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SOLUTION SPACE DEVELOPMENT 2.0: REFRAMING PRODUCT ADAPTATION AND AI-BASED ENGINEERING TOOLS

Paul Christoph Gembarski [0000-0002-2642-3445]
Institute of Product Development, Leibniz Universität Hannover,
An der Universität 1, 30823 Garbsen, Germany

Abstract: *To enable product customization, validating the design solution spaces is necessary to ensure safe manufacturing and operation. Implementing product models with component families to choose from serves as a basis for tools such as product configurators. Today, advancements in production technology, digital functionalities of products, and emerging capabilities of business ecosystems result in additional possibilities to adapt products and services to customer needs. This has consequences for solution space models, i.e., the inclusion of corresponding degrees of freedom. This article seeks to align this with research on solution space development in the fields of action knowledge-based design and design automation, design for adaptive-cognitive manufacturing, and (re-)configuration of business ecosystems and to motivate prospective research avenues focussing on AI-based engineering tools for solution space development.*

Key Words: ***Complexity Management, Solution Space Modeling, Knowledge-Based Engineering, Algorithmic Design, Design Automation***

1. INTRODUCTION

Adapting products and services to customer needs requires a high degree of validation to ensure that a variant can be manufactured and operated safely (Dong et al., 2023; Zimmermann & von Hoessle, 2013). Complexity management is of particular importance here to deal not only with variety but also with uncertainties that arise (Pavanelli Stefanovitz & Lopes de Sousa Jabbour, 2022; Gembarski & Lachmayer, 2017). Complex product portfolios contain myriads of different variants due to their product structure, i.e., well-designed modules and interfaces and various options that can be chosen by the customer (Modrak & Bednar, 2016; Durhuus & Eilers, 2014; Pil & Holweg, 2004). Defining the underlying solution space and maintaining it over time is the goal of solution space development (Gembarski & Lachmayer, 2018; Brunø et al., 2014).

The implementation of the corresponding product models has been supported by artificial intelligence (AI)-based engineering tools right from the beginning (Verhagen et al., 2012; Sabin & Weigel, 1998). Looking back into the history of product configuration, it was 1982 when McDermott (1982) published his work about R1/XCON, the first documented configurator in literature. It was a rule-based expert system implemented in OPS5 that was online for nearly ten years, finally describing over 31,000 configurable components and over 17,500 rules, from which nearly 50% needed to be maintained and adopted per year (Barker et al., 1989). Fig. 1 shows an example rule from R1/XCON which illustrates the nesting of the conditional part of the rules.

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    IF: THE MOST CURRENT ACTIVE CONTEXT IS DISTRIBUTING MASSBUS DEVICES
        AND THERE IS A SINGLE PORT DISK DRIVE
              THAT HAS NOT BEEN ASSIGNED TO A MASSBUS
        AND THERE ARE NO UNASSIGNED DUAL PORT DISK DRIVES
        AND THE NUMBER OF DEVICES THAT EACH MASSBUS SHOULD SUPPORT IS KNOWN
        AND THERE IS A MASSBUS THAT HAS BEEN ASSIGNED AT LEAST ONE DISK DRIVE
              AND THAT SHOULD SUPPORT ADDITIONAL DISK DRIVES
        AND THE TYPE OF CABLE NEEDED TO CONNECT THE DISK DRIVE
              TO THE PREVIOUS DEVICE ON THE MASSBUS IS KNOWN

  THEN: ASSIGN THE DISK DRIVE TO THE MASSBUS
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Fig. 1. *Rule from R1/XCON (McDermott, 1982)*

R1/XCON perfectly shows the working principle of early solution space models: The first key feature was the development of a product model that coded component families as variables and the single options for a component as their domains (Simpson et al., 2014; Tseng et al., 1996). A second key feature was integrating expert system techniques to reason from user requirements to product characteristics and to configure the right components from these domains (Zhang, 2014; Forza & Salvador, 2002).

Today, determining the right components is still relevant for many products, even when expert system technologies developed over time (Felfernig et al., 2014; Hvam et al., 2008). But it is yet not the only way to adapt products and services to customer needs. Modern manufacturing technologies, the virtual capabilities of smart connected products, and the different ways of operating products in multiple services require new capabilities in solution space development.

