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Exploring Historical Data Utilization in Skill-Based Production Systems

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Abstract

This paper explores the enhancement of skill-based production systems through the application of historical performance data and new data-driven methods. It examines case-based reasoning, knowledge graphs, and simulation environments in detail. The study assesses the capability of each method to analyze historical activities and generate valuable insights for future production tasks. It discusses how case-based reasoning utilizes previous examples for decision-making, knowledge graphs map out data interconnections, and simulation environments allow for safe testing of scenarios. The comparative analysis investigates how these approaches can integrate with skill-based production to improve system efficiency. It highlights the strengths, limitations, and potential areas for future research, emphasizing the need for incorporating these technologies to boost operational efficiency and adaptability in manufacturing settings. This paper aims to assist practitioners and researchers in leveraging historical data to refine skill development and decision-making within production systems.

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Keywords: skill-based production; case-based reasoning; knowledge graph reasoning; simulation environments; historical data

1. Introduction

Considering an increasingly individualized product landscape and shorter product life cycles, a flexible production environment is becoming more and more relevant [13] [14]. The requirements for machines used in such an environment are set out on the Industrie 4.0 platform. The Reference Architecture Model Industrie 4.0 (RAMI 4.0) provides guidance for Industrie 4.0 [6]. The RAMI 4.0 describes the three dimensions of communication architecture (OSI layer model), product life cycle [10] and factory hierarchy[8] [9] (automation pyramid [15]) in terms of their interdependence [6]. In addition to RAMI 4.0, cyber-physical systems/cyber-physical production systems (CPS/CPPS) are

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described in the context of Industrie 4.0, where a CPS consists of a physical component, an integrated computing unit and logic that has suitable system interfaces for communicating with global networks and user interfaces [19].

The Capability-Skill-Service-Model (CSS Model) explains Capabilities, Skills and Services in relation to the production process that consists of the product, the process and the resource. A service provides the economic aspects for executing the production capability. The execution or task is only described by the capabilities independently of the machine. Skills, on the other hand, contain the machine-specific description of the execution to fulfill the task [5].

This paper looks at a machine tool that enables skill-based manufacturing in machining with a geometric cutting edge. This machine can be regarded as a CPS and simultaneously provides information that is necessary for the execution of services. The advantages of machining production with geometric cutting by using optimum production parameters are clear. This applies in particular to the optimum tool utilization and the reduction or optimum production time. The reuse or approximation of previously performed manufacturing operations ensures the quality and safety of the machine, workpiece and tool.

The main motivation for using historical data in skill-based production is the more accurate prediction of quotations and the reuse of known production parameters. In addition, the offer should include the individual production steps and transport processes so that the product can be manufactured in shared production plants. The quotation can more accurately determine the duration, costs and CO_2 footprint of the order based on similar orders or characteristics from the past. In manufacturing, the reuse of already realized cutting parameters with the corresponding tools and set-ups should help to shorten the machining time while maintaining the same product quality. Safety aspects are also considered before execution by reusing the production parameters and set-up.

Artificial intelligence methods and mathematical description that deal with the processing of data from previous events are discussed below. In this context, methods such as case-based reasoning, knowledge graph reasoning and simulation environments should be mentioned. This is followed by a comparison of the methods mentioned and a discussion of the possibility of integrating the methods into the existing skill architecture.

2. State of the Art

The following chapter provides an overview of the terms and methods relevant to competence-based production, such as CBR, KGR and SE, which are necessary for understanding the paper.

2.1. Skill-based Production

In skill-based production, the individual manufacturing capabilities of production are summarized in individual functional blocks, so-called Skills. The concept of encapsulating individual Skills in functional blocks is similar to that described in [7] standard. The view of the manufacturing capabilities described above enables a machine tool to offer its Skills as a service. The manufacturing capabilities described above can respond to requests from users in a network and execute the requested manufacturing step or process independently.

