21 Artificial Intelligence in Design: A Look into the Future of Axiomatic Design

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Abstract

In the previous chapters, we learned all about Axiomatic Design (AD), where AD comes from, how it was developed, the axioms, complexity theory, and in-depth content for learning AD. This chapter looks at how AD will evolve in the future and introduces an approach based on Artificial Intelligence (AI). The approach presented is to be understood as a hypothesis to venture into the future together with the students analyzing how AI will change not only their daily lives, but also the work of a design engineer.

Many of the technological innovations related to Industry 4.0 pave the way for achieving a next level in engineering and especially in manufacturing. For the next decisive steps, we need the combination of disciplines such as engineering design and AI to create assistance systems for designers of highly complex systems, which support them step by step in the design process as well as for the re-design of systems affected by time-dependent complexity.

In the proposed AI-assisted design approach, we propose to combine AD as an established and proven theory for the design of complex systems with the latest methods of AI. For the design phase, AI offers an enormous potential to transform customer needs into functional requirements (FRs) and to support the designer in identifying and selecting the best design solution for a design problem based on existing data sets of previous successful or not successful designs.

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Similarly, the combination of modern technologies for data collection and AI also holds great potential to monitor complex systems determined by time-dependent complexity, like manufacturing systems. Based on improved technologies for data collection and processing as well as AI we can generate data-based predictive suggestions for system adaptation or even optimization, either with or without the interaction of the designer.

The presented AI-assisted design approach has potential to usher in the next era of engineering design, which will take us a huge step toward the vision of intelligent and self-optimizing systems.

21.1 Introduction

For many years, designers have dreamt about having an intelligent design machine that automatically generates designs or design concepts superior to those currently available. Already in 1990, Suh and Sekimoto (1990) presented the idea of the "Thinking Design Machine" (TDM) with the aim to provide designers a powerful and computer-aided design tool to improve the quality of the design and to reduce the time needed for creating a high-level design concept.

Since 1990, the world has changed rapidly and significantly. Computer-aided tools have been improved and further developed in order to take later stages of the design process on a new level. Especially recent developments in computer-aided design (CAD) and computer-aided engineering (CAE) facilitated the work of designers in geometrical modeling and drawing as well as in structural and dynamic engineering of parts and products. In the meantime all larger and most of the smaller enterprises are equipped with latest computer software for 3D CAD drawing, which allows a completely new level of visualization and a better platform for discussing designs together with other specialists in the product development and realization process (manufacturing specialists, material specialists, quality experts, …). Technologies like Virtual Reality (VR) give designers now the possibility to immerse in the virtual world and to inspect their design in a virtual but realistic and three-dimensional environment by using VR headsets for some hundreds of dollars of investment. Such powerful 3D CAD tools allow to creation of a Virtual Mock-Up (VMU). Instead of testing a product design via crash tests or fatigue tests in the laboratory using Physical Mock-Ups (PMU), most of the testing can be done nowadays on a virtual level. As a result, costs for engineering and time to market could be reduced significantly over the last 30 years. Examples of such tools in the engineering phase of product development are tools for Finite Element Analysis (FEA) or multibody dynamics simulation. The ongoing trend toward open-source software especially allows also smaller enterprises to get access to simulation software and modern CAE technologies. Further developments in computational engineering will lead also in the near future to a further increase of tools that assist designers in their daily work.

While the last 30 years show many innovations in the later stages of the design and engineering process, there is little to no computational aid system available today in the early and conceptual design stage. As the most critical decisions are usually taken in the conceptual design phase this implies in many cases that a design with a lot of potential for optimization is handed over to the colleagues in CAD and CAE and thus creating problems and costs in later stages of the design or even worse during manufacturing or assembly of the product. Thirty years ago designers using AD in the conceptual design phase had only Microsoft Excel spreadsheets with very limited space and no automation to document and visualize their design decompositions and matrixes in a digital way. Nearly 20 years ago, Acclaro DFSS has been launched providing the designer with a computational tool to support the AD process in the early design stage. Acclaro DFSS allows the designer to document the steps from one domain to another by encoding CNs, FRs, and DPs. During the mapping and decomposition process, Acclaro DFSS helps the designer significantly to analyze the design according to Axiom 1 (Independence Axiom) providing an automatic check if a design is coupled, decoupled, or uncoupled. Further, the software tool includes a function to rearrange a decoupled design matrix in such a way that the designer automatically gets the ideal sequence for implementation. In addition to the before-mentioned functionalities, Acclaro DFSS provides different forms for visualization like the design matrix, the FR–DP tree, or process flowcharts.

After this pioneering step forward in the automation of the design process and computational support of designer using AD, there has not been any further innovation over the last nearly 20 years. Compared to the developments in CAD and CAE as well as in manufacturing and assembly (e.g., rapid increase in flexible automation, robotics, advanced manufacturing technologies as well as smart and connected factories) the early stage of design is still working with "stone-age" design tools.