This article seeks to align the different ways of product adaptation and research on the respecting solution space models and the necessary AI-based engineering systems to model and explore them. To do so, the following section 2 introduces the term *degree of* *freedom* in the context of solution space models and deduces different types based on different ways of product adaptation. Section 3 then takes the bird's eye view by applying a systems engineering approach to adaptive products and services and linking them to the supply chain and the environment in which these products and services are applied. The resulting mental model motivates three fields of action which are discussed in section 4 regarding AI-based engineering systems for creating the respecting solution space models. For these fields of action, current research and future avenues are framed. Section 5 then contains a summary.

2. PRODUCT ADAPTATION IN THE YEAR 2024

As mentioned above, adapting products by exchanging components is a common practice. From a modeling point of view, the innovation of the early solution space models like the one from R1/XCON lies in the introduction of variables and their domains as representatives for component families. The consequence is a *compositional degree of freedom* in the product models (and products themselves), i.e. the necessity to correctly assign a distinct component from a set of (given) alternative components respecting constraints due to requirements and engineering intent.

The following sub-sections introduce other ways of product adaptation and discuss them regarding further degrees of freedom necessary for solution space models.

2.1. Design degree of freedom

Regarding the physical components of a product, another way of adaptation is changing the design of a component in the sense of dimensions and design features (Gembarski & Lachmayer, 2018; Chen & Shea, 2015). This is enabled due to advances in production technologies, especially manufacturing systems for producing at lot size one.

Depending on perspective and maturity, flexible, reconfigurable, cyber-physical, and smart manufacturing systems are discussed in literature among others. The principles behind this include the (automatic) configuration of a process chain based on geometric data, scheduling and routing the production order through the system, and monitoring production quality (Romero & Stahre, 2021; Leng et al., 2021; Yelles-Chaouche et al., 2021). In adaptive cognitive manufacturing systems (ACMS), the increased sensing of the production machinery will raise the level of automation and make them more robust to achieve the desired product properties and reduce waste and rejects. All information processed and all decisions taken by the system are stored in a comprehensible manner so that human operators can easily follow them and are supported in their day-to-day work in the most efficient way (Zhang et al., 2023; ElMaraghy et al., 2021).

As a special building block in such process chains, additive manufacturing enables to create a physical part directly from the geometric model by powder-bed or metal deposition processes, usually without the necessity for additional tooling (Abdulhameed et al., 2019; Frazier, 2014). Although explicitly not the game changer in customization due to its costs and scattering regarding product properties, the ability to produce complex geometries and reach functional integration makes it attractive for many applications, including repair and refurbishment (Ehlers et al., 2022; Ganter et al., 2021; Gibson et al., 2021; Thompson et al., 2016).

As a consequence, the solution space models need to include a *design degree of freedom*, i.e., the necessity to determine a parameter for dimensions or feature occurrences that do not violate manufacturing restrictions, aesthetic principles, or other constraints (Gembarski & Lachmayer, 2018; Gembarski & Lachmayer, 2015).

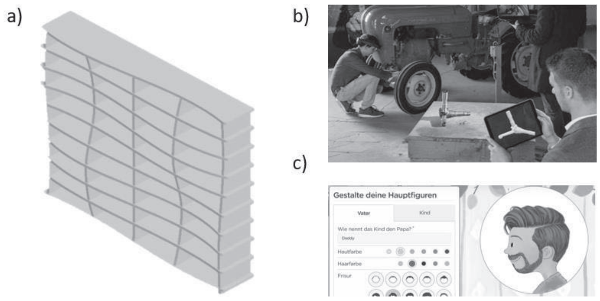

Fig. 2. *Design degree of freedom: a) Free-form bookshelf, b) Additively repaired structural component, c) Personalized book*

Fig. 2 shows three examples of products with design degrees of freedom from subtractive, additive, and print manufacturing. The first example is personalized furniture such as free-formed bookshelves, which are distributed in the Okinlab form.bar ecosystem. A digital platform hosts an advanced configuration system that enables customers not only to choose from options but make adaptions to the design of parts and assemblies. When the order is completed, the digital production data set is transmitted to a manufacturer near the customer who has the corresponding CNC manufacturing equipment and is then produced and distributed to the customer (Scheer, 2019; Quaranta & Feth, 2017).

