

The Thesis of the PhD dissertation

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A NOVEL APPROACH FOR PROPOSING AND ASSESSING
COMPUTATIONAL TOOLS IN MANUFACTURING INDUSTRIES

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1. BACKGROUND OF THE WORK AND ITS AIMS

Manufacturing systems are undergoing a paradigm shift characterized by increasing complexity, dynamic market demands, and an imperative for sustainable and circular production. As manufacturers seek to navigate this evolving landscape, the adoption of Artificial Intelligence (AI), particularly Machine Learning (ML), has emerged as a critical enabler for process optimization, quality assurance, supply chain resilience, and resource efficiency. The integration of AI/ML into engineering and managerial decision-making in manufacturing holds the promise of augmenting traditional problem-solving methodologies with adaptive, data-driven, and scalable solutions.

Despite the growing body of literature on AI/ML applications in manufacturing, a critical gap persists. Amidst a multitude of new AI and ML methods and tools, as well as their combinations with traditional computational tools (Naser, 2025; Plathottam et al., 2023), identifying and matching workable solutions to various specific manufacturing tasks is challenging. According to our knowledge, there is no systematic overview for structuring different types of conventional and AI/ML applications across various levels and tasks of problem-solving. Most existing reviews and case studies focus on individual applications, technologies, or isolated use cases. What is often missing is a systemic classification that captures the multi-dimensional nature of AI/ML applications across the full spectrum of tasks, problem-solving phases, organizational levels, and performance objectives within manufacturing systems. That complex interrelation between conventional and AI/ML-based methods remains underexplored, hindering the development of holistic strategies for AI adoption.

Compared to traditional manufacturing objectives, sustainable manufacturing is subject to a different and extended set of challenges. Among them are trade-offs between economic, environmental, and social objectives; and effects extending beyond current operations, affecting long time frames, industries, and systems.

Additionally, sustainable manufacturing is subject to the dynamic development of regulatory requirements, such as environmental standards, reporting obligations, and compliance frameworks.

Dissertation addresses this gap by proposing and demonstrating a knowledge-based, feedback-driven methodology to map and analyze the possibility space of AI/ML-based and conventional computational problem-solving methods applied to manufacturing tasks.

Accordingly, this dissertation aims to provide an overview of various engineering tasks and tools, focusing on AI/ML methods in manufacturing. A systemic perspective is added to the overview by structuring AI/ML applications in manufacturing along multiple dimensions, represented by equivalence classes of features, determining the tasks to be solved, the levels of application, the phases of problem solving, the objectives, as well as the various types of conventional and AI/ML-based methodologies. The resulting classification allows us to describe and better understand the interconnectedness of conventional and AI applications in manufacturing. Accordingly, the *main objective* of this work is to introduce and to test a methodology for the systemic categorization and evaluation of conventional and AI/ML applications in manufacturing, in a way that supports a clear overview of the existing methodological combinations, as well as contributes to the automatic generation-based discovery of new solutions from a continuously evolving, but uncertain knowledge base of the existing methods. The *specific aims* are the following:

- to classify the properties, characterizing
 - a) the engineering and management tasks, as well as
 - b) the applied conventional and AI/ML-based methods and tools used for developing sustainable manufacturing;
- to assess the usefulness of computer-supported problem solving in manufacturing, based on published case studies and experts' knowledge;

- to create a learning knowledge base and a methodology for the discovery of feasible solutions.

2. MATERIALS AND METHODS

2.1 Methodological overview

The research begins with a comprehensive literature review to extract a wide range of conventional and AI/ML-based computational problem-solving methods in manufacturing. Through equivalence classification, six equivalence classes of properties are identified. These classes capture critical dimensions such as problem-solving phases, task types, performance objectives, levels of application, and methodological approaches. Between these classes, 15 compatibility relations and amongst the classified properties, 733 binary relations are defined.

Valid solution strategies are described as complete combinations, each comprising one property from each class. Starting from a heuristically selected subset of complete (maximal) combinations evaluated by experts, a feedback-based learning algorithm is implemented. This algorithm maps the normalized, real-valued assessments in the form of [Min, Max] subintervals within the unit interval $[0, 1]$, associated with the binary (minimal) combinations. These subintervals represent uncertain knowledge about the value of minimal, binary combinations.

The algorithm then proposes new complete combinations that are evaluated by experts, while their evaluations are aggregated in the binary knowledge base. The process iterates between reevaluation and generation, allowing the knowledge base to evolve. Before the detailed study, a simplified illustrative example about the essential features and main steps of possibilistic learning from the evaluated lattice of equivalence-classified properties is analyzed.

2.2 Systematic review

In total, 1161 findings were ingested in Mendeley reference manager software. After eliminating duplicates and entries lacking authors, the number of studies was 1007. Screening against the inclusion criteria eliminated 722 studies. Of the 285 full text articles in the database, 269 were retrieved, 16 full text articles could not be retrieved. Finally, 269 studies were included in the review.

