# INDUSTRIALISING INNOVATION IN DIGITAL MANUFACTURING WITH AUTOMATED SEARCH – A DESIGN-BASED APPROACH

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## Abstract

The increasing availability of comprehensive digital models of manufacturing and other contained industrial operations creates potential to apply automated search procedures for innovation purposes. Such procedures are already well known from the context of operations research. This paper investigates how they can be related to the wider scope of innovation. The theoretical background is provided by C-K Theory, which allows the distinction of different operations in the course of innovation regarding knowledge and concept generation. Using the prominent example of genetic algorithms, the paper discusses different steps of automated search procedures in relation to C-K theory and its underlying considerations in formal-symbolic logics and set theory. The results show many correspondences between the search logic and innovation, particularly in the constructive approach to concept generation. The findings suggest that the usage of automated search procedures for innovation will have a layering effect on the different operations which are involved, which is in some respect similar to industrialisation patterns from the early 20th century, but completely different in regarding the treatment of knowledge.

## Keywords

C-K Theory, digital transformation, manufacturing, heuristic search, industry 4.0, artificial intelligence.

## Introduction

The ubiquitous presence of digital technologies in today's society opens up new directions for innovation which are likely to disrupt existing business structures and create new fields of economic growth (e.g. Lee, 2008; Porter and Heppelmann, 2014). According to Yoo et al. (2010; 2012), digital technologies make it possible to conceptualise business operations in ways which have so far not been explored. One of the driving factors behind this development is the concept of cyber-physical systems (Lee, 2008), which merges physical and symbolic representations of business operation in a single computational structure. Using sensors and actuators, the properties of physical objects are directly linked to comprehensive computational structures, such that any event observable in the physical world can be directly mapped to an event in an information system (Geisenberger and Broy, 2015). Various authors claim that cyber-physical systems will cause a new industrial revolution (Kagermann, Wahlster, and Helbig, 2013; Rajkumar et al., 2010). Based on virtual representations of material objects, organizations can implement completely new value streams which have so far been out of scope (Lee et al., 2015; Jazdi, 2014).

Scientific literature discusses the application of cyber-physical systems in contexts like automatization, autonomous operation, augmented and virtual reality, decentralised organisation, cyber-security, knowledge management and qualification (Oks, Fritzsche and Moeslein, 2017). While there are many different industries which are expected to benefit from the implementation of cyber-physical systems (Rehm et al., 2015), manufacturing seems a particularly promising field for innovation (Brettel et al., 2014; Monostori, 2014). This can be explained by the fact that manufacturing takes place in a confined space with little interaction with the outside. It is therefore comparably easy to create comprehensive digital models of industrial operations in manufacturing and control their further development into a certain direction to capture new business opportunities (Chryssolouris et al., 2009; Bracht and Masurat, 2005).

Digital models of industrial operation have already assumed an important role for innovation in the context of manufacturing (Chang and Wysk, 1997; Groover, 1980). They support the search for new ideas and better problem solutions in at least three different ways:

- Digital models provide the basis for the analysis of business operations and value streams to identify opportunities for improvement and further development with the help of modern big data applications (Goelzer and Fritzsche, 2017).
- They create virtual environments in which expert and non-expert users can creatively work on innovation, using different kinds of digital toolkits, configurators and virtual design studios. (Scheer, 2012; Naik, 2017).
- They provide the basis for a completely automated algorithmic search for solutions to given problems, for example in the context of plant design and facilities management, inventory management, production design and planning (Tompkins et al., 2010; Nahmias, 2009; Silver, Pyke, and Peterson, 1998).

The ongoing digital transformation of industry will further expand the range of application of information technology in manufacturing and all surrounding processes. It will create new opportunities to interconnected systems architectures which take over different functions at the same time. Innovation will be increasingly supported by information systems, and a lot of activities in the search of new ideas and improvements will be performed automatically without active user involvement (Monostori, 2014).

