?
- What are major advances in digital transformation? (Industry 4.0, Deep Learning...)
- Can the consistent application of AI help the steel industry to accomplish the transformation task ahead of the steel industry?
- What level of knowledge does an industrial company want from future steel engineering graduates?
- How will work with automation technology change in the next years?
- How well protected is the industry against hacker attacks and the automatic control of industrial plants, as well as the risk of access to sensitive data?
- To what extent should security aspects be considered in complete networking?

3. Fields of Future Research A: Applications

3.1. Control and automation technology for supporting the hydrogen transition in steel industry

General description of the hydrogen transition

One of the biggest challenges of the coming decade will be the transition from fossil-fuels such as coal or gas, towards a hydrogen-based energy generation. This shift is essential for reducing greenhouse gas emissions as hydrogen produces water when being burned. Moreover, it is presumed as a renewable energy source. Supplying hydrogen to industrial users is now a major business around the world.

Relevance to steel industry

Supporting the hydrogen gas transition was identified as central topic of future research activities in [1], [2], [3] and [4], and within the topical webinar [6] focused on sustainability (where the [x] follow the numbering according to the definition given in Sec. 2). One primary role of hydrogen in steel industry is the usage as reducing agent, to convert iron ore into usable iron. We then speak about the hydrogen reduction, and this is seen as a valuable candidate for replacing traditional routes of using coke. The latter is detrimental for the environmental, as the carbon emissions of coke are substantial and the transition to hydrogen is apparently impacting these emissions in a highly effective way.

Challenge of this technology is the efficient production of hydrogen. In other words, steel industry transfers the environmentally critical processes to a different stage of the production route: the production of hydrogen at the supplier of this gas. Nonetheless, once hydrogen is used, the follow-up process route can be seen as ecologically optimized.

The iron and steel industry is responsible for about 4% of anthropogenic CO_2 emissions in Europe, and 9% worldwide, due to the massive use of coal.
Replacing coal by hydrogen generated with renewable energy would make it possible to largely decarbonize the industry. The way in which hydrogen can replace coal is well understood in principle, and the first pilot plants currently being set up will make it possible to further refine the processes. However, as ControlInSteel focuses the downstream processing of steel, hydrogen can be used in several furnaces of the downstream route such as:

- **Electric Arc Furnaces** (EAF): As a matter of fact, hydrogen can the source of energy that powers the electric arc in the corresponding furnace technology, which is used to melt scrap steel to produce new steel products. EAF are considered effective, and they also underline the recycling route of steel very well. In the sense, that also steel quality is highly affected by the inserted scrap and these quality aspects are considered of interest in the downstream chain, process optimization will have to consider feedback from downstream aggregates into the EAF process as well, when using novel hydrogen application.

- **Continuous Casting**: Indeed, hydrogen can also be used to cool down molten steel as it is being cast into a solid shape. It is assumed, that this can improve the properties of the steel and reduce the amount of energy needed to cool the steel. Consequently, new control techniques must be developed to make this cooling efficient. The casting process is even today not fully automatized.

  This will ignite research work in simulating the hydrogen cooling effect on crystallization of steel, on the geometrical shaping of slabs and billets and lastly also its potential alteration of microstructural details. The latter are of tremendous importance for reaching the actual steel qualities of a plant.

  Beneath simulations, quick prediction models will be needed to accompany the process online. In many cases, complex microstructural simulations will not be applicable in an online fashion (except transition towards Quantum computing, see 3.2. is feasible). According to control concepts for this special cooling will also have to be researched.

- **Ladle Furnaces**: Hydrogen can be injected into the molten steel in a ladle furnace to improve the quality of the steel by removing impurities such as oxygen and nitrogen.

- **Continuous annealing**: The "FlexHeat2Anneal" project being carried out by Thysenkrupp-Rasselstein in Andernach focuses on the use of hydrogen in the so-called continuous annealing process. There, the material is unwound, guided over rollers and recrystallised at high temperature in short cycle times. Natural gas has been the main fuel used in this process, but the addition of green hydrogen is now being tested.

  This technology will also require research in terms of how impurities can be removed. For the case of Continuous annealing, waste gas includes large amount of water vapour, which requires careful handing due to inner oxidation.

Those aggregates will be of primary reinterest of research projects within the next decade, regarding the revamping towards hydrogen gas. Still in its early stages of development, hydrogen applications in full scale commercial applications require far more research needed to make it cost-effective, efficient, and environmentally sustainable.

3.2. Cybersecurity of operational technology

General description of cyber-security

The term cybersecurity refers to the general protection of computer systems, network infrastructure and data pipelines against intentional attacks and unwanted access. Cybersecurity is not only implemented in terms of computer software and hardware; it is essentially also a question of company moral and the code of conduct.

Technologies, such as Blockchain, has increasingly been applied to ensure secure data transfer. However, a major step in data protection can be performed through major evolutions of both architectures and learning paradigms. Centralized industrial cloud platforms are progressively losing their capability to fulfill all of the requirements of industrial IoT in terms of performance, security and reliability. For instance, the cloud cannot always provide the needed response within bounded latency requirements, and low latency requirements are often critical for AI applications such as automatic control, video surveillance/delivery, power distribution, and fault alarm. The massive number of assets connected to the cloud requires a large amount of bandwidth to transmit the raw data, and the implementation on the cloud of AI procedures needs large computation and storage resources. The leakage of raw data from the cloud may cause harm to the business, but also major failures at the cloud or network level may severely impact fully centralized industrial operations. **Decentralized solutions**, which distribute computational and storage resources as well as intelligent decision tasks, appear a feasible robust and flexible solutions to this issue. Technologies such as Edge Computing and collaborative approaches with distributed intelligence such as Multi-Agent Systems can limit the need to transfer data by enabling more robust approaches to systems protection from intrusions and faults and by increasing system resilience with respect to variable process conditions

Industrial control systems are widely deployed in process industry. They control the production processes, monitor the quality of processes, and are deployed to nearly any machinery and equipment that is required to produce materials and goods. All these systems represent the operational technology (OT) of a production plant. The corresponding security has been quite uncared-for so far and most cybersecurity solutions focus rather on the information technology (IT) layer in a company’s infrastructure than on the OT.