A challenge is that complex systems of sustainable manufacturing require sophisticated methodologies along with a clear systemic analysis of the underlying complex tasks and of appropriate combinations of conventional and AI-based computational applications for the solution of these tasks. The literature, based on real-life use cases, provides exemplary assessments of utilizable methods and tools. However, a methodology is still needed to systematically learn from these solutions, and to propose possible new combinations from the accumulated knowledge base.

Existing method-discovery approaches are either probabilistic, optimization-driven, or population-based evolutionary. However, they lack a structured classification-based knowledge representation, combined with expert feedback, which would enable the development of a possibilistic uncertainty-aware knowledge base for the discovery.

2.3 The method of Reevaluable Possibility Space: an equivalence classification and evaluation feedback-based uncertain learning

Considering the dissertation's objectives and specific aims, the following features must be taken into consideration in the development and application of a new method for the discovery of methodological combinations:

- The constructive equivalence classification of underlying properties of the tasks and the applicable methods or method combinations;

- Commutative and associative character of (compatibility) relations between the properties within the combinations (in graph representation, it is described by non-directed edges);
- Rather a possibilistic than probabilistic kind of associated uncertainty (In discovery, the value of a new solution does not depend on its frequency, similarly to innovation);
- Consistent representation of the lack of knowledge;
- Expressing of some essential properties of evaluation distributions, coming from expert' suggested heuristic values;
- Algorithmic generation of aggregation and optionally the consent of evaluations from multiple experts.

Accordingly, the applied methodology is based on the iterative reevaluation of the lattice of the compatible properties, classified into equivalence classes. A lattice is an abstract structure studied in the mathematical subdisciplines of order theory and abstract algebra (Grätzer, 2003). The special compatibility lattice of the discrete properties was introduced by Blickle (Blickle, 1977). This lattice belongs to a family of optionally fuzzy valuated relational algebras (Arva & Csukas, 1989). An example was published in (Csukás et al., 2012), where the methodology was applied for supporting polymer composite experimentation. The mathematical foundation of

- the reevaluable compatibility lattice,
- the maximal (complete) property combinations,
- the minimal (binary) relations, as well as
- the applied measure of uncertainty

are described by Eqs. 1-21 of the dissertation.

3. RESULTS AND DISCUSSION

3.1 Simplified illustrative example for possibilistic learning from the reevaluated lattice of equivalence-classified properties

Before the implementation and analysis of Reevaluable Possibility Space (RPS) for proposing and assessing computational tools in the manufacturing industry, a simplified illustrative example was analyzed. This fictitious ("toy") case study:

- was built from arbitrarily chosen property classes, properties, and binary relations between the classified properties;
- applied evaluations of multiple “simulated” experts, from configurable randomized intervals around the previously fixed hypothetically “true” random values of complete combinations; and
- excluded the experts' preconceptions.

The lessons from this simplified fictitious “toy” example can be summarized as follows:

- The reevaluated lattice of equivalence classified properties worked also in the case of simulated randomized evaluation of arbitrarily chosen property classes and properties. The essential functioning was the consequence of the structure behind the evaluation feedback, as the structure of binary relations carried foundational ‘a priori’ knowledge.
- The applied method resulted in fast elimination of “lack of knowledge”, and in an increasing tendency for the accumulating knowledge in all studied cases.
- The randomized feature of the example illustrated that the essential functioning of RPS is not affected by the number of evaluating experts, essentially.

- As it can be seen in Figure 1, the increasing uncertainty of already evaluated known binary relations consists of two parts. The major part comes from the inherent uncertainty, expressing the situation that a single binary relation can participate in multiple complete combinations with different values. The second part expresses the possible erroneous and/or subjective evaluations of the experts. This is higher as the number of experts increases, as it incorporates their diverse experiences, while aggregation of evaluations is affected by the more uncertain expert opinions.
- A cyclically generated consensus, followed by continuation of evaluation feedback of each expert, starting from the same consent-expressing evaluations, cyclically decreases uncertainty.
- The example illustrated the main steps of the implementation of RPS, as well as emphasized the possibilistic character of uncertainty in this knowledge discovery process.