According to [20], a skill consists of the three phases *FeasibilityCheck*, *PreConditionCheck*, and *SkillExecution*. With the help of these phases, it is possible to execute Skills automatically and without CAM programming. The FeasibilityCheck checks the feasibility of executing the geometric shaped element using a transferred parameter set. The result is then returned with an ID to enable the parameters to be transferred and reused between the asset administration shell, the PreConditionCheck and the SkillExecution. The Asset Administration Shell contains the necessary information to represent an asset with information and technical functionality [6]. An asset is an object that has a value for an organization [6]. The PreConditionCheck is used to check the boundary conditions that are necessary for the execution of the skill. The SkillExecution is where the skill is executed, and the process data is recorded. Archiving the individual Skills with the ID in the asset administration shell enables identical queries to be queried and executed again. A similarity analysis or an adjustment of the production parameters is not provided within the framework of the skill structure presented here [20].

This paper deals with the production parameters in the machine tool area. The production of these geometric shaped elements requires the consideration of various parameters, including the in infeed in the Z direction, the transverse in infeed in the XY plane, the spindle speed and the feed rate. Fig. 1 shows the production parameters for milling a rectangular pocket. When machining the workpiece, these parameters are primarily decisive for the quality of the roughness and accuracy during the production process on the machine tool. Vibrations in the tool or workpiece caused by these parameters are not considered in this case.

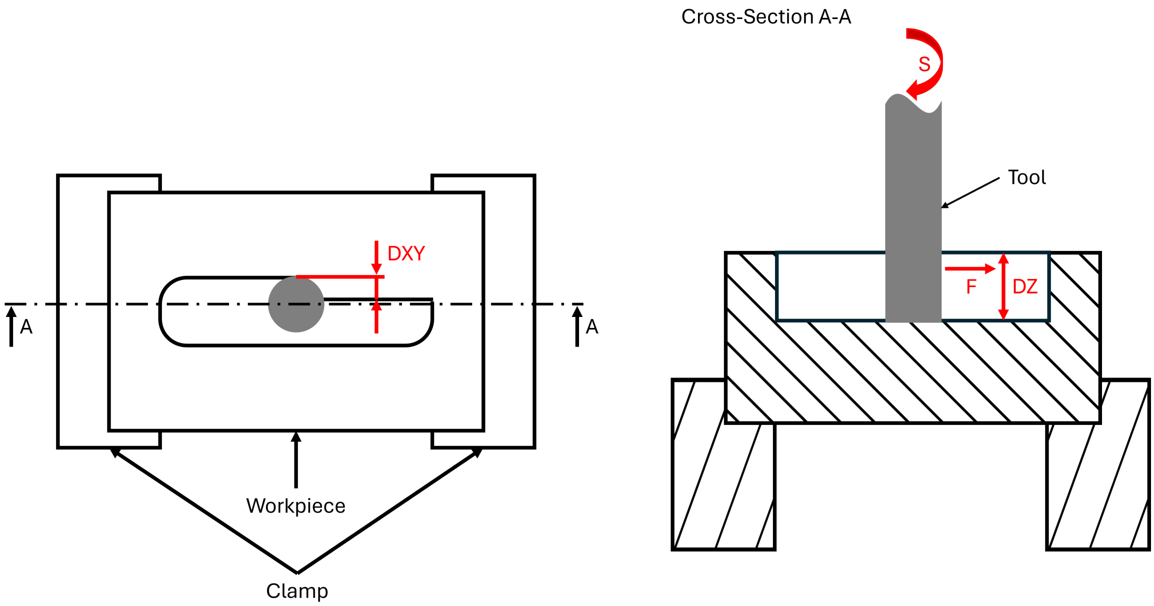

Fig. 1. Milling parameters such as depth infeed in the Z direction (DZ), cross infeed in the XY plane (DXY), feed rate (F) and spindle speed (S) for a rectangular pocket

2.2. Case-Based Reasoning

Case-Based Reasoning (CBR) is an area of research in artificial intelligence that involves the study of theoretical foundations, system development, and the development of practical applications for solving problems based on previous experience [3]. At the center of CBR is the case database, which interacts with the individual phases of CBR. The phases of CBR can be divided into *Retrieve*, *Reuse*, *Revise* and *Retain*. The knowledge in the database is encoded using a similarity measure and must be considered when developing applications.