Actually, the convergence between IT and OT technologies opens a clear path for a more integrative perspective. Because using the "cloud" is not typically regarded for process control, it is especially important to pay attention to control procedures. However, when employing advanced process control, the situation is slightly different.
It creates set-points and control moves that are superior to those produced by conventional PID algorithms by using predictive models of a process.

Advantages are typically employed in situations where responses are nonlinear or even discontinuous and where it may be necessary to construct the right control move using various process values.
Building the model, verifying the model using data from a running system, and then executing the model to produce set-points and control moves are the typical three processes in the implementation of the Advanced Process Control method.

Model building is suitable for building from first principles, allowing to use knowledge of the processes to construct mathematical models, accounting for all required product quality attributes and all possible process parameters needed to achieve the attribute targets.

Even something as simple as a blending operation may require so much physical modelling as to make it impractical for general use. In these cases, you can use pattern analysis tools to discover the mathematical relationships between the process parameters and the quality attributes to develop an empirical model. A cloud-based solution may be a system as a service (SAAS), in which the cloud service vendor provides an operating system environment that runs your application. Another option is a platform as a service (PAAS), in which the cloud service vendor provides a bare-bones machine that you load with your operating system and application. A third option is an application as a service (AAAS), in which the cloud service vendor provides a full application and the environment. Any one of these options should provide a lower cost solution than locally hosting and maintaining an application that you will use only rarely.

Relevance to steel industry

Being an essential part of material production, steel industry represents a major target of OT attacks, as these episodes show:

- 2014: a steel mill in Germany was victim of a severe cyberattack. It led to severe damages to the facility with extensive repair costs. Attackers gained access to the mill control systems by applying malware. This malware infiltrated the automation of a blast furnace and then produced critical destructions.
- A critical attack on energy companies also affected the US steel production in 2016. The attackers also stole sensitive information about the details of the control systems.
- 2018 saw the attack of the Industroyer malware. It targeted an important steel plant in Ukraine, leading to power outages that affected the operation of the plant and long-term production halts.
- The EKANS cyberattack was directed on a US steel plant to damage the production and cause financial deficits at the targeted company.

These are just a few examples shown during the dissemination events [4], [5], [8] and [9], yielding cyber security as a top priority research field for the upcoming years. In fact, only one single project, RFCS-AutoSurveillance, was dedicated on this topic.

Acceleration of the urgency of this topic due to political circumstances in 2022

Not only due to this underrepresentation, but cybersecurity has also gained a new urgency because of the Russian war against Ukraine. Cyberattacks have been part of the military strategy and might become an even higher threat for European steel industry, in fact for the whole European industry, in future. Out of this reason, we see the relevance of this topic dramatically increased and strongly recommend future research activities to secure European production plants.

Model execution is implemented in real-time control systems, and while it wasn't historically feasible to move model execution to the cloud, things have drastically altered. Although cloud response times can vary, they have recently increased along with accessibility, making this a setting for any real-time control.

A distributed control system (DCS), programmable logic controller (PLC), or an attached PC are frequently used for model execution. In their control systems, the majority of DCS providers have Advanced Process Control (APC) components, however they are typically just model execution blocks that presuppose you have previously generated and tested the APC mode[1]. However, spending efforts from the design phase of Operational Technologies (OT) helps to reduce the overall effort and complexity during the life-cycle of OT systems (ISA/IEC 62443)[2,3].

The ISA/IEC 62443 is one of the standard series addresses the Security of Industrial Automation and Control Systems (IACS) throughout their life-cycle. Unfortunately, there are many systems in operation for which their design has not considered the potential vulnerabilities derived from their complexity.

With Industry 4.0, machinery, electrical equipment, and contemporary Information Technology (IT) systems are intelligently networked to improve productivity throughout value creation chains while also enabling processes to be optimised. Nürk[4] explained how steel industry could benefit from the application of lean manufacturing. Some other authors have suggested that some lean principles are probably inapplicable or partially applicable while others are applicable.

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[1] Kim, Kyounggon, et al. "Cybersecurity for autonomous vehicles: Review of attacks and defense." *Computers & Security* 103 (2021): 102150.

[2] Li, Yuchong, and Qinghui Liu. "A comprehensive review study of cyber-attacks and cyber security; Emerging trends and recent developments." *Energy Reports* 7 (2021): 8176-8186.

[3] Isaksson, Ola, Sophie I. Hallstedt, and Anna Öhrwall Rönnbäck. "Digitalisation, sustainability and servitisation: Consequences on product development capabilities in manufacturing firms." *DS 91: Proceedings of NordDesign 2018, Linköping, Sweden, 14th-17th August 2018* (2018).

[4] Nürk, Jochen. "Smart information system capabilities of digital supply chain business models." *European Journal of Business Science and Technology* 5.2 (2019): 143-184.

An adaptation from the Purdue model can be considered, combining the physical layer involving Sensors and actuators with the Real Time Control layer where PLCs and Scada systems are located in the local infrastructure. Alternatives enabling hybrid Supervisory Process Control accommodating the existing local configuration but allowing an on-Cloud based extension exists. Different mechanisms to feed data to Cloud have been considered, including synchronous alternatives based on JMS, AMQP, MQTT or Kafka producers5, but also S3 storage of a set of records through Minio S3 compatible6. Such hybrid configuration becomes rather suitable for these Cybersecurity additional applications, since they allow to keep the originally defined functionality untouched, and the extra monitoring actions are going to be handled from a complementary perspective.