The second example is the rarely available spare part for the steering knuckle of a historic tractor. The original part was broken but could be repaired using additive manufacturing. The necessary preprocessing of the broken part and the manufacturing restrictions due to the process chain were both generated by a knowledge-based engineering system as a model of the corresponding (generalized) solution space. The knuckle was digitally reconstructed, repaired by metal powder-bed fusion, and then post-processed by subtractive manufacturing to achieve the necessary tolerances (Ganter et al., 2022; Gembarski & Kammler, 2022).

The third example originates from digital printing. The idea to customize print material to generate additional customer touch points for mass customization businesses is rather old (Müller & Piller, 2004; Kotha, 1995). Real customer co-creation takes place using digital platforms for creating, e.g., personalized photo books (Engel et al., 2015). These platforms usually offer templates and perform checks and optimizations to guarantee a good printing result (Corrigan-Kavanagh et al., 2023; Sandhaus et al., 2008). A relatively new development is letting customers adapt the content of books to their characters or create personalized packaging (Kucirkova & Mackey, 2020; Zhou et al., 2013).

2.2. Digital degree of freedom

The digital capabilities of smart connected physical products enable product adaptation in a different way (Raff et al., 2020; Porter & Heppelmann, 2014). The integration of a digital layer in complex products is rather not a new development. Monitoring, adapting, and optimizing, e.g., production machinery to environmental or usage conditions via its control units is essential in many businesses (Beverungen et al., 2019; Salvador et al., 2009). But the ongoing merger of hardware and software leads to new real-time applications and decision-support in human-machine collaboration (Wilhelm et al., 2021; Romero et al, 2020). A huge potential results from making physical changes to the product obsolete by reconfiguring virtually (Abramovici et al., 2017; Brettel et al., 2014).

The consequence for solution space models is a *virtual degree of freedom*, i.e., the necessity to determine digital functionality that does not violate the limitations of the physical capabilities of the (smart) product and the flow and processing of data (Gembarski, 2020).

Fig. 3. *Digital capabilities of a modern vehicle headlamp*

An example of this is a modern vehicle headlamp. Digitally controlled light sources largely decouple light distribution and lens geometry. In such a way, traffic signs or visual communication between the car and other traffic users can be realized (Fig. 3). As a consequence, the system is robust against changes in traffic regulations: If a new light distribution for, e.g., the low beam is negotiated, such a headlamp simply needs new input data (Knöchelmann et al., 2018; Hung et al., 2010).

The reconfiguration of a (smart) adaptable product is commonly based on data, independently from being sensed by the product or input by others. Thereby the product and the service state requirements for the quality of the data which needs to be considered during product development (Batista et al., 2005).

Another question is what additional benefit can be achieved by the data, e.g., in other related services. Referring again to the automotive sector, active suspension integrates, e.g., camera vision of the road in front of a car to detect potholes with adaptive shock absorbers (Tseng & Hrovat, 2015; Gysen et al., 2009). The car usually also has a GPS module so that the controller signal of the suspension intervention can be combined with the location of the car (Kim et al., 2022; Eriksson et al., 2008). This enables two additional services: First, the real-time data about the condition of the roadway surface enables road construction state prediction and planning on-demand maintenance. Second, car owners without active suspension can opt for the most comfortable and, regarding the car, most careful route for driving.

2.3. Operation degree of freedom

Understanding products as resources to achieve added value sets a different focus on its purpose. Current research in the field of circular economies advocates integrating the 9R strategies into development processes (Muñoz et al., 2024). Although many of the single Rs, such as reuse, repair, remanufacture, and recycle should be common practice, especially repurposing is challenging as it requires a different view rather than the functional and build-structure of the product. The question moves to what capabilities are achieved by a product and to which other use cases are these capabilities beneficial (Chen et al., 2022).