During *Retrieve* phase, cases are retrieved that are most similar to the requested case. As the number of cases in the database increases, the challenge shifts from finding similar cases with a given similarity function to improving the retrieval efficiency of CBR searches to find the best case. Index structures such as kd-trees, case retrieval nets or discrimination networks are used to solve this problem [1, 3].

In the *Reuse* phase, both simple and complex solutions can be found. This depends on the type of task. When searching for classification tasks with limited solutions (simple solution finding), the manufacturing parameters found can be reused directly. When searching for more complex solutions, such as configurations or planning, it is necessary to adapt the solution. Two main methods can be distinguished here: the modification of the existing solution or the generation of the solution from general solutions. Generating the exact adaptation knowledge is a time-consuming and complex process. For this reason, detailed adaptations of solutions are avoided in CBR [1, 3].

The *Revise* phase receives feedback on the developed solution and passes the revised solution to the Retain phase. This is based on the accuracy of the result or on manually changed parameters [1, 3].

In the *Retain* learning phase, the findings from the implementation and processing are saved. For this purpose, new cases of the experience gained are entered into the database. The expansion of the database results in an increase in the knowledge base, yet simultaneously impairs the efficiency of retrieving individual cases [1, 3]. The entire cycle of CBR is shown in Fig. 2 based on [1].

The findings from the manufacturing process can be fed back into the feasibility check of the competence with the help of the CBR. This enables the choice of manufacturing parameters and the prediction of the process parameters

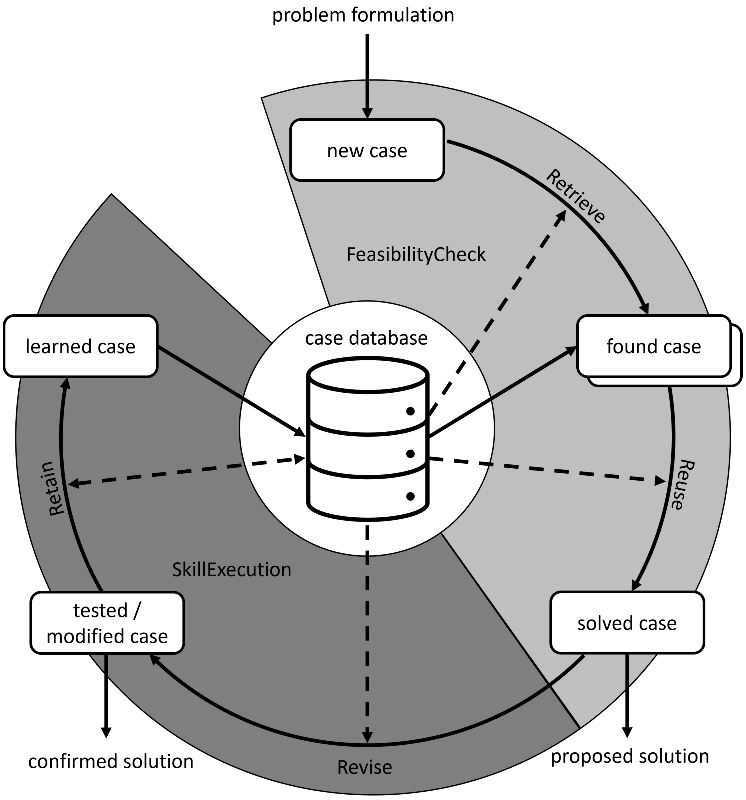

Fig. 2. CBR cycle in the context of the FeasibilityCheck and SkillExecution phases of a skill on [20] based on Aamodt and Plaza [1]

to be optimized. In the retain phase, a manufacturing process analysis can be integrated, which indicates the accuracy of the problem solution implemented for the respective case.

The CBR can only process new cases that are already stored in the database in a similar form. This means that cases that do not meet this similarity measure cannot be processed by the cycle.

2.3. *Knowledge Graph Reasoning*

Knowledge Graph Reasoning (KGR) is based on a knowledge graph that is processed with the help of Knowledge Graph Embedding (KGE) and therefore provides the basis for KGR. A knowledge graph is a semantic network that structures knowledge and contains it semantically. This allows the formal interpretation of concepts from the real world [4].