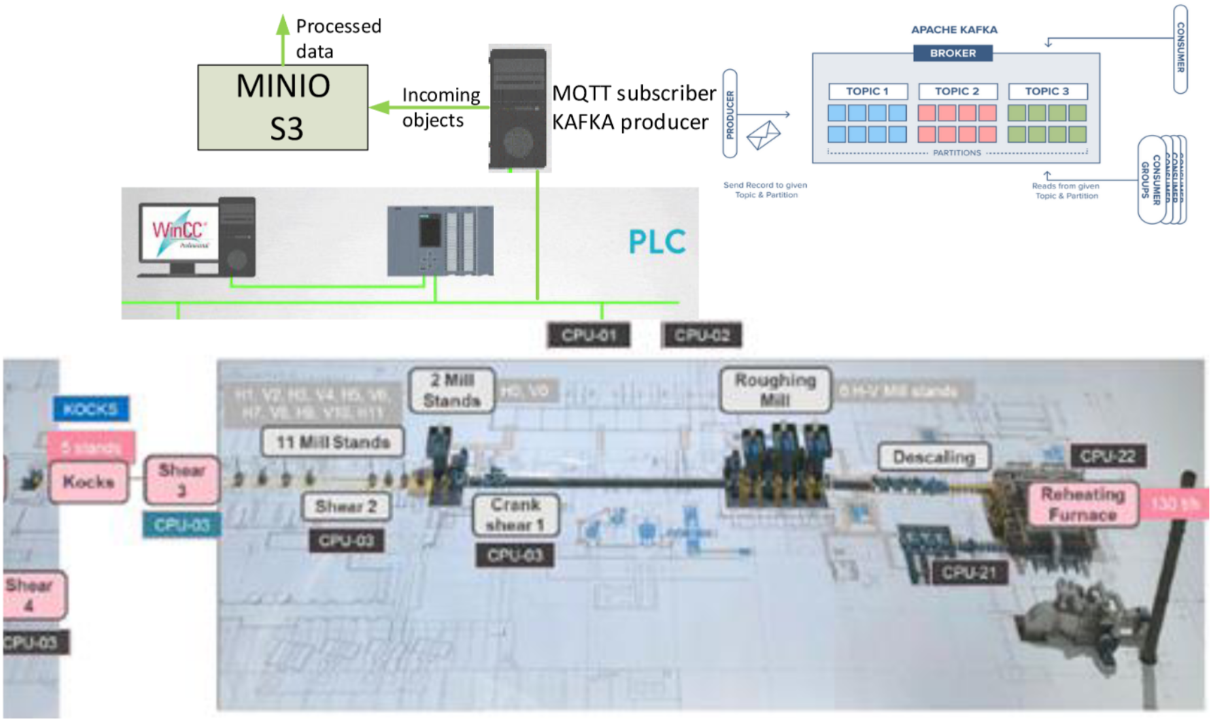

Figure 1.- Structural design compatible with the Purdue model[7].

Recent advances in cloud technologies and on-demand network circuits have created an unprecedented opportunity to enable complex scientific workflow applications to run on dynamic, networked cloud infrastructure. However, it is challenging to reliably execute workflows on distributed clouds because performance anomalies and faults are frequent in these systems[8].

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[5] Hugo, ̊A., Morin, B., and Svantorp, K. (2020). Bridging mqtt and kafka to support c-its: A feasibility study. In 2020 21st *IEEE International Conference on Mobile Data Management (MDM)*, 371–376. IEEE

[6] Naranjo, D.M., Risco, S., Molt ́o, G., and Blanquer, I. (2021). A serverless gateway for event-driven machine learning inference in multiple clouds. *Concurrency and Computation: Practice and Experience*, e6728

[7] Ordieres-Meré, Joaquín, et al. "Cybersecurity challenges in downstream steel production processes." *IFAC-PapersOnLine* 55.40 (2022): 283-288.

[8] Gaikwad, P., Mandal, A., Ruth, P., Juve, G., Kr ́ol, D., and Deelman, E. (2016). Anomaly detection for scientific workflow applications on networked clouds. In *2016 International Conference on*

Such workflows based on hybrid configurations enable both approaches, cybersecurity checks and alerting, and added value processes, such as quality, learning optimization operational conditions.

High Performance Computing Simulation (HPCS), 645–652. doi: 10.1109/HPCSim.2016.7568396.

3.3. Future of workplace and staff

General description of workplace changes in future

Industry4.0, artificial intelligence, smart robotics, all those revolutionary developments of the past decades are already affecting the automation branch and with it, they are affecting the people working in this field. In this context, social aspects will play an increasingly important role.

In process industry, generally, we will see production work being performed by a growing robotic workforce. The efficiency of those robots in assembling products or monitoring processes is simply higher compared to human workers. Consequently, human workers will be displaced or relocated to other fields of work – in part surely overseeing the robotic production.

Emphasized by the COVID crisis, remote work will have a lasting impact on our understanding of work in future. This new definition is accompanied by new tools for reviewing production processes. We will see that upcoming generations of engineers will rely on different tools that foster remote work.

Future work will require more skills specialized on digital technologies like software development or adaption and data analysis. To this aim, an increasing demand is observed concerning training and upskilling paths related to digital technologies, as companies do not want any more to externalize these kinds of services, as they want to keep the full value of their data and knowledge firmly in their hands[9]. Digital technologies, as well as AI, Big Data and advanced control solutions are nowadays seen as important enablers of C-lean steel production processes, as well as to promote energy efficiency and Industrial Symbiosis solutions[10].

The importance of the worker is also emphasized in the new emerging revolution Industry 5.0 which aims to be human-centric, sustainable, and resilient. The Industry 4.0 implementation, with a lot of challenges, has aspired to setup near-total automated factories taking advantage of cost savings. But in the current competitive market the key to success is the agility and innovation. From the new perspective of Industry 5.0, the future of work is timeless and placeless, supported by solid union between the technologies and the workers. The technology serves the worker and replaces repetitive tasks while people-centric activities support the creativity and teamwork increasing their well-being and strengthening mental health. Then the human and machines co-working breaks the manufacturing into two parts: using robots for repetitive and labor-intensive work and by means humans for customization and creativity.