A single product or service can be seen as part of a super system. All of its products and services, their capabilities, and their emergent features due to their combination form a different type of solution space and introduce an *operation degree of freedom*, i.e., the necessity to determine the product usage in the context of multiple services that does not violate capability as well as resource allocation and consumption constraints (Gembarski & Kammler, 2022).

Fig. 4. *Repurposing of a cargo e-bike*

Fig. 4 shows a simple example of this. An electrical cargo bike offers the capability to move forward cargo up to a specific weight according to traffic regulations in a supported way so that the power of the rider is raised. A manually operated lawn mower offers the capability of cutting the lawn when it is moved forward. What now if both are merged? First of all, new requirements for the e-bike appear, especially regarding stability and energy support.

To anticipate such requirements during product development is particularly challenging but essential for (smart) product-service systems and business ecosystems (Bulut & Anderl, 2022; Wang et al., 2019).

3. MENTAL MODEL

A traditional view on solution space development is modeling the design solution space and the way it is explored to get from customer needs to a respecting product or service configuration. Adding the time dimension to this, products and services can also be re-configured over time, adapting them to changed requirements and conditions. For this reason, a configurable product or service can be understood as an adaptive system.

From a systems engineering perspective, besides the system structure, the interaction between a system and its environment is of particular interest. Following the above logic, a mental model can be developed to describe elements, relations, and engineering activities in solution space development (Fig. 3).

At the center is the adaptive system. As mentioned before, adapting it can encompass changes on three different layers. Firstly, on the physical layer, this can involve the replacement or modification of physical components to accommodate new requirements. Secondly, on the digital layer, the product's operation can be adjusted by changing its behavior, integrating new digital controls, or incorporating additional digital functionality. Finally, on a service level, the physical product can be embedded into a new service, involving the integration of support services, maintenance, or other value-added features.

The adaptive system itself is an instantiation out of a design solution space that incorporates all feasible configurations of the adaptive system. Both are related to each other. Adaptive systems are designed to flexibly adjust and respond to changing requirements, ensuring ongoing functionality and performance in evolving conditions. In such a way, the change in requirements triggers a request to adapt the system. On the other side, the design solution space ensures that the (re-) configuration is valid, either by an instant evaluation or based on an already pre-designed reaction pool for certain change requests.

If the design solution space is incapable of reconfiguring the adaptive system according to the requirements, the system can request or propose an extension on physical, digital, or service level that can be, e.g., engineered to order.

The design solution space itself is an instantiation of the collective capabilities of a set of organizations. These capabilities contribute to the creation of a supply system solution space, which plays a crucial role in ensuring the production and operation of viable variants within safe parameters. As a result, the supply system solution space acts as a restriction, allowing only feasible variants to be included in the design solution space. If the design solution space ought to be extended, this can create new demands for capabilities in the supply system.

On the other hand, the adaptive system is operated in a dynamic environment with the consequence of a continuous influx of new or modified requirements that the system must accommodate and trigger its adaptation. The adaptive system also provides feedback to the environment through its various interfaces, actively contributing to and influencing its dynamics. As a result of this interaction, new requirements and use cases are continually identified and developed, creating a cyclical pattern of ongoing evolution and improvement that is constantly served from the design solution space.

The mental model incorporates three engineering processes at the interfaces between its elements that can be seen as fields of action for solution space development research.

The first between adaptive system and design solution space largely includes all activities that allow for reasoning from requirements to a (new) variant of the adaptive system. This field of action aligns with knowledge-based design and design automation. The second between design solution space and supply system solution space involves all activities to automatically check variants for manufacturability and operability as well as the support and organization of manufacturing processes. This field of action focuses on design for adaptive-cognitive manufacturing. The third integrates the adaptive system and the dynamic environment, shifting the viewpoint on the capabilities the system contributes to the environment as a super system and its purpose. That field of action is business ecosystems engineering.