The introduction of new machinery to support human work is a key feature of industrial development. So far, however, it was mostly directed as simple, repetitive tasks. Complex, creative processes like innovation are a fairly new terrain for technical support, but with the ubiquitous availability of digital technology, it might now gain momentum very fast. This paper therefore intends to explore how such an "industrialization of innovation" with the support of digital technology might proceed. In order to do so, it studies existing technical support for problem solving in manufacturing to understand how the underlying algorithmic logic relates to innovation. More exactly, it looks at heuristic algorithms for automated search and optimization procedures which have already been recognized as tools for innovation (Goldberg, 2013; Fogel, 2006).

As a theoretical basis for the investigation, the paper uses C-K Theory of innovative design (Le Masson, Weil and Hatchuel, 2017), which allows the discussion of a variety of qualitatively different operations necessary for innovation. The analysis of the heuristic algorithms performed on the following pages shows that technical support changes the way how these operations are related to one another, creating different levels of design activity which have to be considered at the same time for digital innovation.

As this is a merely conceptual paper, the paper focusses on the discussion of algorithmic procedures according to the current state of the art in operations research and engineering (Gendreau and Potvin, 2010; Talbi, 2009; Yang, 2010; Goldberg, 2013). For illustration purposes, insights from practical application are also used which were gained during various research activities in the automotive industry (see also Fritzsche, 2009).

## Theoretical background

### C-K Theory of innovative design

The point of view which will be taken on the following pages is informed by the Concept. Knowledge Theory (or in short: C-K Theory) by Hatchuel and Weil (1999; 2002; 2009). The central element of C-K Theory is the interaction between two spaces of propositions: space K which contains what the authors address as knowledge, and space C which contains what the authors address as concepts. According to Le Masson, Hatchuel and Weil (2017:126), "C-K theory proposes as unified a language as possible to facilitate dialog between the major design professionals, namely designers, engineers and architects, independently of the specific objects they design and handle". Furthermore, the authors are also interested in economic questions related to design and the treatment of innovation as a design capability (e.g. Hatchuel, Le Masson and Weil, 2006; Hatchuel, 1999). The distinction between a knowledge space and a design space enables the authors to distinguish different kinds of operations in design and the reasoning processes they involve (see also Hatchuel, Le Masson and Weil, 2004; Agogué and Kazakçi, 2014). They will provide the point of reference for the further investigations in this paper.

In C-K Theory, the propositions in the space of knowledge K have a logical status, which the authors describe as the degree of confidence assigned to a proposition (Hatchuel, Le Masson and Weil, 2004). For the propositions in the space of concepts C, this is not the case. The logical status remains unclear. (Without exploring all the formal details, one might think of an empiricist as well as a rationalist interpretation of this situation: the former would refer to the propositions in K being satisfied by having the real world as a model, the latter would refer to the propositions in K being decidable on the background of a given set of axioms. For C, satisfiability or decidability would be missing.)

C-K Theory defines design as the set of operations which are performed within C and K and between C and K. Roughly speaking, operations leading from K to C can be interpreted as a generation of alternatives or expression of possibilities on the basis of existing knowledge, but surpassing it. Operations leading from C to K can vice versa be interpreted as the introduction of a new artefact in the world as a product, service etc. which concludes a design process. Operations which proceed in C and K respectively are related to two different practices in mathematics: set theoretical operations lead to partitions, expansions, etc. of concepts in C, while logical rules and propositional calculus lead to conclusions/ proofs of new theorems in K. (The latter might again be interpreted from an empiricist perspective as an expansion of knowledge by the means of correct experimentation or as a mere formal, mathematical process from a rationalist perspective.)