As part of KGE, machine learning algorithms are used to structure the data from the knowledge graph and make it more precise for further processing in reasoning. The preparation of the data, which is available in the form of a knowledge graph, is an essential prerequisite for its use in Skills. To this end, the data is first prepared with the help of KGE functions and then applied with KGR.

KGE has the task of preparing the data stored in a knowledge graph according to the subject, predicate, object method in a simplified structure for further processing. Various methods exist for preparing the data for reasoning in a distributed representation, including tensor decomposition, the distance model, semantic matching models and loss functions. Tensor decomposition involves the decomposition of high multidimensional arrays into several low-dimensional matrices [4][11][18]. The distance model represents an evaluation function that views each relationship in the knowledge graph as a translational transformation from subject to object. The evaluation is carried out by minimizing the translation error [11] [17]. As part of the semantic matching model, the entities and relations are mapped as vectors so that correlations between entities and relations can then be modeled [4]. Loss functions are an effective tool for distinguishing a valid triple from negative samples [11].

The KGE also offers the option of building knowledge using neural networks. Convolutional neural network (CNN), recurrent neural network (RNN) and reinforcement learning can be used for this purpose.

A CNN is a network that consists of several small kernels (so-called filters), which are applied over local areas with the help of convolutional operators. This extracts features from these areas. By applying the kernels to several local areas of the entire field, it is possible to extract features from the entire field [12].

The use of different knowledge path representations is an essential aspect in the application of RNN, as significant results can be achieved in this way. The RNN makes it possible to analyze entities that were previously described textually. Long Short Term Memory (LSTM) networks can be used to generate the embeddings of the knowledge graphs. In this way, a description of the entities can be created [18].

The reinforcement learning method makes it possible to independently deduce a question with an unknown answer from an incomplete knowledge database because of existing triples. The process of inferring the answer can be characterized as a serialized decision problem [4].

Extending the KGR involves more effort than extending the CBR, as the graph is extended by adding data. The knowledge graph described above then needs to be processed again using the embedding algorithms mentioned above to update the database with the new findings from the production step.

2.4. Simulation Environments

According to [2], a simulation is the reproduction of the functioning of a real process or system over time. To create these simulations, environments are required that have, for example, physical environment properties, such as weight force and air resistance, stored to integrate the models that are built in the respective environments. Furthermore, a priori knowledge and measurement data about the model to be simulated is of major importance in advance, as the simulation model must be calculated on this basis. The calculated model must then be validated against the real model to be able to say with certainty that simulation and reality match as closely as possible. The model only needs to be sufficiently accurate for the application and cover the relevant parameters. If changes have been made to the simulation model due to wear or modifications. The model must be completely recalculated so that the changes can be adopted [2]. Modeling the Skills in the environment can be used for multiple Skills. This means that a simulation model is not required for each skill.

Furthermore, these simulation environments (SE) can be described as digital twins, which are primarily used for visualization, simulation and virtual commissioning of the control logic. However, it is not possible for the digital twins to plan independent trajectories; instead, the previously planned trajectory is merely checked for validity [16].

3. Comparative Analysis of Methodologies and Strategies

In the following, the three methods for utilizing historical data in skill-based production are examined in terms of their effectiveness, usability and integration and then compared with each other.

The effectiveness of CBR is largely dependent on the quality and quantity of the stored cases. The precision and speed of problem-solving increase with the number of relevant cases. CBR proves to be particularly useful in domains where experience and empirical knowledge play a prominent role. In skill-based production, CBR can help to transfer production strategies that have already been successfully implemented to new but similar situations. This leads to a reduction in the time and resources required, as proven methods can be used again. The integration of CBR into existing systems requires a comprehensive case library and a robust retrieval system. However, implementation is relatively straightforward, as CBR systems are often modular and interact well with other IT systems. The continuous updating and maintenance of the case library can be identified as a potential challenge.