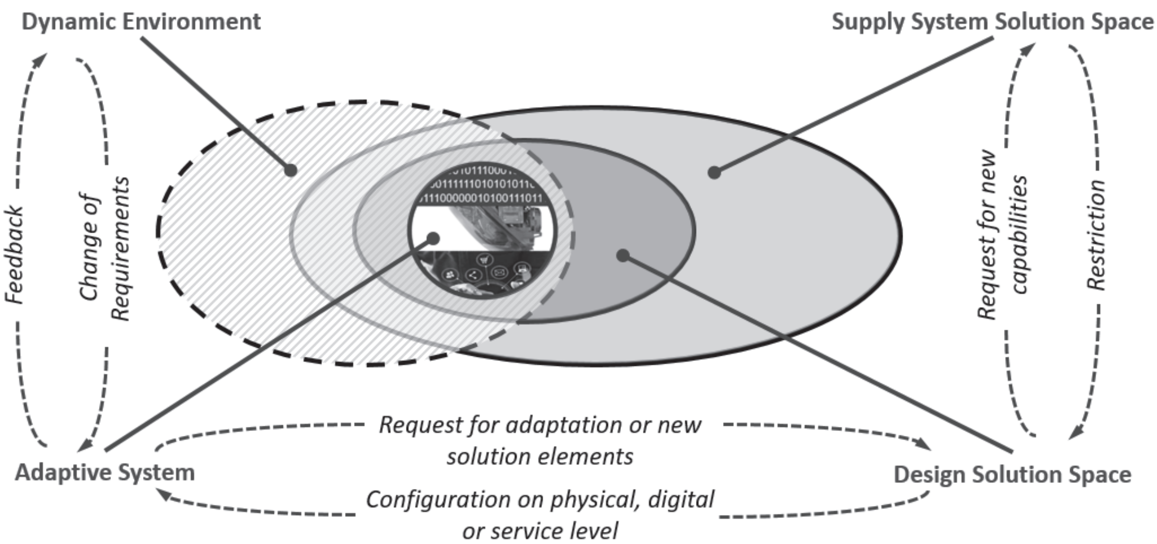

Fig. 5. *Mental model for solution space development*

4. FIELDS OF ACTION

Following a knowledge-based systems engineering paradigm, AI-based engineering tools need to support the above activities and model the corresponding solution spaces.

In the following sub-sections, the present research background is showcased based on (meta) reviews from the corresponding domains. These are enhanced by actual relevant works about AI-supported engineering tools. From this, a main research avenue is framed and detailed into guiding questions for future works in each field.

4.1. Knowledge-based design

Knowledge-based design involves a paradigm shift in computer-aided product modeling. The focus switches from modeling single product variants to whole solution spaces where a variant can be derived based on a set of requirements (Frank et al., 2014; Amadori et al., 2012). This involves two activities, first to develop product models that represent the solution space and second methods to explore it and reason to the target variant (Gembarski & Lachmayer, 2018).

The literature contains various reviews on the topic. Kuegler et al. (2023) performed a meta-review and enhanced this with findings from their own review targeting the period between 2012 and 2021. The conclusions can be summarized as follows:

- Methodological support and theoretic foundations are still missing to a big extent,
- Reported systems lack detailed descriptions regarding knowledge bases and are often isolated implementations for a specific use case,
- Knowledge re-use is hardly assessed for the reported systems,
- The discussion of AI techniques, both symbolic and sub-symbolic, is underweighted.

From a modeling principle perspective, knowledge-based computational design has different forms. Knowledge-based CAD makes use of today's parametric CAD systems and integrates design intent by, e.g., mathematical constraints, design rules, and AI with a strong focus on expert system techniques (Gembarski & Lachmayer, 2018; Hirz et al., 2013).

Algorithmic modeling puts the focus on automating the design process itself rather than pre-formulated solutions (Tedeschi & Lombardi, 2018). Algorithms are used to extract product properties from requirements and build product design rules, also taking into account external data or numerical simulations (Brockmöller et al., 2020). Therefore, a parametric product master model is unnecessary as this approach aims to generate an individual product for each set of customer requirements. This is particularly favorable for complex geometries (Müller et al., 2022).