The actual design solution depends mostly on the individual experience and knowledge of the designer itself. Up to now, there is no tool available for archiving past (successful and not successful) designs and to support the designer in decision-making or in finding better design solutions outside of the individual experience and knowledge of the designer. At the same time, we can observe that since some years AI has become a trend and will become much more important in the next years. Due to the introduction of the concept of Industry 4.0 (mainly used in Europe and Asia) and Smart Manufacturing (used in the US) data has become a new status in engineering. Based on new sensor technologies, industrial Internet, and smart and connected factories the amount of available data increased exponentially. This leads currently to a stronger focus on computational methods for taking advantage of this new quantity and quality of data. According to many experts, "data will become the new gold" and those that are able to use advanced AI methods for analyzing data in an intelligent way will benefit from a competitive advantage on the global market. The race to become leader in AI has already started. United States, China, and Europe are already developing and implementing important initiatives to develop their competences in AI.

Therefore, the hypothesis for the future development of AD is to take advantage of recent developments in AI. The time has come to make use of computational power, Big Data technology, and new AI methods to fundamentally renew and automate the design process. After many years of insufficient computational aid, AI has the potential to introduce a new era of AD and to realize the dream of the Thinking Design Machine.

21.2 Artificial Intelligence—The Next Hype?

AI is currently on everyone's lips. There are many examples of AI in our lives. Apple's Siri is one such example. Another is Amazon's Alexa. Natural language processing technology, a form of AI, is used to translate languages in Google Translate. Indeed, up to $30B has been invested in AI in the past five years and 90% of it on research and development by companies such as Google and Microsoft (Bini 2018).

In the annual Gartner Hype Cycle Curve, new promising innovations are examined again and again and their status is presented on the so-called "hype cycle curve." The main aim is to show to what extent a certain technology is still in an initial "hype phase" or whether it has already reached the "plateau of productivity" and is thus ready for practical application. AI is currently at the zenith of the hype curve, which means that a great deal of future potential is currently seen in this technology, but the extent to which AI will really change our lives and work is still outstanding. Besides the general Gartner Hype Cycle Curve there is also an own hype cycle curve for AI technologies, which allows an even deeper view into the current development and the future technology leaps of AI (Goasduff 2019). The following can be read from this curve, for example:

- **Speech Recognition** has already reached the "plateau of productivity" and is already used in many daily applications.
- Text- or voice-based **Chatbots** are still on the top of the hype curve offering a high potential for increasing efficiency in customer service. For example, the car manufacturer KIA talks to 115,000 users per week, or Lidl's Winebot Margot provides guidance on which wine to buy and tips on food pairings. Chatbots are changing customer service from "the user learns the interface" to "the chatbot is learning what the user wants."
- **Machine Learning** already passed the top of the hype curve moving toward a more realistic use of this technology. ML uses mathematical models to extract knowledge and patterns from data. Adoption of ML is increasing as organizations encounter exponential growth of data volumes and advancements in computer infrastructure. For example, Volvo uses data to help predict when parts might fail or when vehicles need servicing, improving its vehicle safety.

- **Augmented Intelligence** is at the beginning of the hype curve with an expected time of 2–5 years to reach a practical use in daily business. Augmented intelligence is a human-centered partnership of people and AI working together to enhance cognitive performance. It focuses on AI's assistive role in advancing human capabilities. AI interacting with people and improving what they already know reduces mistakes and routine work. The goal of augmented intelligence is to be more efficient with automation, while complementing it with a human touch and common sense to manage the risks of decision automation.

In other words, AI will have a huge impact on both our daily lives and the world we work in, perhaps more than any other technological innovation in recent years. This also means that engineers and engineering students should be more involved with AI to be prepared for these technological changes. For this reason, this chapter pays special attention to this topic. However, before we get into the application of AI in engineering and then in engineering design, we first want to better understand what we mean with terms such as AI, machine learning (ML), or deep learning (DL). Basically, we can say that these three terms are different concepts of different levels. In general, deep learning is a subset of machine learning, and machine learning is a subset of AI (Garbade 2018; Nicholson 2019) (Fig. 21.1).

Artificial Intelligence can be seen as the science and engineering of making intelligent machines. AI is a branch of computer science dealing with the simulation of intelligent behaviors in computers. A goal of AI is to further develop the capability of a machine to imitate intelligent human behaviors. In AI, a computer system is able to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages (Skymind 2019). The main objective of AI is to teach the machines to respond like humans do to flows of data. Although AI is a branch of computer