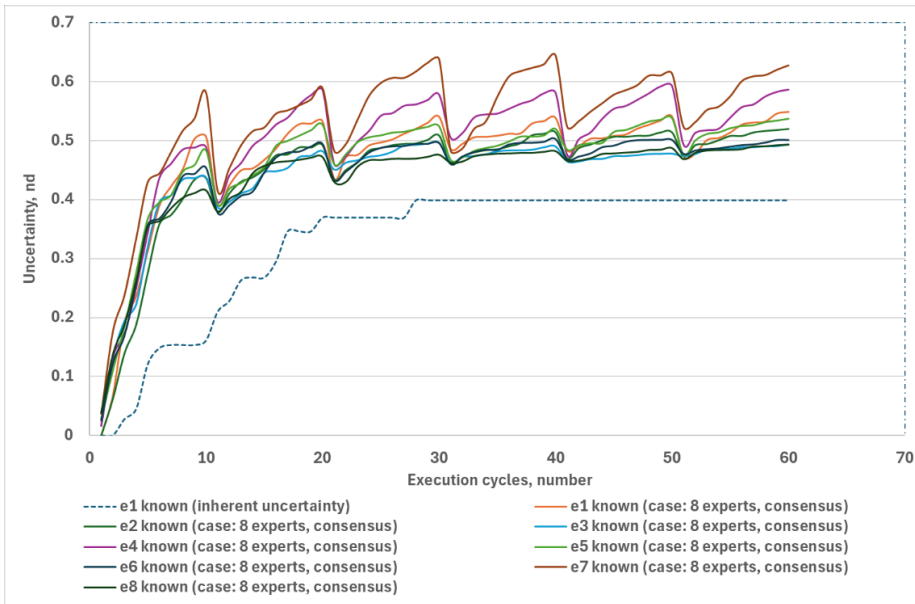


Figure 1 Inherent and expert-related uncertainties for 8 simulated experts with cyclic consent

3.2 Property classes and properties of manufacturing tasks and computational problem-solving methods

The manufacturing tasks to be solved can be described by the property classes and properties presented in Figure 2:

P1 – Task of application	P2 – Level of application	P3 – Phases of problem solving	P4 – Development goal
• p1_1 Product design • p1_2 Process design • p1_3 Process control • p1_4 Fault diagnosis and troubleshooting • p1_5 Operation planning • p1_6 Operation scheduling • p1_7 Supply chain management • p1_8 Maintenance • p1_9 Quality control • P1_10 Worker training	• p2_1 Process unit • p2_2 Technology (a connected set of process units) • p2_3 Company • p2_4 Industry • p2_5 Trans-sector	• p3_1 Preparatory analysis of possibilities • p3_2 Implementation and testing of method/tool • p3_3 Execution and evaluation of method/tool	• p4_1 Safety • p4_2 Economic objective • p4_3 Environmental impact • p4_4 Circularity

Figure 2 Property classes and properties of manufacturing tasks

As described in Figure 2, the manufacturing tasks are structured into four equivalence classes, which are the application tasks, the levels of application tasks, the stages of problem-solving tasks, and the evaluation objectives of the assigned task. This expresses a structured methodology enabling a clear and aggregate understanding of manufacturing processes and associated management aims.

The problem-solving methods can be characterized by the property classes and properties, presented in Figure 3.

P5 – Conventional problem-solving methods	P6 – AI/ML-based problem-solving methods
• p5_1 (Dynamic) simulation • p5_2 Model-based Predictor-Corrector (MPC) • p5_3 Stochastic Process Control (SPC) • p5_4 Mixed Integer Linear Programming (MILP) • p5_5 Mixed Integer Non-Linear Programming (MINLP) • p5_6 Finite Element Analysis (FEA) • p5_7 Data Mining and Analytics • p5_8 Computer-aided Design (CAD) • p5_9 Computer-aided Manufacturing (CAM) • p5_10 Real-time Monitoring and Control Systems • p5_11 Simulation-based Optimization • p5_12 Expert Systems • p5_13 N/A	• p6_1 Convolutional Neural Networks (CNNs) • p6_2 Support Vector Machines (SVMs) • p6_3 Random Forests • p6_4 k-Nearest Neighbors (k-NN) • p6_5 Fuzzy Logic and Reasoning • p6_6 Genetic Algorithms (GAs) • p6_7 Evolutionary Learning Strategies • p6_8 N/A

Figure 3 Property classes and properties of computational problem-solving methods

The computational problem-solving methods relevant to the study fall into two classes: conventional and AI/ML-based methods. In the manufacturing context examined, they operate in parallel, each addressing problem types that the other handles less well. Understanding where their capabilities overlap and diverge is necessary for evaluating the complete combinations.

By combining these dimensions, the framework can represent a wide variety of practical manufacturing scenarios. For example, a complete combination may represent the application of a random forest model for predictive maintenance at the process-unit level during the execution phase of problem solving with the objective of improving operational reliability and economic performance.

The aim of introducing the classification in abstract form is not to isolate the framework of the practical manufacturing applications, but to allow the representation of the combinatorial relations among tasks, goals, levels of organization, and methods for solving the problems systematically. This structured representation forms the basis for the compatibility lattice and the

RPS, which allows the systematic evaluation and generation of feasible methodological combinations.

3.3 Algorithm in the sense of Reevaluable Possibility Space

The simplified scheme of the evolving knowledge base (Weber & Varga, 2025a) (in form of reevaluated binary relations) can be seen in Figure 4.