## Digital technologies and industrial innovation

The digital transformation of industry is enabled by important achievements in engineering regarding the development of sensors and actuators which allow the implementation of cyber-physical systems (Kagermann et al., 2013; Lee, 2008). The potential for innovation resulting from this development, however, has little to do with new technical devices. The so-called "digital innovation" (Fichman et al., 2014) is rather concerned with the integration of existing technology across larger organizational structures (Brettel et al., 2014), the creation of new business models (Porter and Heppelmann, 2014) and the establishment of systemic structures in which new services can be offered due to the interaction between different actors (Lee, Kao and Yang, 2014; Lusch and Nambisan, 2015). Digital innovation is in this respect closely related to many problems of facility and production management which have been discussed in the field or operations research for a very long time, such as the planning of jobs sequences in production, the design of manufacturing networks, or various routing and scheduling tasks related to it (Potts and Strusevich, 2009; Schrijver, 2005).

Such problems usually receive little attention in the field of innovation management, as they are expected to involve fairly little creativity, because the potential solutions of the problem are well known. They are either solutions of a given equation or elements of a search space whose elements can be clearly defined (Bixby, 2012; Graham et al., 1979). From a mathematical perspective, however, this appears to be true for most of the examples which are given for digital innovation in manufacturing. Inasmuch as manufacturing takes place in a contained environment, which is furthermore represented by a digital model, the number of solutions is finite. Without any further structural information, the number of atoms fitting in the physical space of a factory or the number of bits available for computation of the digital model can be used as rough upper bounds. It can in this sense be reduced to a mere combinatorial problem where general concerns about decidability or choice are irrelevant. Elements of finite spaces can be sorted and enumerated, which, given enough time and computing power, makes it possible to identify best elements with respect to any given information source which provides consistent information about preferences for all elements of the space. Furthermore, comprehensive digital models can be expected to allow simulations of industrial operation which provide statement about efficiency etc. as preference information. Big data analytics on customer behaviour can provide similar data from a marketing perspective.

Nevertheless, there is good reason to assume that digital innovation, like many instances or problems discussed in operations research, still involves creativity. Enumerations of the solution space may be possible in theory, but not in practice, because the number of possible combinations or permutations entities which need to be considered is not computable. While selection methods like branch and bound (Lawler and Wood 1966) can considerably reduce the effort under certain conditions, size and structural complexity can even turn simple combinatorial tasks into wicked problems (Rittel and Webber, 1973, Conklin, 2005), which makes it necessary to take refuge in heuristic search methods (Simon and Newell, 1958).

As a consequence, it seems possible to apply C-K Theory to combinatorial tasks in the context of the digital transformation as well – not from the point of view of general constructive set theory, but rather an intuitionist stance which replaces arguments based on the cardinality of infinite sets by arguments based on simple practicalities. It might be worth noting that the necessity to be creative in proving new theorems by the means of propositional calculus has been explained in a very similar way by Polya (1945).

## Heuristic search and creativity

Based on the previous considerations, it seems appropriate to focus all further investigations in this paper on scenario of digital innovation involving algorithmic search with the following properties:

- Innovation takes place within a finite search space. The elements of the search space are different arrangements of resources and sequences of operations in which they interact. The space is well defined regarding its extension, inasmuch as the elements can be characterised as the set of all different combinations of resources and operations in the basis of a digital model of manufacturing.
- There is a function which returns consistent information about preferences for all pairs of elements from the solution space. To simplify things, this function is considered as a measure on the whole space. This function, however, may only be available as an "oracle", which means that it can be called at any time, but its analytical properties remain unclear, like in the case of a complex factory simulation.
- The solution space is so big that an enumeration of its elements cannot be performed in due time. Furthermore, the topology induced on the space by the evaluation function is unknown, which means that there is no further information where good solutions can be found and how similar they are regarding the arrangements of resources and operations they express.

Under these conditions, innovation can be discussed as a search for best elements in the solutions space. This fits to a long tradition of thought about innovation as a combinatorial exercise, ranging from Pappus over Leibniz to Weber (see Hubig, 2007).