The use of KGR allows complex queries and inference processes to be carried out, enabling more in-depth insights to be gained from historical data. The effectiveness of KGR is largely dependent on the quality of the knowledge graphs and the inference algorithms used. The KGR is extremely useful for understanding and analyzing complex connections and relationships in production. In skill-based production, KGR can be used to link knowledge about Skills, machines and processes and to make optimizations. Decision-making is supported by providing a comprehensive overview of the production environment and its history. The integration of KGR into existing production systems requires careful modeling of knowledge and the creation of comprehensive knowledge graphs. Modeling involves a great deal of effort and often requires the availability of expert knowledge. After the initial creation, however, KGR systems can be flexibly expanded and easily updated.

Historical data is used in SE to create virtual models of the production environment. The models can be used to test different scenarios and their effects on production. The effectiveness of SE depends on the precision of the models and the quality of the simulations. The application of SE is of great benefit for the planning and optimization of production processes. Skill-based production enables the risk-free evaluation of various production strategies before they are implemented in real production. This leads to a reduction in errors and optimizes the use of resources. The integration of SE requires extensive data and powerful computing resources. Building adequate models and carrying out complex simulations can be time-consuming and costly. Nevertheless, SEs provide valuable insights and allow proactive planning and the avoidance of errors.

Compared to SE, CBR and KGR do not require a mathematical description of the production step to carry out the analysis and prediction. Summary of the generic comparison of CBR, KGR and the simulation environment about the factor's effectiveness, usefulness and integration.

CBR:

- Effectiveness: High if the quality and quantity of cases in the database is sufficient.
- Usability: Useful for recurring cases, new cases that are not known, less so.
- Integration: Uncomplicated integration due to the modular structure. Challenges in maintaining and updating the case library.

KGR:

- Effectiveness: High, with good quality of the knowledge graph.
- Usability: Particularly helpful for complex analyses and decision-making. New, as yet unknown cases can be solved.
- Integration: Careful modeling, flexible maintenance and updating.

Simulation Environment:

- Effectiveness: A great deal of a priori knowledge is required to generate accurate models. The more accurate, the higher the effectiveness.
- Usability: Benefit in the planning and optimization of cases.
- Integration: Complex, extensive knowledge of the process and computing resources are required.

3.1. Analysis in the context of skill-based production in machining production with geometrically defined cutting edge

In conventional machining production, the tool paths are programmed on the computerized numerical control of the machine tool or on the PC with computer-aided manufacturing. During programming, the functions offered by the respective computer unit are used to produce the desired workpiece. The capabilities of the machine tool can be derived from these available functions [20]. Shape elements that can be assigned to the functions of the machine tool can also be derived from the computer-aided design. The machine tool capabilities offered so far on our demonstrator are, for example, rectangular pocket, circular pocket, drill holes, slots, through slot and side slot [19]. The following conclusions can be drawn from this for the individual processes. In the Table 1, the pros and cons of the proposed methods and strategies are shown.

Updating the database in a CBR system is straightforward, as it involves simply adding new entries. This continuous learning ensures that the knowledge within the CBR system is retained and expanded over time. However, a significant limitation of the CBR algorithm is its inability to process new cases that are not yet stored in the database, requiring external intervention for such scenarios. Furthermore, as the database grows, optimizing runtime by recognizing similarities between individual cases becomes increasingly challenging. Despite these drawbacks, the CBR algorithm excels in making accurate predictions about feasibility, duration, costs, and CO_2 consumption by analyzing recurring shaped elements in skill-based production. When similar shaped types and diameters are produced again, the algorithm's predictions are highly reliable. However, the algorithm cannot independently evaluate or predict outcomes for previously unknown cases. Additionally, while collision detection can be predicted, it cannot be calculated precisely using the case database.

Creating solutions based on a knowledge graph offers the advantage of considering cases not yet present in the knowledge base. The knowledge graph can be updated using KGE and once optimal parameters for the KGE are determined, updates can be consistently applied with the same parameters. However, setting up and modeling the knowledge base for KGE is a time-consuming and complex process. Nevertheless, predictions of collision detection, time, costs, and feasibility are possible. Predictions based on the knowledge graph can handle recurring shaped elements that vary only in dimensions, positions, and orientations (such as rectangular pockets, circular pockets, grooves, and bores). Additionally, the capability of KGR algorithms allows for predictions involving new and constantly changing shaped elements and free-form surfaces. However, achieving this level of predictive accuracy necessitates a well-developed knowledge graph.