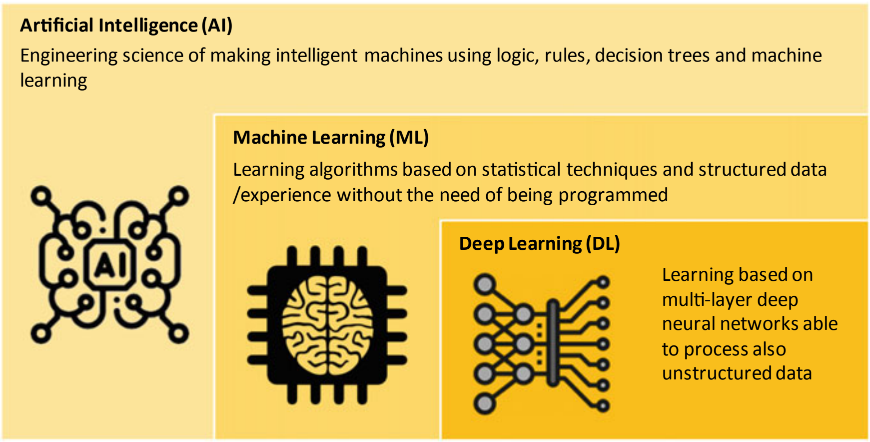

Fig. 21.1 Artificial intelligence, machine learning, and deep learning

science, there is hardly any field which is unaffected by this technology (Sadiku et al. 2019).

Machine learning is a subset of AI. That is, all ML counts as AI, but not all AI counts as ML. For example, rules engines, expert systems, and knowledge graphs—could all be described as AI, and none of them are machine learning. To give an example for rules engines: rules engines could be like an accountant system with knowledge of the tax code, which takes information you feed it, runs the information through a set of static rules, and gives you the amount of taxes you owe as a result. One aspect that separates machine learning from the knowledge graphs and expert systems is its ability to modify itself when exposed to more data; i.e., machine learning is dynamic and does not require human intervention to make certain changes. That makes it less brittle, and less reliant on human experts. As the name suggests, machine learning can be loosely interpreted to mean empowering computer systems with the ability to "learn." The intention of ML is to enable machines to learn by themselves using the provided data and make accurate predictions. In 1959, Arthur Samuel, one of the pioneers of machine learning, defined machine learning as a "field of study that gives computers the ability to learn without being explicitly programmed." The "learning" part of machine learning means that ML algorithms attempt to optimize along a certain dimension; i.e., they usually try to minimize error or maximize the likelihood of their predictions being true. This has three names: an error function, a loss function, or an objective function, because the algorithm has an objective. Here we need also "neural networks." They keep on measuring the error and modifying the parameters until they cannot achieve any less error (Garbade 2018; Skymind 2019).

Deep Learning is a subset of machine learning and also the next evolution of machine learning. DL algorithms are roughly inspired by the information processing patterns found in the human brain. Whenever we receive a new information, the brain tries to compare it to a known item before making sense of it, which is the same concept deep learning algorithms employ. Usually, when people use the term deep learning, they are referring to deep artificial neural networks, and somewhat less frequently to deep reinforcement learning. Deep artificial neural networks are a set of algorithms that have set new records in accuracy for many important problems, such as image recognition, sound recognition, recommender systems, natural language processing, etc. "Deep" is a technical term. It refers to the number of layers in a neural network making it able to process also unstructured data compared to machine learning techniques where features for classification need to be provided manually. Multiple hidden layers allow deep neural networks to learn features of the data in a so-called feature hierarchy, because simple features (e.g., two pixels) recombine from one layer to the next, to form more complex features (e.g., a line). Nets with many layers pass input data (features) through more mathematical operations than nets with few layers, and are therefore more computationally intensive to train. Requirements of DL are high-end computing machines and considerably big amounts of training data to deliver accurate results (Garbade 2018; Skymind 2019).

21.3 Examples of Artificial Intelligence Applications in Engineering

The literature contains various applications of Industrial AI in the fields of engineering and manufacturing. In the following, we want to give an overview of examples and applications of Industrial AI in engineering.

AI Technologies are already used also for **engineering design**. As an example, the generative design platform DesIA uses an object-oriented and open-source language to describe the specifications and the desired product/system. Afterwards, a rule based system combined with decision trees generates a number of admissible design concepts. In the next step, machine learning algorithms are used to choose the best design concept. In the last step, modern and advanced simulation and CAE tools help the designer to optimize the concept in its details (Masfaraud and Dumouchel 2019).

Kumar (2017) in his literature review describes a number of applications in **production planning**. AI technology has already been used in many computer-aided process planning (CAPP) applications in the past. Furthermore, AI is used in knowledge-based expert systems where AI technologies access the experience of experts (collected in databases) and give a designer or user suggestions for design solutions.

A further field of application of AI is **domestic or industrial robotics**. Today's AI-powered robots, or at least those machines deemed as such, possess no natural general intelligence, but they are capable of solving problems and "thinking" in a limited capacity. From working on assembly lines at Tesla to teaching Japanese students English, examples of AI in the field of robotics are plentiful. Home robots use AI to scan room size, identify obstacles and remember the most efficient routes for cleaning (Daley 2018). Fanuc, the robot manufacturer, uses AI-based tools to simplify to teach industrial robots to do their work. AI simplifies the training process, so the human operator just needs to look at a photo of parts jumbled in a bin on a screen and taps a few examples of what needs to be picked up, like showing a small child how to sort toys. This is significantly a less training than what typical vision-based sensors need and can also be used to train several robots at once (Shu 2019).