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[9] T.A. Branca, B. Fornai, V. Colla, M.M. Murri, E. Streppa, A.J. Scroeder: "The challenge of digitalization in the steel sector," Metals Vol. 10, No. 2, 288, 2020.
[10] Branca, T.A., Fornai, B., Colla, V., Pistelli, M.I., Faraci, E.L., Cirilli, F., Schröder, A.J. Skills Demand in Energy Intensive Industries Targeting Industrial Symbiosis and Energy Efficiency. Sustainability 2022, 14, 15615.

Relevance to the steel sector

In the ControlInSteel analysis, we found out a significant underrepresentation of this topic in former research and pilot projects. The topic "work" was nearly not covered at all, while the topic "safety" was only covered scarcely. We think that the amount of time and money spent on those topics is by far not adequate to their importance.

The general remarks in the previous section also hold for steel industry. Worker safety could be and should be a rising field of future research since the steel manufacturing process involves the use of high technology and physical labor making safety management a complicated task. The main aspects to take in consideration which can turn into possible safety risks for workers are those concerning: the worker skills - the failures in performing highly developed skills or for example making wrong body movement; the application of rules - failures due to incorrect application of rules for tasks of coordination, verification, monitoring, compliance and application of protocols; knowledge based - the workers inability to apply their own knowledge to a new situation; mechanical - failures due to mechanical issues; culture and others - such as failures beyond the control and responsibility of the organization, improper organization of the workplace, lack of protective equipment. Automation and control are here the right tool to support and drive these future innovations. contributing to the improvement of work safety and to the reduction of the causes of accidents at work to a different extent. Optimization techniques should include worker safety and worker performance as goals. Sensorial developments should help to monitor human presence in harmful situations and artificial intelligence should be enabled to predict the risk of accidents, all with the final objective to prevent injuries and fatalities.

One of the crucial demanding aspects is to add safety considerations while working with an autonomous robot combining artificial intelligence technologies. The scope is to have a high production rate while keeping workers and the hardware equipment safe using AI technologies. In this context main cases are related to human intention recognition aimed to detect human activities and predict their next actions (based on history of daily activities), which is combined with robot navigation to create a safer environment. Other case is the robot reconfiguration based on dynamic layout which has the aims to dynamically update the navigation route of a mobile robot by considering static and dynamic objects in the environment, human or other. And finally, both the cases can be combined into a third case with the aim to ensure a safe environment for workers and hardware equipment where predicting human behavior is essential to configure the mobile robot, avoiding possible collisions, and creating safety zones. All those safety increasing tools must still comply with modern data regularizations and privacy laws.

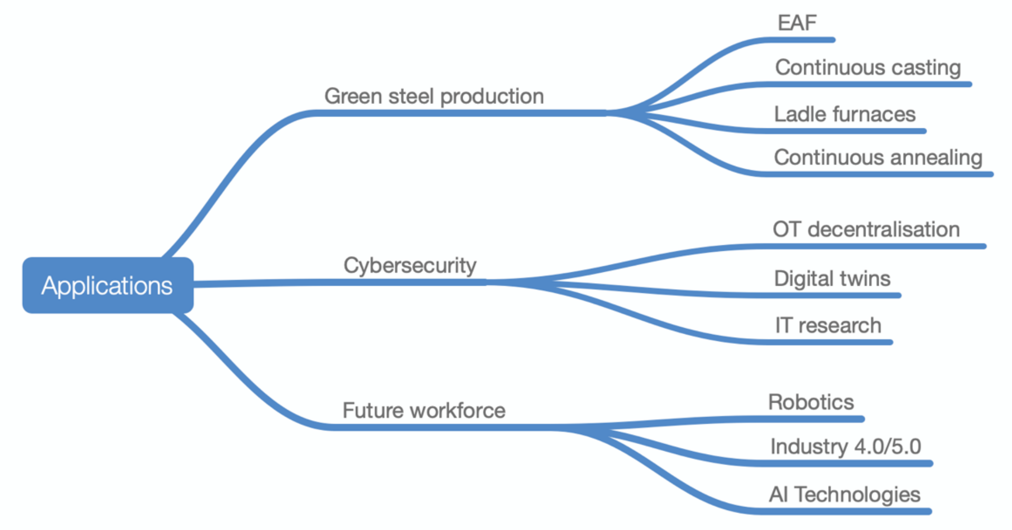

Figure 2. Mindmap of future application fields.

3.4. Summary

In Fig. 2 we show a visual summary of the above future application fields. These are by far not all fields we see, but the most important and frequently discussed topics of our events.

4. Fields of Future Research B: Methodology

4.1. Quantum Computing

General description of quantum computing

Quantum computing is a field of computing that uses the properties of quantum mechanics to perform operations on data. Unlike classical computers, which use bits to represent data and can be in one of two states (0 or 1), quantum computers use quantum bits, or **qubits**, which can exist in multiple states at once. This allows quantum computers to perform **certain types of computations much more quickly than classical computers**.

One of the key properties of qubits is **superposition**. It allows them to exist in multiple states at the same time. For example, a qubit can be in a state of 0 and 1 at the same time. One of the most important properties of a qubits is the so-called **entanglement**, which allows them to stay connected to each other in a peculiar way: the state of one qubit always affects the state of the other. Being still in its early stages of development, there are several different approaches to make a quantum computer become reality, including **superconducting qubits**, **trapped ions**, and **topological qubits**.

One of the main advantages of quantum computing is its ability to perform certain types of computations **much faster than classical computers**. This includes certain types of optimization problems, such as the travelling salesman problem, and certain types of encryptions, such as RSA. However, it is not yet clear how to use a quantum computer to solve problems that are not well-suited to its unique abilities. There are also a few challenges that need to be overcome to build a practical quantum computer, including the need to maintain a large number of qubits in a stable state and the need to develop new algorithms that can take advantage of the unique properties of quantum computing.