In absence of information about the topological structure of the space in terms of solution quality and no possibility to process the space in its entirety, heuristic algorithms can perform an iterated local search to identify best elements of the solution space. The search can proceed in numerous different ways (Gendreau and Potvin, 2010; Talbi, 2009). One of the most popular approaches take to local search is known by the term genetic algorithms. Genetic algorithms are inspired by patterns of reproduction and selection studied in evolutionary biology (Holland, 1975). However, there are claims that genetic algorithms actually a general pattern of search and discovery found in numerous innovation projects (Goldberg, 2013), which makes them particularly interesting in the context of this paper. The operation of a genetic algorithm can roughly be described in the following way (cf. Mitchell, 1998):

1. A small subset of the solution space is chosen as the initial population for the search (arbitrarily chosen or informed by precious considerations)
2. From this population, new elements of the solution space are identified by performing simple combinatorial operations at random on the current population.
3. The external evaluation function is used to compare old and new solutions. The best ones are taken over to form the new population.
4. The algorithm iterates this process from step 2 onwards until some kind of stopping criterion is satisfied.

The notion of local search results from the fact that the algorithm processes only small subsets at a time, which continuously evolve as the search advances. Due to their limited size, the algorithm can gain full transparency over the content of these sets. This makes the sets comparable to the space of knowledge discussed in C-K Theory. If the topology of the solution space was sufficiently transparent to use an analytical solution procedure in it, the entire space including its topological structure could be described as K. Since this is not the case, however, it rather has to be considered as (part of) the universe in which the space of concepts is located. What remains unclear is the actual creation and modification of concepts in the course of the algorithm.

**Research Design**

In order to find out where concepts are addressed in genetic algorithms, it is first necessary to establish a framework which allows the identification of concept-related operations in the search process. This is not trivial, because there are different aspects to consider at the same time.

Heuristic algorithms simplify problem solving in order to make it possible to address complicated issues in practice and cope with them in a feasible time frame. Wolpert and Macready's (1997) No Free Lunch theorems indicate that such simplifications must necessarily go along with a customization of the algorithms for application so certain instances of problem. If an algorithm was uniformly able to simplify the solution of a problem and yield good results, it would contradict the formal measurement of complexity measure which describes the effort necessary for problem solving using exact analytic procedures. For any given heuristic algorithm, it can therefore be proven that there are therefore problem instances on which it fails to perform well (see also Yang, 2010).

As a consequence, it is not only necessary to study the general procedural logic of an algorithm, but also its relation to a given problem instance, which results from customised settings of specific parameters which affect the way how the algorithm navigates through the solution space. For the same reason, it is also necessary to examine the way how the problem is expressed in the input information supplied to the algorithm. This concerns in particular the notion of quality. According to the definition of the problem types which are addressed, some kind of an evaluation function is required on the solution space. Without further knowledge about the solution quality which can actually available in the space, this prerequisite remains an empty statement, as it does help with the decision whether a solution is satisfactory or whether there are significant improvements which still can be reached by other elements of the solution space.

To pay respect to all these different concerns, the analysis performed on the following pages dissects the application of genetic algorithms in different stages, from the definition of the problem up to the communication of the result. The analysis is driven by the intention to identify correspondences between the application of the algorithm and the operations described in C-K Theory which go beyond mere processing of knowledge in K. these operations are:

- the generation of alternatives in transition from K to C
- the partitioning (refining, choosing, structuring) within C
- the finalization of the design in transition of C to K

Simplier said: the analysis takes all procedures under scrutiny which do not lead to a decision which is rationalized on the basis of a ruleset and calculus available in the space of knowledge.

**Analysis**

Problem definition

Before an algorithm can start to operate, input information about the given problem must be supplied. In this respect, algorithmic search is no different than any other project-based activity which starts with a description of the current situation and the intended changes of the situation motivating the activity. Inasmuch as industrial projects, in particular those concerned with design and innovation, are usually concerned with wicked problems, they involve vagueness and ambiguity, which are only resolved in the course of the solution process when the problem is better understood (Conklin, 2005). While heuristic search algorithms have been suggested for an algorithmic treatment of problems which are ill-defined, meaning that there is insufficient transparency for an analytic approach (Simon and Newell, 1958), the input information they receive consist of determinate values for predefined variables. If there is any kind of vagueness and ambiguity to consider, it has to be made explicit in the modelling.