In **maintenance**, AI technologies are used for realizing predictive maintenance in the form of machine learning and artificial neural networks to formulate predictions regarding asset malfunction. Knowing that a certain component of a machine will fail with a defined probability on a certain day and at a certain time has an enormous influence on the way we organize maintenance work in the company in the future. AI in predictive maintenance allows for drastic reductions in costly unplanned downtime, as well as for extending the remaining useful life (RUL) of production machines and equipment. In cases where maintenance is unavoidable, technicians are briefed ahead of time on which components need inspection and which tools and methods to use, resulting in very focused repairs that are scheduled in advance (Kushmaro 2018).

Another potential field of application of AI in industry is **quality management and quality inspection**. Manufacturing units that make complicated items like microchips and circuit sheets are already making use of machine vision, which furnishes AI with amazingly high-goal cameras. Advanced vision systems combined with AI algorithms can pick even minute defects unmistakably, more reliably than the human eyes. Defects are identified immediately and a response is automatically configured, sent, and managed in order to reduce inefficiencies and waste of material due to non-quality. This helps to increase productivity and at the same time to improve, also, the ecological sustainability of modern manufacturing processes (Admin 2019).

The use of Industrial AI is not only increasing in manufacturing but also in **logistics and supply chain management (SCM)**. Supply chain planning is among the most important activities included in SCM strategy. Therefore, it is crucial to have reliable tools for developing efficient plans. Implementing AI or machine learning, the supply chain decision-making processes can be optimized significantly. The advantage in logistics and SCM is that we usually have a lot of data, which is a prerequisite for using AI or ML techniques. Analyzing huge data sets and applying intelligent algorithms, we can balance demand and supply, and at the same time optimize the delivery processes. In addition, human intervention is minimal. AI algorithms will do everything autonomously and save companies from making mistakes.

In addition to the above-mentioned examples of AI in engineering, a number of other examples for the application of AI could be listed (warehouse management, manufacturing system design, self-optimized machining, etc.). In summary, it can be said that AI is still in its infancy in the industrial environment and that not all potentials have been exhausted. In the future, the interdisciplinary combination of engineering competences and AI methods from computer science will enable us to take full advantage of AI in industry and engineering.

21.4 Axiomatic Design Knowledge Database as Basis for Artificial Intelligence in Axiomatic Design

As already mentioned in Suh and Sekimoto (1990), a computational aid system for AD requires a database. According to them, such a database needs to have at least enough knowledge to give the designer plausible design solutions. Such a database should also have the knowledge of many designers by providing a function to store past designs and to retrieve possible design solutions for a common set and subset of FRs. A FR–DP database may also be convenient to evaluate various functional aspects of a candidate DP, such as side effects not considered by the designer. According to Suh and Sekimoto (1990), DPs may be constructed and stored in different ways, such as (i) parts/components, (ii) systems and subsystems, (iii) materials, and (iv) physical phenomena/status. Since 1990, such a database has never been realized as the technical possibilities for storage of Big Data has been limited over the last years. Also Floss and Talavage (1990) already proposed in 1990 such a knowledge-based design assistant. Khan and Day (2002) developed a similar concept of a knowledge-based database some years later.

Due to poor scalability and low performance, many traditional computing technologies were inadequate for handling Big Data, which are characterized by the volume, velocity, variety, and veracity of the data (Cheng et al. 2018). The latest developments in the area of Big Data today also allow large amounts of data to be handled and processed. Big Data concern large-volume, complex, growing data sets with multiple, autonomous sources. With the fast development of networking, data storage, and the data collection capacity, Big Data are now rapidly expanding in all science and engineering domains (Wu et al. 2014). Research in the areas of computer graphics, database management systems, and AI along with the development of faster and more powerful hardware platforms accelerated and widened the use of computers for engineering problem-solving. Knowledge-based expert systems (KBESs) are one of the first realizations of research in the field of AI, in the form of a software technology. KBESs are computer programs designed to act as an expert to solve a problem in particular domain. The program uses the knowledge of the domain coded in it and a specified control strategy to arrive at solutions. Such systems consist of a knowledge base and an inference engine subdivided in one or more inference mechanisms (Krishnamoorthy and Rajeev 1996). The research findings of Quintana-Amate et al. (2015) provided by literature survey confirm the existence of a gap on knowledge sourcing in engineering, and more precisely they underlined the need for an extended knowledge-based engineering (KBE) development process which integrates AI tools and expert intervention to systematically manage the knowledge efficiently captured and modeled (employing AI algorithms and expert involvement). Therefore, there is a need for further research on the integration of KBE systems and AI implementations as a potential solution to achieve a next level of engineering design.