Relevance to steel industry

Overall, quantum computing is an exciting, revolutionizing field, which rapidly develops towards great potential for the steel industry. In different events of ControlInSteel, quantum computing was identified and discussed as upcoming activity for applied research: [1],[3],[5],[8], and [9] according to the numbering of crucial ControlInSteel dissemination events introduced in Section 2 of this text. The following aspects must be considered to yield the highest success:

> **Simulation & Optimization**: Quantum computing can be used to simulate and optimize the complex processes of steel production. Such as the behavior of molten steel in a blast furnace or the properties of different steel alloys during rolling. It is assumed, that this can lead to more efficient and

sustainable production methods and the development of new steel products with improved properties.

- **Steel product quality improvement**: Quantum computing can be used to analyze large amounts of data from steel production processes in order to identify patterns and relationships that can be used to improve the quality and consistency of steel products. For example, it can help identify the factors that lead to defects in steel products and develop methods to prevent them. A convenient introduction has been provided in some recent papers[11].

- **New material development**: Slightly leaving the actual focus of ControlInSteel, quantum computing can also be used to design new materials with specific properties, such as high strength, high conductivity, or high resistance to wear[12]. This can lead to the development of new advanced steel alloys or other materials that can be used in the steel industry.

- **Optimization of the process chain and logistic steps**: Quantum computing can be used to optimize logistics and supply chain management in the steel industry, such as scheduling and routing of transportation, or forecasting demand for steel products[13].

Overall, quantum research is still in its infancy, and much study is required to bring the full capabilities.
The field is, nevertheless, opening up new possibilities. Manufacturing will be disrupted and redefined as a result of quantum computing, with the steel industry serving as just one example of the ground-breaking goods and services that are anticipated.
However, it is anticipated that in the future, quantum computers will be able to mimic the interactions between the parts of intricate hardware systems, more thoroughly and accurately computing the system loads, load routes, noise, and vibration. This comprehensive analysis can reduce the cumulative effect of many individual safety margins, improve cost without compromising system performance, and optimize the production of individual components within the context of the total system.

Modern control processes in manufacturing test the limits of advanced analytics, especially when employing machine learning and analyzing multiple variables.

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[11] Villalba-Diez, Javier, et al. "Quantum Deep Learning for Steel Industry Computer Vision Quality Control." *IFAC-PapersOnLine* 55.2 (2022): 337-342.
[12] Liu, Yunpeng, et al. "Towards energy level cascaded "quantum armours" combating metal corrosion." *Applied Surface Science* 593 (2022): 153369.
[13] Liu, Yanxin, et al. "Multi-objective coordinated development paths for China's steel industry chain based on "water-energy-economy" dependence." *Journal of Cleaner Production* 370 (2022): 133421.

Quantum computing might help find new correlations in data, enhance pattern recognition, and advance classification beyond the capabilities of classical computing. The combination of quantum computing and machine learning is expected to have significant impact to optimization applications.

4.2. Artificial Intelligence

General description of AI

Artificial intelligence makes machines mimic the way of human problem solving, including complex deductions and inferences, as well, as actuatory and sensorial tasks. While a lot of previous research was spent on exploring the value of machine learning, a subfield of AI, the breakthrough of real AI systems has still to be accomplished.

AI needs databases with expert knowledge, autonomous access to this information and a specific technique of incentive to perform actions. We saw the rise of very powerful AI systems in the years 2020, 2021 and 2022, yet industry is reluctant to embrace this technology.

However, part of such reluctancy is due to the fact that AI has often been perceived in the past as an alternative approach with respect to physical modelling, which exploits a-priori knowledge on the process or phenomenon under consideration. On the other hand, purely data-driven methods, such as the ones based on Machine Learning (ML), apparently do not need any a-priori assumption and are capable to extract information from raw data, provided that they are available, possibly in large volumes and in adequate quality. However, experience showed that the exploitation of both sources of knowledge (physics/practice and data) is often a key solution for successful applications. The lack of trust in AI that is often experienced in the industrial community derives from the difficulties in preserving consistency of AI models with respect to first-principles models and in embedding well consolidated know-how in AI-bases solution. An emerging trend for ML application to industrial and environmental systems is represented by **Hybrid-AI** and **Physics-Guided ML techniques**, which integrate physical knowledge in ML systems design[14] [15]. Such approach appears particularly suitable to the implementation of Industrial Cyber-Physical Systems[16] and starts finding promising uses also in basic metal science, for instance, in the design and optimization of material properties[17].
A further barrier in the adoption of AI lies in the difficulty of interpreting the outcome of AI-based models and solutions in a way that can be understood by

[14] Karpatne, A., Atluri, G., Faghmous, J.H., Steinbach, M., Banerjee, A., Ganguly, A., Shekhar, S., Samatova, N., Kumar, V. (2017) Theory-guided data science: A new paradigm for scientific discovery from data, IEEE Transactions on Knowledge and Data Engineering, 29 (10), 2318-2331.
[15] Willard, J., Jia, X., Xu, S., Steinbach, M., Kumar, V. (2020), Integrating Physics-Based Modeling With Machine Learning: A Survey. https://doi.org/10.1145/1122445.1122456
[16] Rai, R., Sahu, C.K. (2020) Driven by Data or Derived through Physics? A Review of Hybrid Physics Guided Machine Learning Techniques with Cyber-Physical System (CPS) Focus, IEEE Access, 8, 71050-71073
[17] Shen, C., Wang, C., Rivera-Díaz-del-Castillo, P.E.J., Xu, D., Zhang, Q., Zhang, C., Xu, W. (2021) Discovery of marageing steels: machine learning vs. physical metallurgical modelling Journal of Materials Science and Technology, 87, 258-268.

human operators and that can enrich their knowledge and understanding of processes behaviors as well as of the phenomena that are relevant for control purposes. However, recent years have seen aver increasing research efforts toward means and solutions to overcome such barrier, which often lie in the domain of the so-called **Explainable-AI**[18], and some first attempts to implement such solution in the industrial field are being implemented. Moreover, research efforts are being spent toward the elaboration and implementation of Human-AI co-learning paradigms, where AI and end-users actively interact during the learning process in a way that improve the performance and the capabilities of both parties. The Horizon Europe framework program is also sponsoring research initiatives in these directions.