However, algorithmic modeling is defined by a correlation between the algorithm and the outcome. Thus literature discusses this as a special case of generative modeling, where this correlation is not immanent (Caetano et al., 2020). The workflow is the same and so are the engineering environments. Today, the design process is commonly modeled in visual programming tools, such as Rhino Grasshopper and Synera. The idea behind this is to enclose functional blocks like geometric features or optimization procedures in nodes which can be linked with each other and with input variables and restrictions. The workflow then executes the node network to generate the design (Boretti et al., 2023). This includes also the specification of geometric drafts as input whereupon the system automatically elaborates it, evaluates alternatives, and thus enables qualified degrees of freedom in the design. Since these technologies are still comparatively young, there is only little scientific literature reporting about this or giving methodological guidance.

The potential of AI to formalize design requirements and restrictions, e.g. based on mass data is seen (Gräßler et al., 2023). The actual burst of research on generative AI has reached the design tools only to a small extent.

In conclusion, the main research avenue of this field of action is to rethink knowledge-based design as a model of the design solution space and to implement it as a task-specific combination of intelligent tools within algorithmic and parametric modeling. Research questions include:

- What are the underlying algorithmic formulations of design problems and generalized solving methods for them?
- What are suitable data structures and methods for automated derivation of domain knowledge for subsequent storage and application in engineering environments, e.g. based on graph-based product representations or through generative AI processes?
- How to evaluate and optimize designs multi-perspectively (e.g. concerning functional fulfillment, manufacturability/tolerances, eco-efficiency) in engineering environments automatically, e.g. using AI in the form of multi-agent systems and distributed CSP?
- How to complement generative AI with expert system technologies and vice-versa and integrate them into computational design?

4.2. Design for adaptive-cognitive manufacturing

In the future, engineering tools will perform design tasks under human guidance. The aforementioned principles and tools for algorithmic modeling offer multiple potentials also for the design for manufacturing in general (Brockmöller et al., 2020). This includes the question of how to integrate manufacturing analysis systems to close the gap between design and production. These systems go beyond a simple comparison of production restrictions in the form of rules and equations.

Research on that topic is still characterized by a strong emphasis on the single production technologies. Since products are usually manufactured by a process chain, the cross-process manufacturing restrictions are hard to capture and thus under-represented in the literature (Beckers et al., 2022).

Reviews such as from Shukor & Axinte (2009) point out, that a complete geometric model, including all tolerance and material data, is highly beneficial as input for such systems. Nonetheless, the relation between functional and manufacturing domains is only considered to a small extent. The analysis systems themselves commonly rely on expert system techniques or multi-agent systems (Plappert et al., 2021)

A relatively new development is the algorithmic formulation of the manufacturability analysis as such. An example approach is the portfolio-of-capabilities-constraint-network (Herrmann et al, 2023). The geometry of a part is abstracted into its dimensions and correlated with discretized manufacturing restrictions in a constraint satisfaction problem. The advantage of the approach is that cross-process constraints can be easily included, manufacturing stages can be considered and partly derived, and manufacturing conflicts can be traced and partly resolved automatically. For larger manufacturing chains, the approach is computationally intensive.

An engineering system that takes over both the evaluation of product variants and the control of the manufacturing process can react automatically to deviations and guarantee product safety by generating alternative solutions. One example of this is the compensation of a production deviation by adapting adjacent components if these have been provided with the appropriate degrees of freedom in the design.

Following this, the main research avenue of this field of action is the development of methods and models for manufacturability analyses based on the supply chain solution space and advancing them into multi-perspective optimizers that interact with the design solution space. This leads to questions such as:

- How to operationalize production-specific heuristics and design guidelines/design-for-X approaches through algorithmic formulation and synthesis of tools for automated testing and optimization of product models, e.g. in the context of automated design reviews by multi-agent systems?
- How to model manufacturing capabilities and automated configuration of manufacturing process chains, e.g. as a Portfolio-of-Capabilities Constraint Networks, and how to resolve occurring manufacturability conflicts automatically?
- How to integrate concepts for the digital twin of production with design solution spaces and methods for formulating reaction plans and according to degrees of freedom in product models to compensate for production deviations?