With a robust database of the process, calculations for the simulation model can be performed with the corresponding initial and boundary conditions. AI algorithms can be integrated into the simulation model to incorporate learning aspects, allowing the algorithms to be trained in the simulation. This approach is particularly useful for the simulation of generated paths and collision detection. Updating the functions and methods within the simulation model is relatively time-consuming as it requires a complete recalculation of all functions and methods. In addition, the simulation model lacks autonomous decision-making capabilities.

In production, the reuse of production parameters of shaped elements is increasingly being considered, as the shaped elements usually only differ in their dimensions and positions. The complete simulation of the trajectory execution is very resource-intensive and therefore not well suited for skill-based production. A simulation model can have a practical advantage as a visualization and insight into the decision-making of the AI algorithms.

Table 1. Overview of the proposed methods and strategies with their pros and cons by category for skill-based production.

Categories	CBR	KGR	SE
Update Database	++	○	−−
Find Solution	++	++	○
Find new Solution	−−	++	○
Usability	+	++	○
Integration	++	+	−

4. Discussion and Implications

The use of historical data in skill-based production provides a more accurate prediction of manufacturing parameters and process parameters before the execution of the skill, and allows a more precise preparation of a quotation and use of the tools at the optimum performance level during machining.

4.1. Effectiveness

The concepts of CBR and KGR are both effective methods for utilizing historical data to solve current production problems. The CBR method is based on the reuse of previous case solutions, whereby its effectiveness depends in particular on the availability of an extensive and relevant case library. This enables a timely and reliable solution to recurring problems. In contrast, KGR allows complex relationships and correlations in the production data to be analyzed to make informed decisions. The ability to gain more in-depth insights and answer complex questions makes KGR a highly effective tool in a dynamic production environment. While SE is also highly effective due to the ability to test and simulate different scenarios, the quality of the simulations is highly dependent on the accuracy of the models. The creation and maintenance of such models can be resource intensive, which can reduce their effectiveness compared to CBR and KGR.

4.2. Usefulness

CBR proves to be particularly useful in the timely management of problems that have already occurred in a similar form. The reuse of solutions saves time and resources and enables rapid adaptation to new but similar situations. In contrast to KGR, KGR not only takes past solutions into account, but also generates new insights by analyzing relationships and dependencies in the data. This is particularly useful for optimizing production processes and for strategic planning. SE enables the risk-free testing of new production strategies, which underlines its usefulness in planning and optimization. However, the benefits are heavily dependent on the availability and quality of input data and computing resources, which can limit its practical applicability in numerous instances.

4.3. Integration

The integration of CBR into existing production systems can be realized with comparatively little effort. CBR systems are characterized by their modularity, meaning that they can be easily embedded in existing IT infrastructures. The main challenge lies in creating and maintaining a comprehensive and relevant case library. Although the creation of knowledge graphs requires careful modeling of the knowledge, it subsequently offers flexible expandability and updateability. This makes KGR a future-proof solution that can easily adapt to changing requirements and new data. On the other hand, the integration of an SE is associated with significant investments in procurement, modeling and computing capacities. The creation of realistic models involves a great deal of effort, which can prolong the implementation process. Furthermore, the maintenance and continuous updating of the simulation models is associated with a high expenditure of resources.

4.4. Implication

The preceding discussion leads to the conclusion that CBR and KGR are better suited for integration into skill-based production than SE. CBR is a straightforward and effective solution for reusing historical cases. It is fast and reliable for recurring problems and only requires a well-maintained case library. The KGR method enables a deeper analysis capability as well as support for complex decision-making by linking and analyzing extensive data relationships. The initial effort required to create the knowledge graphs is compensated by the long-term flexibility and expandability. In comparison, although the SE proves useful for detailed planning and optimization, it is less practical for immediate integration due to the high effort required for modeling and the demands on computing resources. This leads to the conclusion that SE is less suitable for organizations aiming for fast and efficient use of historical data. Therefore, CBR and KGR prove to be more suitable methods for integrating historical data in skill-based production, as they offer higher efficiency, usefulness and easier integration.