Relevance to the steel sector

Steel industry, with its rich diversity of steel grades and recipes, relies on experts that precisely adjust the process chain to the requirements of their products. Here, AI will play a vital role in future. AI can design new steel grades and oversee the correct application of recipes. Moreover, once AI has access to a knowledge database that contains the chemical and physical properties and reactions of steel compositions, it will be capable of accompanying the production process in a far more involved way than e.g., digital twins.

AI will impact all areas noted in Section 3:

- **AI impacting green steel production**: AI will help to optimize energy balancing and distribution among complex resource networks. In situations too complex for human improvement, smart algorithms will help to dynamically react on sudden changes. If failures occur, production setups can be adequately restructured for optimized restart. Furnace occupation can be predesigned so that only low amounts of empty and useless furnace operation are necessary. Overarching process chain control will be performed by AI, now optimizing the chain in a holistic and not in a cost center view per aggregate. Moreover, AI enables holistic process modelling to forecast process behavior e.g., in terms of hydrogen, energy, steam, water demands and consumptions to support optimal resource distribution and enhance flexibility in the utilization of different fuels. plant.

  A further relevant field of application of AI and ML lies in the support to fast on-line characterization of by-products and waste streams. Actually, the possibility to reuse and recycle a certain stream is directly connected to its actual features. Therefore, the practical viability of Circular Economy and Industrial Symbiosis solutions is directly and strictly connected to the possibility of punctually and precisely characterize the concerned material.

[18] Kangra K., Singh J. Explainable Artificial Intelligence: Concepts and Current Progression, (2023) Studies in Computational Intelligence, 1072, pp. 1-17.

- **AI impacting future workforce**: AI will provide new tools for workers, that will help to better interact and setup the processes. With preemptive information, the workers will be able to have better insight into the process itself. One example is the online prediction of microstructure. This prediction can help to estimate the consequences of certain process changes in advance. Safety risk can be calculated by AI using sensors in the plant.

  Sensors like WiFi transmission allow to monitor the presence of human beings in plant areas without getting personal information or identification. Such systems will enable the AI to detect humans without breaching the privacy or data security for individuals.

  AI-based vision and control systems are also included in robotic systems replacing human interventions in harsh environmental conditions and cumbersome operations.

  On the other hand, the ever-growing implementation of AI-based system poses some relevant challenges with respect to social aspects that need to be carefully considered. The pervasive implementation of AI-based systems at the workplace can be perceived as a way to limit human intervention and capabilities. Such perception can even hamper full and profitable deployment of AI-based solutions, as workers can perceive AI as a competitor and not as a support in their daily activities. On the other hand, AI should be a means to "empower" people, rather than to replace" them. AI supports workers in elaborating the enormous flow of information and extracting meaningful "knowledge", as it is physically impossible to do it with standard means, and helps taking better decisions and relieves cumbersome, repetitive and tedious operations. However, human operators must remain in the loop, firmly holding in their hands strategic decisions, but with ways and means to focus on this decision process, so that decisions are faster and hopefully better. Therefore, the European steel sector can benefit from the adoption of both Hybrid-AI and Explainable-AI approaches in monitoring and control of downstream processes even in the shot-medium term, while Human-AI co-learning will most probably require more time and a deep upskilling process for workforce.

  AI is the most revolutionary technological advancement of our time. For integrated processes across all business lines and sectors, enterprises are embracing AI solutions and utilizing a variety of data types (structured, unstructured, and semi-structured).

  Organizations are aware of the value and potential effects of AI, but they frequently struggle to make the transition from pilot to production.
  The main obstacles that businesses must overcome in order to scale AI initiatives, according to various authors, are costs (such as hardware

accelerators and compute resources), a lack of skilled workers, a lack of machine learning operations tools and technologies, an insufficient volume and quality of data, and problems with trust and governance.

Explainable AI (XAI) has emerged to help people comprehend, believe in, and control the AI they interact with. To enable transparency, accountability, and trust for industrial AI/ML systems[19], there is a high demand for explicit declarative knowledge related to huge ontologies[20].

But as seen in some papers[21], where the relational link between input and output is not apparent, the biggest explainability issues are related to the deep learning models utilized in the context of cyber-physical systems and based on artificial neural networks. The ability of the rules from many (each trained independently) decision trees to seamlessly and gradually integrate with other (previously available) rules is also crucial.
Sharing common ontologies between rule sets and encoding the rules in a consistent format, such as Semantic Web Rule Language, are necessary for this integration (SWRL)

- **AI impacting cybersecurity**: Mitigating the impact of cyberattacks requires systems that automatically detect them in the first place. AI, more specifically the subfield of machine learning, provides tools for detecting anomalies in process data stream. It can not only detect these anomalies, it can also classify them as a) failure or b) attack. This discrimination is necessary to ensure that the appropriate follow-up actions are considered.