As seen before, with the recent progress in capability for data storage, handling, analysis as well as AI methods, such a database becomes much more realistic and opens completely new opportunities to take advantage for an optimized design. Such a database would be a complete novelty in the AD community as well as in the community for engineering design. Such a database means an immense concentration of knowledge, which would mature over years. As a side effect, this database would also play an important role for the practical application and teaching of AD, as examples can be taken from it for learning purposes. A big difficulty is surely the correct structuring of the database and the form in which the earlier designs are documented and archived, in order to be able to extract and use the data afterward in the best possible way. In the phase of building up such a database, first the ontology, architecture, and data representation of the database need to be defined as this is a fundamental basis that needs to be considered. As there is a great interest from the AD community to support the creation of such a database, there would be a high willingness of designers to fill the database with life. Another way of filling the databases is to use a reverse engineering approach (see also Girgenti et al. 2016; Vickery et al. 2018; Rauch and Vickery 2020). Such a reverse-mapping allows to decompose past designs easily into hierarchical FR–DP pairs. In a first step, such a database could be filled only with freely available designs or designs from Open Access papers. This means that people uploading their past designs give free access to this information. At a later stage, a model might be developed how designs can also be commercially exploited, e.g., by allowing the designer to access more than just the freely accessible data by paying a fee.

21.5 Vision of Combining Artificial Intelligence and Axiomatic Design

According to the sections before, we introduce the vision of an AI-assisted design and re-design of complex systems in engineering design. While a lot of research is currently focused on how to design products and systems according to the principles of the digital transformation in industry and Industry 4.0, the following hypothesis aims to innovate and automate the design process itself and thus to initiate a revolution in the field of engineering design.

Especially in the design of complex systems that are changing over time, e.g., manufacturing systems, the design process can be divided into a "new design" and adaptations ("re-design"). Adapting an existing system to changing environment or new requirements is a difficult mission. The world is becoming ever more short-lived, and product life cycles as well as system life cycles are becoming ever shorter. This also means that many products or systems have to be adapted at ever shorter intervals. Therefore, in the future, the design of products or systems must be as fast and agile as possible and be based on the principles of self-optimizing systems by using intelligent and smart technologies like AI.

Figure 21.2 shows the development of AD over the years focusing on the most important developments in AD theory, its field of applications, and tools to support the designer.

From the early phase of AD to the beginning of the twenty-first century, researchers focused more on the first axiom. In the following years, advances in complexity theory concentrated more on the second axiom and in the detailed analysis and procedure to define CNs in the customer domain and FRs in the functional domain. Regarding the application of AD in practice, it has been used in its beginnings mainly for the design of products and later for the design of complex systems (e.g., manufacturing systems, software design, and organizational design). In recent years, designers started also to use AD for the design of intelligent products and systems according to Industry 4.0 and Smart Manufacturing (Vickery et al. 2019). With the work of Kim et al. (2019), the first time researcher started also to use AI technologies for making a next important step in the development of AD in engineering design. As already mentioned in the introduction of this chapter there are only limited number of tools supporting the designer in using AD during the design process. From the 90s, the designer used Microsoft Excel spreadsheets for the application of AD with all its limitations in space as well as automation.

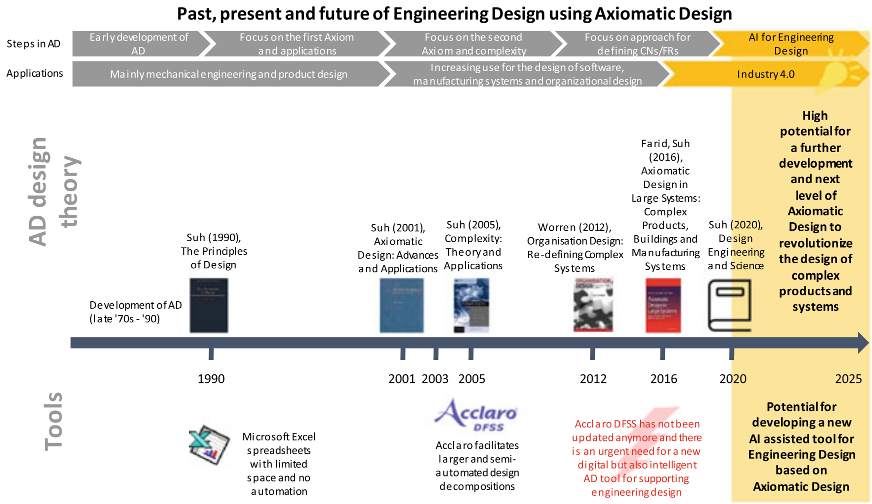

Fig. 21.2 Past, present, and future of complex system design using Axiomatic Design

Roughly ten years later, Acclaro DFSS has been launched facilitating larger design projects and offering functions for a semi-automated FR–DP decomposition. However, over the last nearly 20 years there were no more updates or launches of new aid tools for conceptual design based on AD, which is now (in an increasingly digital world) seriously limiting and affecting the use and dissemination of AD in design projects.