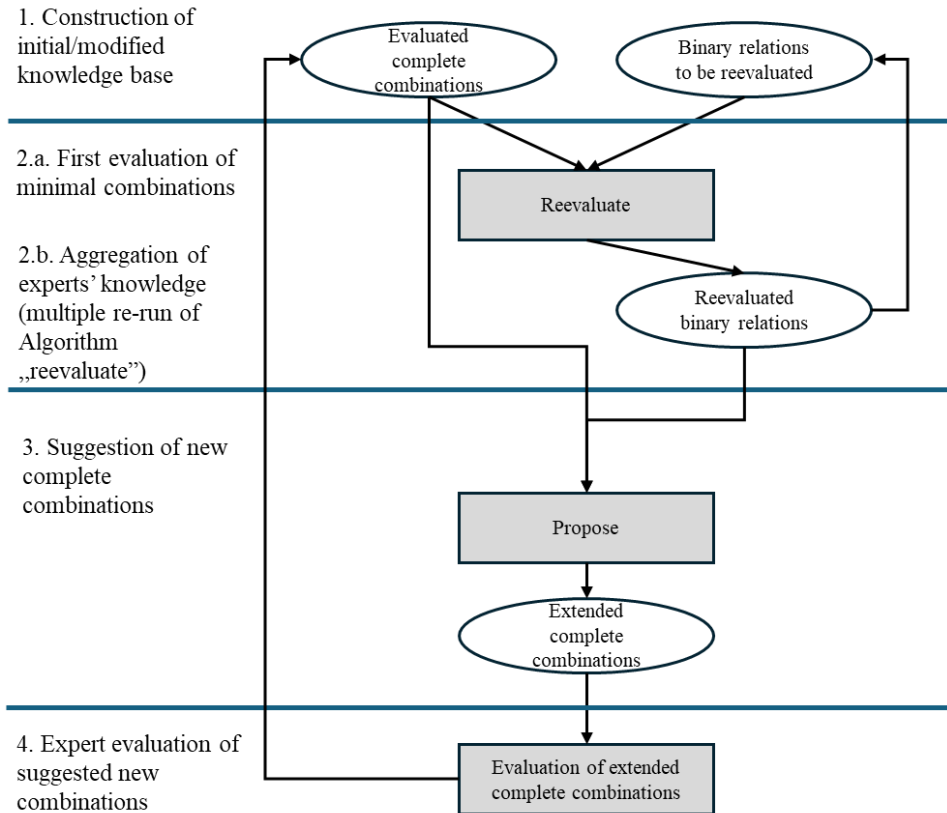


Figure 4 Simplified scheme of the evolving knowledge base of evaluated binary relations.

Ellipses symbolize Rmax files, containing an actual set of possible alternative solutions in the form of complete combinations, as well as Rmin files, containing binary relations, corresponding to the actual state of the evolving knowledge base. Rectangles symbolize computational algorithms or human experts' activity. More detailed interpretations of these elements are the following:

Evaluated complete combination: First input file of Algorithm ‘reevaluate’ that contains previously evaluated combinations only. At the very beginning it was filled with 300 complete combinations, evaluated preliminarily. Also, it serves as an input file of Algorithm ‘propose’.

Binary relations (knowledge base) to be reevaluated: Second input file of Algorithm ‘reevaluate’ that contains an actual state of minimal (binary) relations. Initially it was filled with lack of knowledge (with ‘unknown’ $m = 1$ and $M = 0$) evaluations according to file `Rmin_0.pl`.

Reevaluate: Reevaluates the above binary relations by the above evaluated combinations, resulting in a reevaluated knowledge base. Essentially, the algorithm takes all the possible property pairs in each complete combination and modifies the respective m and M values, as well as the other attributes in the knowledge base.

Reevaluated binary relations (knowledge base): The result of Algorithm ‘reevaluate’ (that incorporates the upgraded knowledge) and the first input file of Algorithm ‘propose’.

Propose: Extends the available complete combinations with new ones in the knowledge of the reevaluated binary relations of the last knowledge base.

Extended complete combinations: The result of Algorithm ‘propose’ and the input for expert’s evaluation.

Evaluation of suggested new combinations: Made by (optionally multiple) experts, while the new combinations will obtain normalized values, heuristically.

The evaluated complete combinations can be used to reevaluate the knowledge base (see the arrow, representing the respective feedback on the left-hand side of Figure 4). The last version of reevaluated binary relations can be applied for further reevaluation of the knowledge base (see the respective feedback on the right-hand side of Figure 4).

In this work, three experts were involved in a single workflow of the above procedure, and their specific knowledge was aggregated (resulting in higher uncertainty, of course). Involving a larger number of experts would improve the knowledge base, but at the same time it would increase uncertainty due to the variability in expert judgements. This can be avoided by the application of consensus calculations (see the simplified fictitious case study in 3.1).

3.4 Evolution of the binary knowledge base

The uncertainties of the binary relations in the knowledge base are changing along reevaluation cycles. The uncertainty from the 'lack of knowledge' is decreasing from 1 to 0, while the uncertainty of the reevaluated binary relations slowly increases from 0 to 0.62. Nevertheless, the sum of these two kinds of uncertainties first decreases, then slowly increases, as shown in Figure 5 below. It expresses that the uncertainty from the lack of knowledge turns into uncertainty of accumulating knowledge. Meanwhile, it results in a continuous accumulation of useful information in the knowledge base. To further clarify, the increase in uncertainty at later learning stages does not indicate overfitting or model deterioration, but reflects the transition from lack of knowledge to richer knowledge. The inherent uncertainty comes from the fact that, even in the case of sound evaluation of complete combinations, the value of lower-order (finally binary) relations is increasingly uncertain, because they participated in various complete combinations of different values. Additionally, uncertainty originates from subjective experts' evaluations and their aggregation.