  Moreover, AI can support decentralized approaches which can limit the vulnerability due to the need of data transfer and sharing. Moreover, emerging ML paradigms can be used, which are more compatible with data privacy and security requirement. A relevant example is provided by Federated Learning (FL), which is defined as a ML setting enabling a collaborative training model based on distributed and secure data sources without data exchange[22]. FL can provide collective intelligence to industries

[19] Gade K., Geyik S. C., Kenthapadi K., Mithal V. & Taly A. (2019). "Explainable AI in Industry". In: Proceedings of the *25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (pp. 3203-3204). ACM*. doi:10.1145/3292500.3332281

[20] Holzinger A. (2018). "From Machine Learning to Explainable AI". In: *Proceedings of the 1st World Symposium on Digital Intelligence for Systems and Machines* (pp. 55-66). IEEE. doi:10.1109/DISA.2018.8490530

[21] Daglarli E. (2021). "Explainable Artificial Intelligence (xAI) Approaches and Deep Meta-Learning Models for Cyber-Physical Systems". In: *Artificial Intelligence Paradigms for Smart Cyber-Physical Systems (pp. 42-67). IGI Global*. doi:10.4018/978-1-7998-5101-1.ch003

[22] Dib, M.A.D.S., Ribeiro, B., Prates, P. (2021) Federated Learning as a Privacy-Providing Machine Learning for Defect Predictions in Smart Manufacturing, Smart and Sustainable Manufacturing Systems, 5 (1), 1-17

without centralized training data, speeding up the implementation and adoption of the Industry 4.0 process by also exploiting the capabilities of edge computing devices

The research potential of AI is larger than sketched above, but those topics should give a snapshot of upcoming fields of interest. AI and machine learning can guard against these advanced threats, which hackers are using to shut down business networks. In fact, these technologies are rapidly advancing into commonplace tools for cybersecurity experts in their ongoing conflict with malicious actors.
Here are three ways that AI and machine learning in cybersecurity might assist as firms plan their use of these technologies:

- *Finding anomalies:* To find abnormalities that might be signs of an assault, AI and machine learning use behavioral analysis and constantly changing parameters.
- *Prediction of future data breaches:* AI and machine learning, which allows for the processing of vast volumes of data of various kinds, can deal with the task.
- R*eal-time data breach response:* AI and machine learning can deliver notifications when a cyber threat is discovered, or they can act independently without human assistance by automatically generating protective patches as soon as an assault is discovered.

4.3. Optimization techniques

General description of optimization

Production and Process optimization consist of making improvements across different critical areas by cumulative addition of more efficient processes to reach more significant outputs with the least resources expended. The main achievement in field of process optimization have as target the improvement of the machine uptime as well as the improvement of maintenance and also the speed of response to an issue. Looking to improve processes efficiency mainly consists of the real-time data collection and contextualization, the bottleneck and downtime analysis and predictive analytics which represents an important point of gain.
With the rise of the term big data and the rigorous digitalization and following data acquisition in industry, machine learning was identified as tool for automatic utilization of those data very early. In fact, optimization procedures are now a very natural next step and can surely be considered part of the more general term AI presented in the previous section. Nevertheless, we wanted to explicitly denote the term optimization a separate section, because it will be an essential method for achieving impact for green steel production.Optimization refers to a set of mathematical tools that help to find best working points for processes. It helps to avoid non-preferable situations. Finding the best energy distribution to get proper balance of energy mixes, composing the timing schedule of aggregates or steering the procedural flow of products through the processing chain, all those examples require the application of optimization techniques.

Relevance to the steel sector

Steel production is an energy intensive industry. Cutting production costs by reducing the energetic footprint of plants is one of the predominant goals of steel research. Optimization will address this question. It will help to find optimized distribution of energies. Moreover, it will help to identify re-use potential of existing energy storage. In ControlInSteel, we saw a lot of examples in past projects, following this concept: RFCS-Encom, RFCS-Gasnet or RFCS-Soprod to name just some projects. While GasNet e.g. optimized the usage of off-gases and their heat content, SoProd tried to use the flat steel coils as energy carrier – keeping the steel warm enough to be pickled without letting the pickling bath loose too much energy.

In all those cases, optimization was the key enabler for the solution. We also saw, in those former projects, that successful optimization projects were relying on their mathematical model of the process, the process chains or the distribution networks. If those models are not established, the optimization technique will fail. In that sense, any work of finding suited models for processes will also have a positive effect on optimization tasks. Such models must be sufficiently precise for predicting the right behavior, but essentially be small and compact enough to run quickly on existing computer infrastructure.

Future steel research should therefore focus on a) developing process models that are reduced for online execution, but precise enough for optimization and b) new optimization approaches that can be applied to the steel production.

4.4. Koopman control systems

General description of optimization

The Koopman operator[23] is a mathematical operator, that focuses on the dynamics in nonlinear systems. Once found, in some cases the Koopman operator allows a lossless transition to a fully linearized state model[24], which consequently helps to apply the established apparatus for linear control on those nonlinear system. There are several ways to find the operator, either using Koopman eigenfunctions, singular value decomposition[25], dynamic mode decomposition[26] (DMD) or specially designed neural networks. Once determined, it can be used to simplify the control theory of complex systems.

Over the last 5 to 10 years, a plethora of works appeared that utilize the Koopman theory or related approaches for control solutions. The cited papers reflect only a small amount of them. A common tenor of those works is the fusion of analytical mathematics with machine learning – a tenor that was also emphasized in our previous discussion in Sec. 4.2 of AI in steel industry. In that sense, Koopman theory can be interpreted as a concrete realization of modern machine learning for the control domain.

Relevance to the steel sector

Neither was there any former project dedicated to these techniques, nor was the Koopman theory as such covered in former RFCS research. Nevertheless, the potential impact on improving the existing process control systems could be high. In other contexts, the Koopman control systems showed successful application to complex system behavior, as e.g., controlling fluid flows or viscosity.

As the rolling process, the cooling process and most other downstream aggregates have to be considered highly nonlinear, Koopman decompositions could prove as a helpful tool for a) simplifying the control approach b) reducing the complexity of the control and c) increasing the reliability.