Therefore, the hypothesis is to realize in the future the vision of a Thinking Design Machine, as mentioned by Suh and Sekimoto (1990) by using recent AI methods or AI technologies to be developed in the near future creating the basis for a new platform of a computer-aided tool for conceptual design. In the following two sections, this hypothesis and vision of an AI-assisted design and re-design of complex systems will be described more in detail, thus giving an outlook on possible future developments in AD for engineering design.

21.6 Artificial Intelligence-Assisted Design of Complex Systems

Figure 21.3 shows the new proposed AI-assisted design approach (see Fig. 21.3). It starts with an automated clustering of customer feedbacks into meaningful CNs with the help of data mining and knowledge discovery methods. In previous approaches, this was usually done manually by collecting and looking over the customer feedback. The big challenge for users of AD in this phase is that large quantities of information in the customer domain can only be reduced with great effort to meaningful CNs in a manual way, whereby also a guarantee to consider all

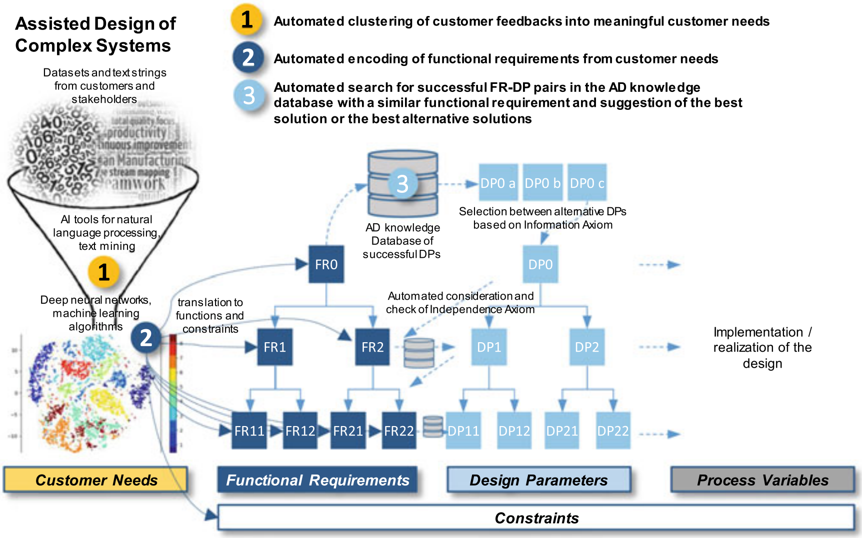

Fig. 21.3 Concept of AI-assisted design of complex systems

information as completely as possible is usually not given. Therefore, for the future, the development of assisted and intelligent methods is needed to simplify this and improve the quality of the data. Kim et al. (2019) are taking a first step in this direction showing in their work a first attempt/experiment based on available data of Airbnb (customer feedback) using Pytorch, an open-source deep learning platform, and MATLAB. By using a hierarchical clustering algorithm, customer feedback can be translated and clustered into key features, and therefore relevant customer needs. According to them a challenge will be to deal with different types and abstraction levels of customer feedback, which requires in future to find appropriate state-of-the-art algorithms for the automated identification, extraction, and clustering of CNs. Further research is still necessary, in particular, due to the need to transform unstructured and, sometimes, ill-defined user specifications into meaningful key CNs, which requires the research and application of state-of-the-art natural language processing techniques (Kulkarni et al. 2019; Kang et al. 2019a, b).

In the second step, these CNs will be encoded to FRs and to constraints. This describes the link from the customer domain to the functional domain, which should occur as automated as possible and without expensive involvement of the designer (except for logical checks). As also described in the work of Kim et al. (2019), one challenge lies in the automatic encoding and transition from natural language expression of customer needs to FRs that can be then further used in the AD design approach. First tested AI abstraction tools for natural language by Kim et al. (2019) have resulted to be not effective in extracting FRs. Word embedding tools are currently not directly capable of translating key CNs into functions of a system. It is also necessary to research, test, and validate possible AI solutions for this step in the AD design approach, or to determine whether fully automated solutions can be implemented or to what extent humans should intervene in a semi-automated solution. Using the proposed AD knowledge database, also a knowledge-based encoding of FRs could also be done, where based on earlier transitions from the customer domain to the functional domain, the designer is provided with suggestions for possible FRs for recurring or similar CNs.