4.3. (Re-)Configuration of business ecosystems

The research field of business ecosystems is still comparatively young (Tsujimoto et al., 2018). It has a strong focus on the mechanics within the ecosystem itself, i.e., mediating between the interests of the participants and decision-making principles. Many works emphasize the evolutionary nature of ecosystems as highly dynamic entities which leads to the question if ecosystems as a whole can be actively designed (Cobben et al., 2022). The literature discusses two views on that: Actor-centric views prioritize network partner composition and their respective roles in the ecosystem. This perspective assumes that a business designs an ecosystem from the top down by adding complementors to enhance capabilities. On the other hand, activity-centric views focus on organizing activities among partners to create a valuable offering (Adner, 2017), thus reflecting a bottom-up approach where portfolios of capabilities are designed before configuring solutions for customers individually.

From a methodology point of view, approaches from other engineering disciplines have already been adapted as design concepts. To those belong modularity, complementarity, and fungibility, which can be sub-summed as design for flexibility or design for (re-)configuration of the ecosystem (Jacobides et al., 2018). Rong et al. (2015) visualize this in the example of well-designed map services with an open application programming interface: The system can be utilized in delivery services by providing essential features such as finding destinations and establishing the most efficient routes. In combination with tracking, this allows for real-time monitoring of vehicles and predicting arrival times for individual customers and creates emergent functionality for the service. The question arises of how to support the co-evolution of such emerging functions and the definition of cross-ecosystem solution spaces with corresponding degrees of freedom (esp. compositional, virtual, and operational as in the example above) to adapt to individual customer needs and taking advantage of the complex reaction pool that the ecosystem holds. However, deployment typically requires a transparent description of functions contained within the reaction pool as well as their interoperability. To apply this also for managing customer solutions in real-time, modeling the solution space of ecosystem offerings and their single customer instantiations is imperative but lacks foundational research. At present, there are no computer-aided tools that support the design and management of ecosystems.

Following this, the main research avenue of this field of action is to understand business ecosystems as new design objects, which can be developed with methodologies and tools from engineering disciplines. Research opportunities that align with this are:

- Which are (standardized) model elements for designing ecosystems and what are configuration mechanics and generalized examples for that?
- How to model solution spaces for an ecosystem’s offerings and in particular how to capture emerging features at the interaction of ecosystem participants?
- How to synchronize this with theories from the field of strategic alliances, e.g., resource- or knowledge-based theory?
- Which system engineering methodologies and AI-based engineering tools can be transferred to ecosystems?

5. SUMMARY

Digital tools and AI-based engineering environments currently change working paradigms, shifting the development focus from single variants to solution spaces from which individual customer needs can be served. A key aspect here is the introduction of defined degrees of freedom in the product models, ensuring that newly configured variants are valid and can be operated safely. Due to technological advancement, four of such degrees of freedom could be identified, i.e., compositional, design, digital, and operational.

A system engineering approach that puts adaptive systems of products and services in the center then integrates the design solution space as the basis for (re-) configuration, the supply system solution space as a source of restrictions for the design solution space, and a dynamic environment as a super system of multiple adaptive systems as capabilities and resources of an ecosystem. Each interface of the single elements of this mental model leads to an engineering process behind, i.e., knowledge-based design and design automation, design for adaptive-cognitive manufacturing, and business ecosystems engineering. These engineering activities form fields of action for solution space development research, for which research avenues and guiding questions were proposed with a focus on AI-based engineering tools.

In this context, AI-based technologies will leverage efficiency not only for a configuration of adaptive systems in complex and huge solution spaces like those from business ecosystems. Techniques from algorithmic engineering and new generative AI tools will also increase the ability to model the solution spaces as such. Emphasizing the holistic nature of solution spaces as design objects, this work should explicitly motivate research towards a theory of solution space engineering.

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CORRESPONDENCE

Dr.-Ing. Paul Christoph Gembarski
Institute of Product Development,
Leibniz Universität Hannover,
An der Universität 1
30823 Garbsen, Germany
gembarski@ipeg.uni-hannover.de