In several works, examples for the integration of the Navier-Stokes equation are have demonstrated the capacity of those techniques for treating systems of

[23] Budišić, Marko, Ryan Mohr, and Igor Mezić. "Applied koopmanism." Chaos: An Interdisciplinary Journal of Nonlinear Science 22, no. 4 (2012): 047510. https://doi.org/10.1063/1.4772195

[24] S. L. Brunton, M. Budišić, E. Kaiser, J. N. Kutz, „Modern Koopman Theory for Dynamical Systems", 2021, arXiv:2102.12086, preprint

[25] G. Nedzhibov, "On alternative algorithms for computing dynamic mode decomposition", Dez. 2022, https://doi.org/10.3390/computation10120210

[26] J. N. Kutz, S. L. Brunton, B. W. Brunton, J. L. Proctor, „Dynamic mode decomposition – Data-driven modeling of complex systems", 2016, ISBN:978-1-61197-449-2, https://epubs.siam.org/doi/book/10.1137/1.9781611974508

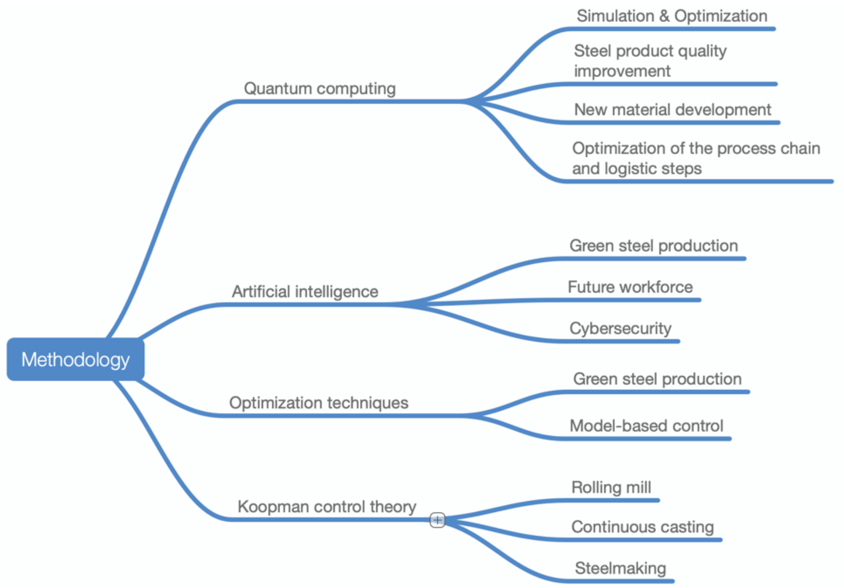

Figure 3. Mindmap of future methodology.

differential equations. The work of Sharma et al.[27] is just one illustrative example. The description of rolling and various problems from the steel making domain require the solution of complex differential equation systems. Control techniques rely on quick and robust solutions of (typically) reduced sets of equations – especially, when the full integration of the differential equation system is not feasible due to computational performance.

In recent works, the stochastic Koopman operator was successfully applied to control of nonlinear systems, e.g., shown by using deep neural networks in Han et al.[28] in 2022. The latter work compactly focuses all relevant aspects of robust control as it could also be applied for steel production.

In those situations, we see a clear favorable application of the Koopman theory. Steel industry should investigate via research projects, how a concise problem can be translated and a corresponding decomposition could lead to benefits for the process control and overall production quality.

4.5. Summary

Fig. 3 contains a visual summary of the presented future methods. It features also the impact vector of the respective technique.

[27] A. S. Sharma, I. Mezic, B. J. McKeon, „On the correspondence between Koopman mode decomposition, resolvent mode decomposition and invariant solutions of the Navier-Stokes equations, Phys. Rev. Fluids 1 (3), 2016, DOI: 10.1103/PhysRevFluids.1.032402
[28] M. Han, J. Euler-Rolle, R. K. Katzschmann, „DeSKO: Stability-assured robust control of nonlinear systems with a deep stochastic Koopman operator", Int. Conf. Learning Representations (ICLR) 2022, https://openreview.net/forum?id=hniLRD_XCA

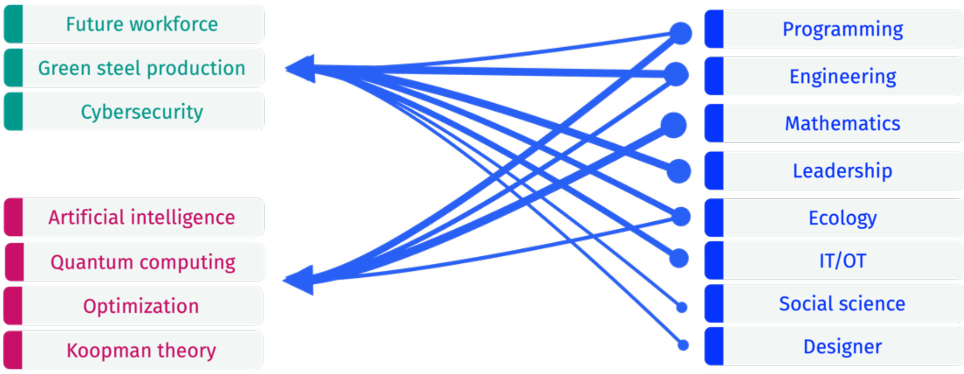

Figure 4. Skill set correspondence for the future roadmap methods and applications.

5. Skill set analysis

We will conclude this deliverable with a short skill set analysis based on the assessment of Sec. 3 and Sec. 4. It focuses on the automation and control in downstream steel processing, asking the question "What future personnel skills do we need to actually move in the direction of the roadmap?". Fig. 4 contains an illustration of the projected skills needed to address the future roadmap topics.

We weighted the skills depending on their relevance to a specific field. Four thickness steps of the arrow width (blue) were used: 1: light dependence, 2: medium, dependence, 3: strong dependence and 4: very strong dependence. The strongest relation is found between engineering skills and green steel production, leadership and green steel production as well as programming with AI, mathematics with Koopman theory and optimization.