Prominent sources of vagueness and ambiguity in manufacturing are temporal dynamics, e.g. regarding the order volume which is produced, the parts which are supplied, or the production schedule, which all change over time with different speed. When information is provided about factory layouts and installations as unalterable constraints in the search, temporal effects are omitted. A decision is made about one specific point of reference for innovation, which combines given knowledge about the problem situation which conceptual interpretations about those aspects of the problem with are considered as hard criteria and those which allow flexibility in the search.

The definition of the evaluation function brings up another need for decision making for which the given knowledge is usually an insufficient basis. It might be justified to assume that the digital transformation of industry yields comprehensive models of the factory which can calculate accurate information about costs, and that big data applications do the same for demand information. As already mentioned, however, this does not explain which quality can eventually be reached on the solution space. Furthermore, it can be expected that there is no perfect solution which uniformly optimizes every single aspect of quality, but only pareto-optimal solutions, which cannot be improved or a single aspect without causing deterioration for another one. Even if there is a "digital oracle" which has full information about potential improvement, innovation still involves normative decisions in setting the direction of improvements which will be pursued. These decisions are partly made explicit when the input information for the algorithm includes preference statements for certain aspects of quality (Fritzsche 2018). For the most part, however, this is left to chance, and the algorithm is designed in a way that it takes the first best solution it finds.

Search procedure

As genetic algorithms are only one out of many different heuristic techniques, the analysis of the search procedure of genetic algorithms covers only one specific case. Other techniques are much more refined and involve knowledge about the problem procedure to a higher degree that genetic algorithms. In this sense, all statements about randomness regarding the operation of genetic algorithms need further refinement to be applicable to other heuristic techniques. There is nevertheless always some degree of randomness involved in every iterated heuristic search, which make findings for genetic algorithms generally applicable to all other cases as well.

The steps for population generation and selection performed by the algorithm during each iteration show parallels to ZF set theory in terms of the underlying principles of construction, specification or refinement. However, they take place in a finite, and therefore – ignoring time constraints – enumerable set, such that concerns about choice are not necessary. In contrast to ZF set theory, a surrounding universe is existent, which makes it possible to generate new populations without further explicitly referring to axioms allowing this. As the properties of the universe remain widely unclear, the populations can nevertheless be considered to be located within an unknown environment. All the elements of the solution space which do not appear in any population remain out of scope. This can be seen as another similarity to the ZF approach in set theory, which constrains itself to those objects whose existence is granted by the given axioms and avoids universal claims as they were made e.g. by Frege.

The fact that the generation of a new population involves a large degree of random change gives reason to distinguish the search from determinate logical calculus. With Brooks (1991), the algorithm can be considered to express “intelligence without representation”. The generation of new populations is at best partially based on actual knowledge as a source of decision making, although the algorithm is likely to approximate good solutions over time. The degree to which this actually happens, however, remains undecidable in the given situation.

From the practitioner’s perspective, one can therefore say that the algorithm proceeds in the space of concepts, as there are no analytical means for solution generation involved, which are only theoretically available for the abovementioned reasons.

## Algorithm customisation

Like the search procedures, the possibilities for customisation vary a lot across the different heuristic techniques. Customization is necessary because solution spaces are too big to be processed completely and there is no further information about the topology of the space in terms or quality. Depending of the frequency in which of good solutions appear in the space and their similarities, different levels of divergence and convergence in the search might be necessary.

Genetic algorithms offer the three main options for customisation (reference anonymised):

- the size of the population,
- the selection criteria determining which elements remain in the population,

- the operators which produce new elements of the population in each iteration.

Population size and selection criteria determine the memory of the process and the about of variety in the solutions which is preserved in the cause of the search. Operators determine the level of novelty produced in each iteration and the relation between old and new elements of the population. Operators increase diversity based on arbitrary choices to alter and exchange random parts of the existing element of the population. The progress which has been made before in terms of solution quality in the population is put at risk to be reversed by the operators. At the same time, the random elements in the generation of the new population can lead the search in new directions and avoid premature focus on specific kinds of solutions.