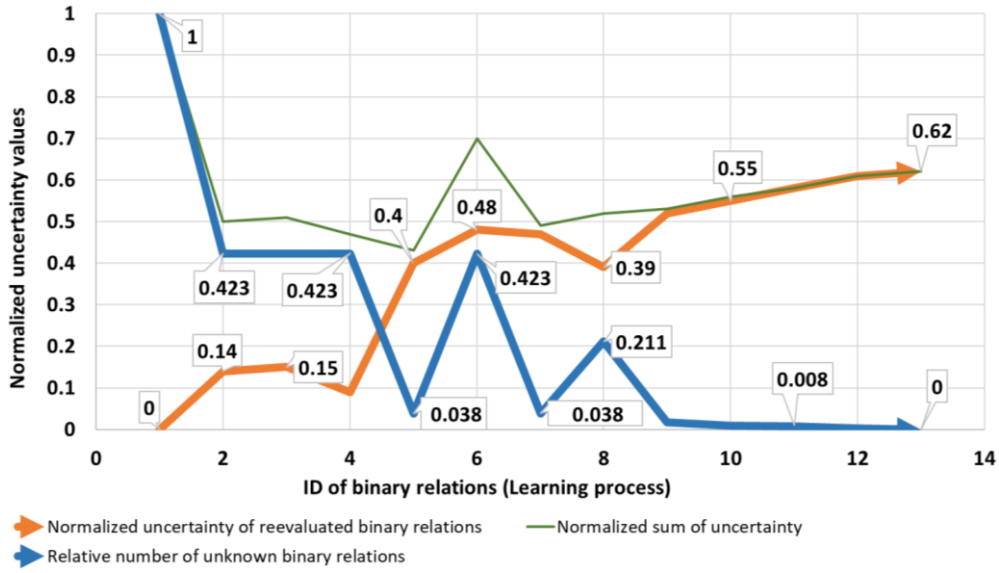


Figure 5 Development of uncertainty of binary relations

Comparing these results with the similar tendencies demonstrated in the fictitious “toy” example, the total uncertainty is a little bit higher (0.62, compared to the 0.54 value in the toy example in case of 3 evaluators). This comes partly from the aggregation of experts’ evaluations. Moreover, it comes from the larger possibility space, where the number of possible combinations is essentially higher, with respect to the number of binary relations. The results outline the scalability of the applied methodology.

3.5 Discussion of the results

With each round of evaluation, new complete combinations were suggested by the algorithm. Rarely repeating a suggestion, the algorithm grows its knowledge base.

In line with the accumulated knowledge in binary relations, the consecutive learning cycles suggest continuously good and bad solutions, while the good solutions may contain advantageous combinations. Analyzing the 50 newly suggested and evaluated combinations (see Rmax_DW1TH1SR1full1_650 in the respective GitHub repository), 10 combinations (20%) are evaluated ≥ 0.8 ,

20 combinations (40%) ≥ 0.7 . Those are high percentages of good combinations compared to the initially suggested combinations.

Comparing the top- and low-level evaluated combinations reveals that performance is linked to the alignment between problem characteristics and method capabilities. The high-performing combinations are characterized by coherence between the type of task, stage of problem-solving, and the methodological approach, whereas low-performing combinations are characterized by the lack of coherence in these dimensions. These findings indicate that:

- Conventional methods dominate in structured, system-level, and early-phase tasks
- AI/ML-based methods are less suited for conceptual or preparatory problem-solving without sufficient data
- Hybrid approaches offer potential when method capabilities are complementary

Compared with the published methods in the literature, the usual discovery methods are either probabilistic, optimization-driven, or evolutionary ones. In contrast to these methods, the RPS framework allows establishing possibilistic compatibility patterns explicitly by the evaluation of combinations, generated from the evaluated relations between the equivalence-classified properties.

RPS offers unique knowledge representation and fast learning capabilities, resulting from the following features:

- Constructive, equivalence-based classification of the underlying manufacturing tasks and of the corresponding methodologies or methodological combinations.

- Characterization of the relations between properties in these methodological combinations.
- Possibilistic formulation of uncertainty, reflecting the nature of the information involved.
- Coherent representation of missing knowledge, ensuring internal consistency.
- Formal expressions of key characteristics of evaluation, especially those derived from heuristic values proposed by experts.
- Algorithmic construction of aggregation procedures, with optional computation of consensus evaluations across multiple experts.

