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ESTIMATING THE POTENTIAL OF STATE OF THE ART DESIGN AUTOMATION - TASKS, METHODS, AND BENEFITS

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1. Introduction

Engineering design automation systems have a history of application and research for more than 40 years [Braha et al. 2013], [Panchal et al. 2015]. However, the types of automation systems in industrial applications is mostly limited to configuration tasks such as mass customization [Forza and Salvador 2007] or configurators for tendering support [Brinkop 2013]. Computational support in the earlier phases of the design process are rare [Bolognini et al. 2012]. Reasons for this lack of application of design automation methods in engineering design practice are manifold including inhibitions against implementing design automation systems due to uncertainties in their potential benefits [Verhagen et al. 2015] and how to select an appropriate method for a given design task [Amen et al. 1999].

In order to tackle these obstacles for industrial application of design automation, first, categorizations and characteristics of design tasks for automation and then studies for both qualitative and quantitative evalution of design automation potentials are analyzed. Findings from application of recently developed design automation methods are used to derive a mapping from design automation task characteristics to design automation methods and highlight corresponding benefits for industrial usage. Thus, this paper helps to better understand how to overcome the current obstacles that inhibit the spread of design automation in industrial environments by creating a better understanding of what type of tasks can be automated, what benefits can be achieved and provides a mapping to different types of methods for automation that exist.

In Section 2, an overview of design task categorizations is given and a mapping of tasks to tools is introduced before automation potential estimation and evaluation techniques are analyzed. Section 3 introduces a set of design automation methods, mostly associated to the field of computational design synthesis. Design tasks are analyzed according to design task characteristics from literature and potential benefits of their applications are highlighted. After that, a qualitative categorization for design tasks is proposed that serves as a basis for mapping tasks to design automation methods and potential benefits. The paper concludes with an overview of the results and future work.

2. Related work

This section introduces categorizations of design tasks for automation as well as approaches for computational modeling of design tasks, i.e. design task characteristics. Further, a mapping of design task characteristics to methods for automation is analyzed and methods to estimate and verify potential benefits are investigated.

2.1 Task categorization and method selection

The design task categorization presented by Brown and Chandrasekaran distinguishes routine, innovative and creative design tasks [Brown and Chandrasekaran 1990]. Domain knowledge and availability of information about problem solving strategies serve as a basis for their categorization. However, a general description of the attributes such as parameters, variables and relations needed for complete formulation of a design task is missing. Thus, this model of design tasks only allows categorization at an abstract level [Dym and Brown 2012].

MacLellan et al. [2013] introduce a problem formulation tool that allows the designer to define a design task by means of attributes such as requirements, functions, behaviours and artefacts. Altogether, these attributes and a proposed meta-level knowledge allow one to judge whether all necessary building blocks needed for automation are given, e.g. the completeness of a design task can be verified. However, the model focuses on design tasks for manually performed design instead of tasks that are meant for automation.

Aiming at a description for task definitions for design automation, Cagan et al. [1997] present a representation of computational problems for design that is based on:

- *variables*, i.e. the degrees of freedom or unknowns, which can be either continuous (con), discrete (dis) or both, whereby discrete refers to variables that are subject to selection from a given set of choices, e.g. standard size, colours etc.,
- *parameters*, which correspond to the user input, and are differentiated whether they are deterministic (det) or stochastic (sto),
- *relations*, i.e. equations and inequalities that are classified to being either:
    - numeric or symbolic, meaning whether mathematial equations or propositional and predicate logic are used,
    - static or dynamic, referring to the time dependence of the task, and
    - spatial or non-spatial, i.e. the dependence of the task on physical space
- *objectives*, which denote the goals of a task which can be either constraint satisfaction or optimization, depending on whether an optimal solution is required or not.

Depending on the characteristics of these attributes, a categorization of design tasks for automation is introduced [Cagan et al. 1997]. It differentiates between tasks that are based on *Declarative* and *Procedural models*, where the latter can be further categorized into:

- *Heuristic Design*, i.e. the solution space is defined by parameters and a set of logical relations. Typically, rule-based systems are used to solve this kind of problems,
- *Superstructure Optimization* denotes types of problems where a subset of given solutions is refined in order to determine optimal solutions,
- *Implicit Generation of Design* corresponds to tasks where the solution space can be explored iteratively, i.e. a new solution is based on a previous one. Hierarchical decomposition of the problem can be used to enable tree search within the solution space.