The question how the parameters for population size, selection and operator usage should be set to optimise the performance of the algorithm can only be answered with additional knowledge about the solution space. Such knowledge, however, is usually not existent when the search starts. In practice, it is usually generated by observing the performance of the algorithm under different conditions in test runs, or over a longer time of repetitive application in practice. An algorithm which is customised to perform well on a given set of problem instances is called "competent", while knowledge about what makes the algorithm competent is acquired by the users of the algorithm (Reed et al., 2001; Goldberg, 2013). This knowledge does not directly contribute to the design process, but it creates a regulatory cycle to enable successful operation of the algorithm.

Again, the question if a certain parameter set is optimal usually remains unanswered. Potential alternative settings which yield similar results are not exhaustively explored, which makes it possible to speak about customization as another design process on an intermediate level, between the overall design of the heuristic technique and the automated execution of the search which yields the actual design artefact regarded as a digital innovation.

Search output

Without knowledge about the overall best solution that can be reached, it is impossible to say how much the elements of any given population can still be improved. The criterion to determine when the search is stopped needs to be provided from the outside. Frequently used criteria are:

1. the search process reaches a time limit,
2. no improvement has been found for a certain number of iterations,
3. the best elements of the population has reached a satisficing quality,
4. the user terminates manually for other reasons.

Setting the stopping criterion can be considered as another case of customisation. To set the criterion in a good way, knowledge about the problem is necessary. Users can acquire such knowledge over time by performing test runs and learning from different configurations, but the situation will always remain intransparent to a certain degree, such that their decision is in any case a matter of choice.

It is worth noting that the output of heuristic search does not always find acceptance in practice and that the application of the algorithm is followed by further negotiation activities (reference anonymised). Once an agreement is reached, the result can be considered to transition into the knowledge base as a reference for further search activities. All this can again be seen as a characteristic feature of design and innovation as one solution out of many which can be controversially discussed.

## Discussion

Summarizing the findings of the analysis, one can say that the application of heuristic search algorithms involved the following design activities which are relevant for innovation:

1. The explication of the problem in a way that it is processable by the algorithm

   The challenge at this point is that this explication is likely to require a determination of factors which would remain indeterminate if innovation proceeded otherwise. Even without further knowledge about the solution space, the outline of the problem has to be fixed. For example, constraints have to be set in a static way or with a clear prediction of changes which may occur over time. In a team of human innovators, the perception of the problem could constantly be renegotiated, implicitly or explicitly. The algorithm enforces a decision which then serves as a basis for everything else which happens.

2. The configuration of parameters to make the algorithm "competent"

   In order to show good performance, the algorithm has to be customised to the problem situation, which involves knowledge about the correspondence between search procedure and the solution space structure with is not there. Such knowledge can only be gained by experience, based on comparisons of algorithm performance in search for solutions. Interestingly, this knowledge has a pragmatic quality: it does not say much about the solution space structure itself, but only how it should be reflected in the parameters. The parameters include the stopping criterion.

3. The actual process of search

   The search is produces the actual content of the innovation. It is performed automatically, without any further intervention by users, such that no further decisions have to be taken (interactive algorithmic exist, but remain insignificant). However, the search performance is where the effects of prior decisions become observable. What makes heuristic approaches unique is that knowledge acquisition in the course of the search is restricted to a small set of the solution space. Probabilistic arguments might allow assumption about the rest of the space, but without firm ground. The solution is generated constructively, not analytically.

In many respects heuristic search is based on a similar kind of strategy as Zermelo and Fraenkel’s approach to avoid Russel’s antinomy (Ebbinghaus and Peckhaus, 2007). It focusses on entities which can actively be generated by applying a well-defined set of operators. Claims about other entities are avoided. Of course, the reasons why this kind strategy was chosen are not the same. ZF set theory needed to avoid contradictions cause by universal statements, which heuristic search has to cope with intransparency of solution spaces. Constructive approaches incorporated in design and innovation, however, rather seem to be driven by the same reason as heuristic search: a general intransparency about the full range of possible results which can be achieved, whereas logical contradictions play a minor role.