The main limitation of the implemented methodology is the necessary manpower for expert evaluation. This obviously limits the number of iterative feedback cycles, also in the context of using an automatic consensus, instead of the uncertainty-increasing aggregation. Regardless, in future work, it would be straightforward to apply stepwise consensus, followed by the in-parallel evaluation, based on this consensus by multiple experts. To decrease manpower, in the knowledge of first evaluations, the combinatorial complexity can be decreased by revision of necessary relations between the property classes and the properties.

The results demonstrate how the knowledge base evolves during the iterative evaluation process of the RPS. The initial state of the knowledge base represents explicit lack of knowledge. The use of interval values $[m, M]$ to represent relations between properties allows the system to represent possibilistic uncertainty, explicitly. These representation of partial knowledge is related to fuzzy and interval-based reasoning approaches (Novák, 2012; Zadeh, 1965), which allows reasoning under incomplete information.

Similar principles of incorporating expert knowledge into computational learning processes have been discussed in the context of knowledge-informed machine learning and hybrid reasoning systems (Hansen & Quinon, 2023; Von Rueden et al., 2023). In contrast to many ML approaches that rely on large data sets, the RPS operates primarily on structured expert evaluations.

This shift from ‘lack of knowledge’ toward structured uncertainty, reflects the phenomenon frequently discussed in literature, where limited knowledge must be refined through iterative improvement (Horvath & Rudas, 2004; Nonaka & Takeuchi, 2000).

These features are essential for correctly understanding the learning behavior of the RPS and its role as a proposal-generating methodology rather than a validated decision-support system.

Another important observation is that the algorithm is able to generate new complete combinations that tend to perform better according to expert evaluation. This indicates that the compatibility lattice, together with the feedback mechanism between maximal and minimal elements, provides a useful representation for exploring large combinatorial spaces of possible task-method combinations. Such combinatorial problems are common in engineering design and manufacturing planning, where different computational tools must be combined to address complex challenges (Groover, 2020; Segreto & Teti, 2014).

The results further illustrate the role of expert knowledge in guiding the exploration of the possibility space. Expert evaluation serves as the primary source of information used to update the knowledge base and guide the generation of new combinations. The importance of domain expertise in guiding computational decision-support systems has been widely emphasized in the literature (Hansen & Quinon, 2023; Miller et al., 2024). In

manufacturing environments in particular, expert knowledge often complements data-driven approaches by providing contextual understanding of process constraints, operational objectives, and feasible conditions.

The aggregation of multiple experts introduces an additional dimension to the learning process. Combining evaluations from multiple experts can enrich the knowledge base by incorporating different perspectives on method feasibility. At the same time, beyond a certain number of iterations, the aggregation of evaluations may increase the uncertainty of binary relations. Similar challenges have been discussed in the literature on expert knowledge integration and collaborative decision making (Nonaka & Takeuchi, 2000).

From a methodological perspective, the observed learning behavior shows that the RPS approach provides a structured mechanism for accumulating knowledge about possible combinations of computational problem-solving methods applied in manufacturing. While conventional computational tools such as simulation, optimization, and statistical process control provide powerful mechanisms for solving specific problems (Law, 2013; Montgomery, 2019; Wolsey & Nemhauser, 2014), the proposed RPS framework focuses on the higher-level task of organizing and discovering combinations of such methods within a structured possibility space.

This distinction is particularly relevant in the context of modern manufacturing systems, where a growing variety of computational tools must be integrated to address complex production challenges (Beyer & Sendhoff, 2008; Cortes & Vapnik, 2020; Goodfellow et al., 2016). The RPS framework contributes to this challenge by providing a systematic method for exploring how such tools may be combined and evaluated to solve specific manufacturing tasks.

For the manufacturing industry, the presented methodology provides value for AI adoption projects. The systematic integration of AI/ML-based and

conventional methods and their compatibility relation with manufacturing tasks provides a holistic perspective. Leaders and deciders do not have to assess AI/ML methods independent of their compatibility and integrability with conventional problem-solving methods. And with the integrated structured manufacturing levels and tasks, the matching of potential problem-solving methods is based on a comprehensive, holistic methodology for decision support. By providing expert-evaluated, tendentiously better complete combinations, decision makers start out at a significantly smaller set of potential solutions, the chance of totally irrelevant suggestions declines with each learning iteration. Thus, the trial-and-error phase of AI adoption is reduced, saving resources and time. The framework supports AI adoption by guiding method selection, not by prescribing deployment.

Every technology implementation project encounters barriers. For the implementation of computational problem-solving methods, those barriers can be divided into technological, organizational, financial, and cultural barriers (Heimberger et al., 2024). Technological barriers include data quality, data labeling, legacy systems, lack of instrumentation, and IT security limitations. To overcome these obstacles, a limited use case with minimal instrumentation and strict data management can help. The use of APIs for the integration of legacy systems and thorough monitoring are helpful, too. (Ahangar & Farhat, 2025; Paleyes, 2026; Wang, 2025)

Organizational obstacles include unclear responsibilities and accountabilities between engineering, IT, and operations, a lack of process integration, or misaligned incentives. A clearly assigned project owner and a comprehensive RACI chart help in this situation. (Heimberger et al., 2024; Paleyes, 2026; Zarour & Alzabut, 2025) Financial barriers include cost uncertainty, diffuse timelines for the return on investment, and competing interests.