Generally, procedural models require iterative problem solving due to implicit dependence of design parameters and variables.

As stated by Cagan et al., this categorization is "rather general" [Cagan et al. 1997], making it difficult to unambiguously map design tasks to this categorization. In a study by Amen et al. [1999], multiple industrial use cases are analyzed based on the task characteristics described by Cagan et al. [1997] and a mapping from the design task characteristics to "solution strategies" and tools is introduced. Table 1 lists the considered superordinate categories and descriptive information of categories. It can be seen, that the proposed "solution strategies" do not consistently categorize according to strategies but also use type of systems used for implementation. Whereas *Optimization* refers to methods such as gradient-based optimization and stochastic, global algorithms, *Procedural systems* and *Expert systems or rule systems* are used to denote the paradigms of procedural and declarative programming for implementation, respectively. It has to be noted that the considered methods of this paper are strongly focused on rule-based systems containing exhaustive rule-bases. Further, categorization is performed mainly based on the type of interrelations of the design variables: *Sequential* refers to linear models, where the sequence of rule application is predetermined; *conditionally sequential* corresponds to models where sequences can be rearranged in order to yield sequential models; *coupled relations* denotes interdependency of variables and *non-explicit* refers to lack of knowledge on the relations, i.e. they are unknown. Coupled relations can be seen as an equivalent to the implicit dependence of parameters and variables in the characteristics by Cagan et al. [1997].

Table 1. Classification of approaches /strategies according to Amen et al. [1999]

	Procedural systems	**Expert systems or rule systems**	**Optimization**	**Agents-based strategy**	**Case-based reasoning**
Method characteristics	• Explicit objectives • Relations sequential • Knowledge and Processing logic mixed • Hard to maintain	• Explicit objectives • Conditionally sequential relations • Separation of rule-base and inference engine • Operation sequence determined at runtime	• Coupled relations • Exhaustive rule-base leads to optimal design • Often iterative	• Coupled relations • Problem parameters determined at runtime; solution sequence multidirectional	• Non-explicit relations • Similar problems from case database

Tong and Sriram [1992] use the previously introduced categorization of routine and innovative design tasks [Brown and Chandrasekaran 1990] and refine it in order to determine method characteristics needed for automated solving of a certain design task. Table 2 introduces categorizations for routine and innovative tasks and provides information on the key characteristics of the design tasks. Interestingly, whereas routine design task categorization is kept independent of methods, innovative design tasks are directly associated with methods, i.e. case-based reasoning and structural mutation.

Analyzing the presented studies, it can be seen that there is no unambiguous categorization of design tasks for automation, yet. Either, classes of design tasks are kept at a very abstract level, which makes it hard to accurately distinguish design tasks based on this categorization, or the categorizations are related to solution strategies and methods, whereby proposed categories are intermixed with methods and programming paradigms and no update according to development of new methods has been performed.

For this paper, the design task characteristics proposed by Cagan et al. [1997] are applied to multiple recently published design automation case studies. Based on commonalities and differences of task characteristics, a mapping from characteristics to design automation methods is created.

Table 2. Categorization of models of engineering design tasks according to Sriram et al. [Tong and Sriram 1992]

Routine design tasks	**Conventional routine design**	**Non-iterative knowledge-based routine design**	**Iterative, knowledge-based routine design**
Characteristics	• Linear constraints	• Top-down refinement	• Usually multiple constraints or objectives
	• Linear combination of real-valued variables	• One-pass through -> no iterations required	• Includes: backtracking, optimization and problem restructuring
Innovative design tasks	**Innovation via case-based reasoning**	**Innovation via structural mutation**	**Innovation by combining multiple knowledge sources**
Characteristics	• Design based on analogies with previous cases	• Refinement or modification of existing designs	• Combination of various approaches

2.2 Estimating potential benefits of design automation

As mentioned in the introduction, inhibitions against implementing design automation exist due to uncertainties regarding the potential benefits. This paragraph reviews methods for estimating potential benefits of design automation applications and approaches that verify success of application of design automation in industry.