Heuristic search requires the provision of information about the conditions under which it proceeds. This also has been the case in ZF set theory, since the theory was set out to describe the domain of mathematical practice, such that all elements of mathematics could be based on a solid foundation. Unlike ZF set theory, however, heuristic search cannot rely upon the structural clarity of mathematics. While digital models of manufacturing create a limited and thus widely controllable space in which solutions can be searched, it still leaves a wide space open for further normative decisions which have to be made in order to set a direction for innovation and define what improvement actually is. This leads to a situation in which design activities shift to a different level: they are not concerned with the specific innovation which results from the application off the algorithm, but rather with the general understanding of the problem situation in which this innovation as well as many others might arise, and the enablement of innovation by setting appropriate parameters for the search procedure.

One might say that the automation of the search procedure turns the attention towards the management and control of innovation, which is itself also a design process where innovation is possible. And even more than that: with respect to the problem definition, it addresses the general narrative of the enterprise as another level on which something is designed. If such narratives are also considered as innovation depends on the external environment in which they may or may not generate value.

The introduction of technical support for innovation procedures thus follows a general dynamic of systemic development. In cybernetic terms, it can be described as shift from the actual execution of certain operations to the regulatory measure which enable and ensure this execution. Speaking of this process as an industrialisation of innovation seems justified inasmuch as automation is introduced to the make the search for solutions more efficient and effective, but there is an important aspect in which this process is radically different from Taylorism and Fordism: it does not involve any claims regarding a full understanding of the process which is industrialised. Innovation does not become any more objective or rational than before. Quite in the contrary, it is very likely that the introduction of algorithms for search creates confusion in such areas as manufacturing, because it shows the limitations of logical calculus in production and operations management more clearly than before. Acceptance issues for digital innovation can therefore be expected to become an important topic, and methods to ensure the commitment of all stakeholders to the process will need to be further explored in the future.

## Conclusion

Automated search procedures have the potential to contribute to innovation in manufacturing just as much as the already contribute to solutions for other complex problems in industry.

The heuristic nature of the procedures is both an opportunity and a thread. On the one hand, in increased the range of applications for the algorithm to a manifold of different problems. On the other hand, the results they produce lack clarity and give easily cause for controversies. Using automated search will therefore not improve innovation in any objective way, but it can be expected to have the same effect which it already had in other fields of application: it will enable the treatment of larger and more complex structures. This might lead to an increased speed of innovation, but also to a lack of orientation.

The content of this paper is limited to a quick conceptual analysis of genetic algorithms and their relation of innovation. Other heuristic techniques have not been considered in detail and a further systematic treatment of algorithms in practical application or simulation has to follow in order to increase the rigour of the argument.

Nevertheless, there is hope that this paper can provide an important contribution to the discussion about the digital transformation of industry and innovation in manufacturing and beyond, based on cyber-physical systems and comprehensive digital models. It raises an important question for innovation management which has so far received very little attention. Heuristic search algorithms, which have so far been studied almost exclusively from an engineering perspective, are put into the context of design and innovation. Furthermore, their discussion is not limited to the actual operation of the algorithm, but is also discusses the wider scope of normative decisions which have to be made regarding the problem definition, customisation of the search and utilisation of the results. The paper builds a bridge between research on the digital transformation in innovation management and research on algorithms in operations management which inspires further work in this context.

At the same time, the author hopes that this paper is also informative for researchers concerned with C-K Theory by approaching the theory from an unusual perspective. In particular, it addresses an application scenario from industry where formal logical and set-theoretical arguments seem replaceable by more practical, complexity-oriented arguments regarding intransparency and missing knowledge. Parts of these arguments are very strongly reminiscent of intuitionist ideas in mathematics. However, the practical background on which they are expressed brings in another aspect as well which might be relevant treatments of innovation from a design perspective, too.

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