Recommendable to mitigate those issues are small-scale pilot approaches, base loss factors, and milestone-based investment after value has been proven. (Paleyes, 2026; Zarour & Alzabut, 2025) Cultural obstacles commonly include trust issues, resistance to change, skepticism about AI, or fear of surveillance. Transparent models at the beginning of the project can help mitigate skepticism. Training can help by focusing on decision support rather than replacement. Human involvement and clear communication of boundaries and responsibilities help to break down barriers. (Ahangar & Farhat, 2025; Heimberger et al., 2024)

4. CONCLUSIONS AND RECOMMENDATIONS

The learning knowledge representation, using a reevaluating algorithm over the lattice of equivalence-classified properties, proved to be applicable for the systemic overview of conventional and AI/ML applications in manufacturing in a way that also supports the algorithmic generation of new solutions from the continuously evolving knowledge base. The proposed algorithms are based on the evaluation feedback between the maximal and minimal elements of a compatibility lattice of the underlying properties.

The practical objective of this work was to systematize the available conventional and AI/ML-based computational problem-solving methods that can be applied to solve various tasks in manufacturing industries. Based on the heuristic evaluation of the related literature, we concluded that the combinatorial complexity of the available methods and tools in the context of the tasks to be solved needs a theoretically established systematic approach.

As a first step, we determined six equivalence classes of properties describing the combinations of the methods with tasks (Task of application, Level of application, Phases of problem solving, Development goal, Conventional problem-solving methods, AI/ML-based problem-solving methods). We also determined the binary compatibility relations between these classes, resulting in 15 binary relations between them.

Next, the relations between the elements in the 15 pairs of equivalence classes were examined, and the possible binary compatibility relations between the underlying properties were determined heuristically, resulting in 733 binary relations.

Accordingly, the possibility space, outlined by the binary relations between the classified properties, was generated.

This qualitative knowledge base made it possible to apply an underrepresented intelligent learning methodology for uncertain quantitative determination of the relations between the conventional and intelligent methods for the solution of various tasks in the manufacturing industry. Accordingly, we applied the theoretically established learning feedback between the complete combinations and the binary relations, determining these complete combinations. The essence of the applied feedback is that normalized, real-valued (within $[0, 1]$ interval) evaluation of complete combinations can generate increasing $[m, M]$ sub-intervals (where $0 \leq m \leq M \leq 1$) for the binary relations. The structured set of these sub-intervals contains an uncertain possibilistic knowledge that, by means of the appropriately developed algorithms, can generate tendentially better new complete combinations.

The initial state of knowledge base can be described by the paradox values of $m=1$ and $M=0$, expressing the 'lack of knowledge' in sense of the four-valued logic (where the other cases refer to 'true', 'false', and 'uncertain').

The learning started with 300 (and later continued with 50) complete combinations, evaluated by the author, as well as by two collaborating experts. Based on the reevaluated possibility space, new complete combinations were generated, and having evaluated them, we continued the procedure iteratively.

This model (as it is demonstrated by the simplified case study) utilizes the structural knowledge of equivalence classification-based lattice. Also, it relies on experts' subjective assessments. It was concluded that along these iteratively repeated learning steps, the uncertainty of 'lack of knowledge' essentially decreased, while the uncertainty of accumulated knowledge increased, resulting in a summarized uncertainty with a minimum period, that continues with a slow increase. This expresses the fact that uncertainty of 'lack of knowledge' is converted to less uncertainty of knowledge, while it makes possible to generate feasible solutions.

The uncertainty can be quantified by the normalized measure introduced in equations (18)-(21). The uncertainty of lack of knowledge was reduced by 100%, as all binary relations were evaluated during the evaluation cycles. Meanwhile, the uncertainty measure of reevaluated binary relations increased stepwise to 62%, and the summarized uncertainty had a minimum at 43%. Accordingly, the lack of knowledge was eliminated completely during the learning process, accompanied by the smaller increase in uncertain knowledge. Having tested various proposition strategies for the generation of new complete combinations, it was found that

- random selection order from binary relations between the property classes, as well as
- random choice of the applied selection strategies (actually maxmin = maximize minimal; maxmax = maximize maximal; maxave = maximize average; unknown = eliminate ‘lack of knowledge’) from amongst the respective binary relations

performed the best.

It is to be noted that automatic logging of execution makes it possible to correspond to the reproducibility issues, also in the case of random execution.

It was found that the opinion of multiple experts can be taken into consideration by aggregation, i.e. the blind evaluations of multiple experts reevaluated the same knowledge base of binary relations, subsequently. However, beyond a certain step of iteration, the aggregation increases the uncertainty.

Having studied the knowledge base after some learning steps, the content of the binary relations was analyzed in the context of their contribution to the value of proposed new combinations.