In the third step, a semi-automated and AI-assisted FR–DP mapping and decomposition process takes place. During the mapping and decomposition, the proposed approach includes automated proof checking (Mantravadi et al. 2019) of the Independence Axiom (Axiom 1) to avoid a so-called coupled, and therefore complex design suggesting possibilities for a re-design or rearrangement of FR–DP pairs. The FR–DP mapping (finding a design solution for a certain FR) is semi-automated in the assisted design approach as the system will propose the designer automatically several alternative DPs for a certain FR. The selection of the best DP will be assisted by an automated check of the Information Axiom (Axiom 2), evaluating the complexity of a design solution. Similarly to this, such an AI-based approach is used also to propose possible decompositions of a higher level FR–DP pair into lower level ones based on similar decompositions found in the AD knowledge database. Prerequisite and crucial for this is a suitable ontology for the formal representation of such knowledge (Akmal and Batres 2013) and a central database in the background, which is fed with labeled successful and unsuccessful designs in order to be able to learn from past successes and failures through supervised AI techniques.

21.7 Artificial Intelligence-Assisted Re-design of Complex Systems

In Fig. 21.4, we can see the behavior of a system, e.g., a manufacturing system, over the time. Future events are very often unpredictable and might shift the system range away from the defined design range, and thus create time-dependent complexity. According to AD, the information content of a system with defined FRs is described by the joint probability that all FRs are fulfilled by the respective set of DPs and measured by the ratio of the common range between the design and the system range. As shown in Fig. 21.4, a system might deteriorate during its service life and its design range will move outside the required system range. According to AD, the first type of time-dependent complexity is periodic complexity, which can be managed through the analysis of previous typical time periods. Simple examples of periodic complexity are tools that wear out (Matt and Rauch 2011). If we are able to define the right periodic intervals for their change and re-design, this information helps to reduce complexity. The second type of time-dependent complexity,

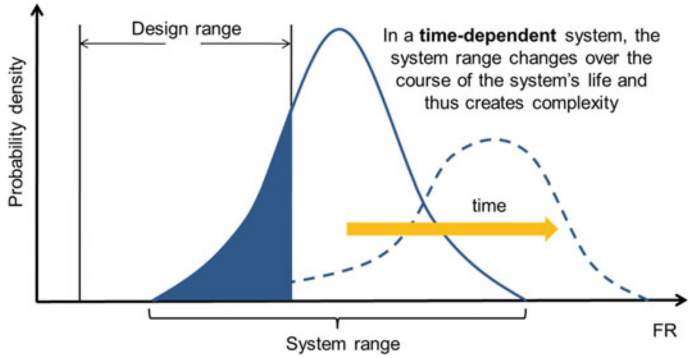

Fig. 21.4 Overlapping and shifting of design and system range

combinatorial complexity (Suh 2005), can be caused in case of a manufacturing system by the dynamics of unpredictable technological, socio-economic, or political influences. According to Suh (2005), this unpredictable combinatorial complexity can be managed by, transforming it into a periodic complexity. When the system does not renew itself by resetting and reinitializing, it becomes a reason for wasting resources. Manufacturing systems are especially characterized by such a combinatorial complexity and in order to be responsive to unforeseen changes. They must be reset in periodic intervals to avoid or minimize the effect of shifting outside of the design range. The time-dependent combinatorial complexity must be changed into a time-dependent periodic complexity by introducing functional periodicity. This allows trigger of the re-design of the system and to re-adjust to changing conditions. If this could be achieved, the system will be more agile and resilient than traditional ones.

In the proposed AD, approach for AI-assisted re-design the analysis of the system over time might show degrees of periodicity, which can be used to actively trigger the re-design of a company's manufacturing system or parts of it, before a too strong deviation of system range and design range force it to (see also Fig. 21.5). The analysis would imply searching for patterns in collected temporal

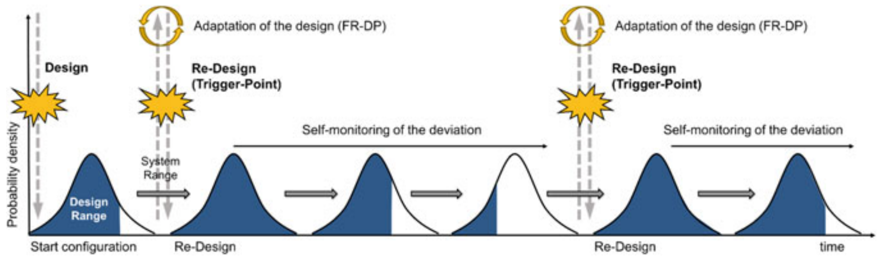

Fig. 21.5 Triggered re-design of manufacturing systems

series, like, for example, sensor measurements, evolution of performance measures, maintenance interventions (Pertselakis et al. 2019), and logging data for functional fault diagnosis (Ye et al. 2014).