5. Conclusion and Future Outlook

In the changing landscape of individualized products and shorter life cycles, a flexible production environment is becoming increasingly important. The RAMI 4.0 and CPS provide a framework for creating such an environment. This paper examines the integration of historical data into capability-based production systems, focussing on three methods: CBR, KGR and SE methods are discussed in more detail below. CBR uses previous cases to solve current problems. It offers high effectiveness and ease of use in environments with recurring problems. Integration is relatively simple as it relies on a well-maintained case library. In contrast, KGR is based on complex data relationships that support informed decision-making and strategic planning. Although initial modeling is associated with considerable effort, this solution is characterized by a high degree of robustness and longevity due to its flexibility and expandability. Although SE is suitable for planning and optimization through scenario testing, it requires extensive modeling and computing resources, making it less suitable for immediate integration compared to CBR and KGR.

In conclusion, for organizations seeking to enhance skill-based production through historical data, CBR and KGR present more practical and efficient methods than SE. CBR provides a quick and reliable approach for recurring problems, while KGR offers deeper analytical capabilities for complex decision-making. Together, these methods align well with the goals of Industrie 4.0, fostering a more adaptable and intelligent production environment.

To be able to apply the KGR and CBR algorithms to existing machine tools, suitable framework conditions for these algorithms must be identified and implemented. In addition, the machine tools must be equipped with advanced measurement technology, e.g. with energy measuring elements and sensors for recording vibrations on tools and workpieces. The results are then validated using these algorithms. By integrating AI algorithms, quality control can also be integrated into the Skills, which requires the use of advanced measurement technology.

References

[1] Aamodt, A., Plaza, E., 1994. Case-Based Reasoning: Foundational Issues, Methodological Variations, and System Approaches. AI Communications 7, 39–59. doi:10.3233/AIC-1994-7104.

[2] Banks, J. (Ed.), 1998. Handbook of Simulation: Principles, Methodology, Advances, Applications, and Practice. Wiley, ; Co-published by Engineering & Management Press, New York : [Norcross, Ga.].

[3] Bergmann, R., Althoff, K.D., Minor, M., Reichle, M., Bach, K., 2009. Case-Based Reasoning - Introduction and Recent Developments. Künstliche Intelligenz 1/2009, 5–11.

[4] Chen, X., Jia, S., Xiang, Y., 2020. A review: Knowledge reasoning over knowledge graph. Expert Systems with Applications 141, 112948. doi:10.1016/j.eswa.2019.112948.

[5] Christian Diedrich, Alexander Belyaev, Rafi Blumenfeld, Jürgen Bock, Stephan Grimm, Jesko Hermann, Tobias Klausmann, Aljosha Köcher, Matthias Maurmaier, Kristof Meixner, Jörn Peschke, Miriam Schleipen, Siwara Schmidt, Boris Schnebel, Guido Stephan, Magnus Volkmann, Andreas Wannagat, Kym Watson, Michael Winter, Patrick Zimmermann, 2022. Information Model for Capabilities, Skills & Services.

[6] DIN SPEC (PAS, CWA), . DIN SPEC 91345:2016-04, Referenzarchitekturmodell Industrie 4.0 (RAMI4.0). doi:10.31030/2436156.

[7] DKE Deutsche Kommission Elektrotechnik Elektronik Informationstechnik in DIN und VDE, German Commission for Electrical, Electronic and Information Technologies of DIN and VDE, a. DIN EN 61499-1:2014-09, Funktionsbausteine für industrielle Leitsysteme_- Teil_1: Architektur (IEC_61499-1:2012); Deutsche Fassung EN_61499-1:2013. doi:10.31030/2203967.

[8] DKE Deutsche Kommission Elektrotechnik Elektronik Informationstechnik in DIN und VDE, German Commission for Electrical, Electronic and Information Technologies of DIN and VDE, b. DIN EN 61512-1:2000-01, Chargenorientierte Fahrweise_- Teil_1: Modelle und Terminologie (IEC_61512-1:1997); Deutsche Fassung EN_61512-1:1999. doi:10.31030/8529860.