The final conclusion is that the learning algorithm of the RPS is able to determine new and tendentiously better solutions from the quite large space of combinations. The apparently forgotten, underrepresented methodology of reevaluated lattice is very familiar with the studied knowledge discovery problem, where the comprehensive evaluation of alternative solutions (complete combinations) needs all the feasible building elements, while the (ultimately binary) parts of the complete combinations can inherit uncertain knowledge from the solutions they previously participated in.

The discussed method discovery algorithm cannot be validated easily. Complete empirical experimental validation requires the realization and testing of the suggested new combinations. Simulated validation would need the generation of a simulation model for the given combinations and their underlying processes. In principle, it could be performed, but would need a configurable simulation model, equipped with the necessary initial conditions and parameters.

Considering methodological transparency, the source code of the algorithm, and the necessary files, as well as the calculated results, are available in the respective GitHub repository (Weber & Varga, 2025b).

In future work, for the evaluation of multiple experts, the explicit application of consent and conflict is recommended and planned. In this case, the individual experts evolve their own knowledge bases in parallel through multiple iteration rounds. Afterward, the program can generate the knowledge base of consensus (in the form of intersections of intervals) and of conflict (in the form of (aggregation—consensus)) from the expert-specific knowledge bases. Next, each expert can continue the work with the generated consensus file.

This dissertation leverages expert evaluation to ensure interpretability and methodological transparency. Recent advances in natural language processing and large language models could enable automated or semi-automated expert support in future extensions of the framework.

Lastly, based on the content of the knowledge base of binary relations, further suggestions can be derived for the possible modifications of property classes, properties, and binary relations.

5. NEW SCIENTIFIC RESULTS

1. Based on a systematic literature review, relevant conventional and AI/ML-based computational problem-solving methods applicable in manufacturing were identified. From this foundation, six property equivalence classes were defined (Task of application; Level of application; Phase of problem solving; Development goal; Conventional computational problem-solving method; and AI/ML-based computational problem-solving method), and the respective properties were classified accordingly. Using the theoretical basis of the compatibility structures, the lattice amongst the binary compatibility relations of equivalence-classified properties was implemented and applied for the representation of the task-describing properties, as well as the conventional and AI/ML-based computational problem-solving methods in manufacturing industries.

2. A Reevaluable Possibility Space was implemented and applied for systematized assessment and discovery of possible methodological combinations of conventional and AI/ML-based computational problem-solving methods in manufacturing industries. The learning algorithm is based on the evaluation feedback between the evaluated maximal (complete) property combinations and the cyclically reevaluated minimal (binary) relations characterizing the compatible pairs of classified properties. Guided by the literature and expert knowledge, a first set of complete combinations was created and evaluated by three experts with feasibility values in the range $[0, 1]$. Next, the respective binary knowledge bases were reevaluated by the 'reevaluate' algorithm, resulting in uncertain $[\text{Min}, \text{Max}]$ subintervals within the $[0, 1]$ interval. These reevaluated knowledge bases were aggregated, and new complete combinations were generated from the resulted knowledge base by the 'propose' algorithm for evaluation by the experts. The evaluation

feedback realized by the cyclically repeated reevaluations and propositions, resulted in the systematic exploration of methodological combinations.

3. Based on the results from a simplified fictitious example with simulated experts, as well as from the detailed case study, possibilistic uncertainties characterizing 'lack of knowledge' and already known knowledge during the learning process were analyzed. The main results were as follows:

- The Reevaluable Possibility Space resulted in fast elimination of 'lack of knowledge', accompanied by the increase of uncertain knowledge in all studied cases.
- Randomization in a simplified example illustrated that the essential functioning of Reevaluable Possibility Space is not affected by the number of evaluating experts.
- The increasing possibilistic uncertainty of the already evaluated binary relations consists of two parts. The major part comes from the inherent uncertainty, expressing the situation that a single binary relation can participate in multiple complete combinations with different values. The second part expresses the possible erroneous and/or subjective evaluations of the experts. This can be higher as the number of experts increases, as it incorporates their diverse experiences, while aggregation of evaluations will be affected by the more uncertain expert opinions.
- A cyclically generated consensus, followed by continuation of evaluation feedback of each expert, can cyclically decrease the uncertainty.
- The comparison of the results from the simplified and the detailed real-world case studies underlines the scalability of the method.

4. The results, obtained from the detailed case study about property combinations representing the features of the tasks to be solved, as well as the conventional and AI/ML-based problem-solving methods in manufacturing were analyzed and discussed in the context of published methods and individual solutions in the literature. It was concluded that the algorithmic learning process of Reevaluable Possibility Space provided practically relevant insights into methodological combinations in manufacturing. Successful solutions often involved both conventional computational techniques and AI/ML-based ones, but not only AI/ML containing methods. The evolving knowledge base enabled the identification of advantageous and disadvantageous solutions, contributing to a structured understanding of feasible methodological combinations. Frequently appearing binary combinations of high uncertainty highlights the optional elimination of these relations.

6. APPENDICES

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