Modern technologies of Industry 4.0, such as sensors and human–machine interfaces, enable the collection of large amount of data and thus the current status of systems like a manufacturing system to be called up in real time. A re-design should not be triggered only after an emergency alarm based on the self-monitoring, as this would mean a reactive re-design. Re-design must be based on the digest of the daily production measured over time (a trend over a longer period), not only in terms of the real-time data generated during the daily manufacturing process. Based on this fact also predictive suggestions need to be generated "it is worth to re-design before the end of the week/month/year" and only trigger alarms of the form "urgent re-design required" when the suggestions had been ignored and the "trigger point" had been reached without any measurable trend improvement. For self-monitoring, the tolerance bands of FRs and DPs are determined by metrics during the initial configuration or design of the system. Depending on whether the adaptation of the system can take place automatically (e.g., an adaptation of parameters of a manufacturing process) or whether human support is required, we speak of self-adaptation or assisted adaptation of the system. Due to technological or organizational changes, it may be that for certain FR–DP pairs, an earlier rejected DP alternative would achieve now a better result. To achieve this the "AI" must be able to doubt about its own beliefs. It is required that an "entity" able to simulate the use of "alternative" DPs to re-weight their influence on the overall performance. This topic is related to Reinforcement Learning (Lison 2012), a ML technique to find the best possible behavior or path in a specific situation. Similarly, new DPs may join the AD knowledge database (e.g., a new technology), which may replace an old DP due to better performance. In these cases, not only the previous status should be restored by self-adaptation, but the aim is to achieve a self-optimization of the manufacturing system. During this process, some DPs may save time and money by automatic adaptation, while other DPs may be of strategic relevance requiring a human-driven decision-making process.

21.8 Impact and Advantages of Artificial Intelligence in Axiomatic Design

In the current application of AD for the design of complex systems, there are and there have been certain limitations. Many experienced designers agree that AD helps them to cultivate insightful thinking. But many still find it difficult to apply AD principles to design practice since using AD effectively also requires designer's insights and experience in AD (Kim et al. 2019). Based on own experiences in research and industrial practice the following are currently detectable weaknesses of AD:

- need of experience in applying AD;
- difficulty in the holistic consideration of customer needs;
- designer very often struggle to define solution-neutral FRs;
- the identification of design solutions/parameters is based on their knowledge and experience;
- existing designs from other sources cannot be taken into account because there is no central data source;
- the process is very manual, and there is a very limited computer-aided support with current systems available;
- current approaches do not allow a real-time monitoring of whether the design parameters (DPs) still meet the FRs over time;
- not possible to automatically determine the time for a re-design of a system (trigger point);
- does not allow an AD-based self-optimization of the system.

However, the time may be now just right to take AD to a completely new and revolutionary level by taking advantage of modern technologies from Industry 4.0 (such as sensor technology, real-time data gathering, AI, deep learning, machine learning, or cloud computing) to eliminate the before-mentioned limitations. Planning can be carried out much faster, with less effort, with more accuracy, and an enormous planning quality through the presented AI-assisted and automated design concept. Table 21.1 shows the most important innovations due to the use of the proposed new AD design approach.

Table 21.1 Assisted (re)design of complex systems—traditional versus new proposed AI-assisted approach

Traditional AD design approach	New proposed AI-based AD design approach
Manual and subjective analysis of key customer needs through the designer or design team	Automated clustering of customer feedback into meaningful CNs
Manual and subjective translation of the CNs into FRs through the designer or design team	Semi-automated translation of CNs into FRs
Designer very often struggle to define solution-neutral FRs	System supports the correct syntax and formulation of solution-neutral FRs
Experience-based approach depending on the experience of the designer or design team	Knowledge-based approach depending on the quality and quantity of past designs in an AD knowledge database
No guarantee of a comprehensive consideration of all potential design solutions (DPs)	Due to an increasing filling level of an AD knowledge database over time, an immense compendium of potential DPs can be created.
Very manual process with only limited computer-aided support	Development of a highly automated computer-aided conceptual design (CACD) tool

(continued)

Table 21.1 (continued)

Traditional AD design approach	New proposed AI-based AD design approach
Difficult to apply for novices or people not experienced with AD	Many of the decisions and reviews (e.g., check of AD Axioms) are done automatically in the background, making it easy to use even for novice designers
No possibility for real-time monitoring of whether the DPs still meet the FRs over time	Integration of a self-monitoring with adjustable sensitivity limits and alarm if defined setting limits are exceeded
No possibility to automatically determine the time for a re-design of a system (trigger point)	Autonomous determination of the trigger point for a re-design of the system (or its parts) based on the self-monitoring
Does not allow a self-optimization of the system	Enables self-adaptation and self-optimization of a system

As mentioned above, such an AI-assisted design approach will have an important impact in the field of the design of complex systems. However going in this direction, there will be many related fields of action, where such an approach may help. A possible additional goal for the future is sustainability. The proposed approach could also provide information on the extent to which certain adjustments could also have positive or negative effects on the environment or sustainability in general in all their facets (economic, ecological, or social).

Problem

Students should concentrate on one domain (customer, functional, design domain) and discuss the potential of AI in the respective domain.

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