[9] DKE Deutsche Kommission Elektrotechnik Elektronik Informationstechnik in DIN und VDE, German Commission for Electrical, Electronic and Information Technologies of DIN and VDE, c. DIN EN 62264-1:2014-07, Integration von Unternehmensführungs- und Leitsystemen_- Teil_1: Modelle und Terminologie (IEC_62264-1:2013); Deutsche Fassung EN_62264-1:2013. doi:10.31030/2156368.

[10] DKE Deutsche Kommission Elektrotechnik Elektronik Informationstechnik in DIN und VDE, German Commission for Electrical, Electronic and Information Technologies of DIN and VDE, d. Industrielle Automatisierungs- und Leittechnik - Lebenszyklus-Management von Systemen und Komponenten (IEC 62890:2020); Deutsche Fassung EN IEC 62890:2020.

[11] Ge, X., Wang, Y.C., Wang, B., Kuo, C.C.J., 2023. Knowledge Graph Embedding: An Overview. doi:10.48550/arXiv.2309.12501, arXiv:2309.12501.

[12] Hogan, A., Blomqvist, E., Cochez, M., D'amato, C., Melo, G.D., Gutierrez, C., Kirrane, S., Gayo, J.E.L., Navigli, R., Neumaier, S., Ngomo, A.C.N., Polleres, A., Rashid, S.M., Rula, A., Schmelzeisen, L., Sequeda, J., Staab, S., Zimmermann, A., 2022. Knowledge Graphs. ACM Computing Surveys 54, 1–37. doi:10.1145/3447772.

[13] Hu, S.J., 2013. Evolving Paradigms of Manufacturing: From Mass Production to Mass Customization and Personalization. Procedia CIRP 7, 3–8. doi:10.1016/j.procir.2013.05.002.

[14] Lindemann, U., Baumberger, G.C., 2006. Individualisierte Produkte, in: Lindemann, U., Reichwald, R., Zäh, M.F. (Eds.), Individualisierte Produkte — Komplexität beherrschen in Entwicklung und Produktion. Springer, Berlin, Heidelberg, pp. 7–16. doi:10.1007/3-540-34274-5_2.

[15] Siepmann, D., Graef, N., 2016. Industrie 4.0 – Grundlagen und Gesamtzusammenhang, in: Roth, A. (Ed.), Einführung und Umsetzung von Industrie 4.0: Grundlagen, Vorgehensmodell und Use Cases aus der Praxis. Springer, Berlin, Heidelberg, pp. 17–82. doi:10.1007/978-3-662-48505-7_2.

[16] Spitzer, F., Froschauer, R., Schichl, T., 2021. ATLAS - A Generic Framework for Generation of Skill-Based Control Logic and Simulation Models for Intralogistics Applications, in: 2021 26th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), pp. 1–8. doi:10.1109/ETFA45728.2021.9613345.

[17] Tian, L., Zhou, X., Wu, Y.P., Zhou, W.T., Zhang, J.H., Zhang, T.S., 2022. Knowledge graph and knowledge reasoning: A systematic review. Journal of Electronic Science and Technology 20, 100159. doi:10.1016/j.jnlest.2022.100159.

[18] Vergara, I.V., Lee, L.C., 2023. A Schematic Review of Knowledge Reasoning Approaches Based on the Knowledge Graph. Journal of Enterprise and Business Intelligence , 179–189doi:10.53759/5181/JEBI202303018.

[19] Volkmann, M., 2024. Modellierung von Dienstleistungen, Capabilities und Skills zur Einbindung von Unternehmen in eine marktplatzbasierte Fertigung. Ph.D. thesis. Rheinland-Pfälzischen Technischen Universität Kaiserslautern-Landau. Kaiserslautern.

[20] Wagner, A., Lamoth, S., Volkmann, M., Hermann, J., Ruskowski, M., 2023. Interaction between FeasibilityCheck, PreconditionCheck and SkillExecution in skill-based machining, in: 2023 IEEE 28th International Conference on Emerging Technologies and Factory Automation (ETFA), IEEE, Sinaia, Romania. pp. 1–8. doi:10.1109/ETFA54631.2023.10275520.