Multiple qualitative approaches that estimate potential benefits of design automation have been published in literature [Cederfeldt and Elgh 2005], [Smith and Bardell 2005], [Forza and Salvador 2006], [Emberey et al. 2007]. Frequently used criteria include product and process maturity or repetitiveness, i.e. if the task solving procedure can be formalized and if it is reasonable to automate from an economic point of view. Other approaches aim at more quantitative evaluation of potential for design automation based on design process assessment according to lean management principles [Verhagen et al. 2015] or measuring the complexity of product design itself [Summers and Shah 2010]. However, these approaches lack application and validation in industrial use cases and rely on the design process or the final product rather than the design task.

Similarly, multiple studies on post-project evaluation have been conducted in order to highlight the benefits of the applied methods. Qualitative benefits include acceleration of tendering, standardization, improvement of cost estimation, shorter time-to-market, higher throughput and faster customization. Quantification of success is mostly linked to time savings within design processes [Chapman and Pinfold 2001], [Colombo et al. 2005], [van der Laan and van Tooren 2005], [Cederfeldt 2006], [Kulon et al. 2006], [Emberey et al. 2007], [Danjou et al. 2008], [van der Elst and van Tooren 2008], [Corallo et al. 2009], [La Rocca and van Tooren 2010], [Ruschitzka et al. 2010], [Bermell-Garcia et al. 2012], [Raffaeli et al. 2013]. To summarize, even though there are multiple methods for estimating the potential of application of design automation, there is no systematic mapping from design tasks to expected benefits.

3. Novel design automation methods

In this section, different approaches from the research fields of structural optimization and computational design synthesis are analyzed according to the design tasks that were solved and the contributions that were achieved.

Jin and Li [2007] introduce a method for functional modeling and mapping of means to functions using frame-based knowledge representation as well as a rule base. They successfully apply the method to a case study on the design of a self-powered personal transporter. Similarly, Wyatt et al. [2012] use a model-based representation and depth-first search for creation of product architectures and use a vacuum cleaner design as an example. Kurtoglu and Campbell [2009] rather focus on generation of a knowledge-base for conceptual design derived from a design repository and demonstrate its application to component to function mapping. Münzer et al. [2013] use first order logic to create multiple solution alternatives of hybrid car concepts including generic mapping of graph-based concepts to bond graph-based simulation models for performance evaluation [Münzer and Shea 2015] and simulated annealing for optimization of design variables. Similarly, Bayrak et al. [2013] apply their method to generation of optimized hybrid car concepts, however, based on bond graphs and heuristics for generation of optimal designs. Moullec et al. [2013] demonstrate a method for system architecture design based on bayesian networks which is able to handel fuzzy inputs and apply it to radar antenna design. Hutcheson et al. [2006] use a functional concept as input and maps components from a library to yield optimized solutions by means of a genetic algorithm and apply it to power-heads for portable tool family design. Also relying on a predefined functional model, Wu et al. [2008] create simulation models of electro-mechanical designs for optimization of the building blocks internal variables based on a genetic algorithm. Bolognini et al. [2007] introduce a hyper-graph based method that uses simulation based performance evaluation for yielding optimized solutions for multidisciplinary design tasks. The approach is validated by means of design of electrical microresonators. Helms [2013] uses a graph grammar based approach in combination with stochastic search for generation of multiple solutions of a large-scale configuration problem, namely design of aircraft cabins. Lin et al. [2009] use a spatial grammar, simulated annealing and domain-specific simulation models for generation of multiple optimized solution alternatives of gearboxes, meeting both functional and spatial constraints. Baldock et al. [2005] present a method for structural optimization of a large-scale design problem, i.e. design of the bracing topology of a highrise building. Stochastic search is shown to exceed the performance of conventional design automation approaches. Shea and Smith [2006] use a spatial grammar and simulated annealing for structural topology optimization of transmission towers and Coorey and Jupp [2014] use model-based representations and random generation as well as a physics based-algorithm for design and optimization of architectural floor plans. Lastly, Hoisl and Shea [2013] introduce a spatial grammar based method for generation of 3D, geometric solution alternatives. The approach only considers spatial aspects and is applied to several examples including the generation of robot arm concepts.

3.1 Design task analysis

The design tasks used in the literature selected for this paper are categorized according to the measures introduced by Cagan et al. [1997] (see Table 3). In addition to these measures, the column *approach* lists the type of representation for knowledge formalization used and the search or optimization algorithm. The last column *Simulation* denotes whether a mapping to simulation models for performance analysis is performed or not.

Following Cagan et al. [1997], all listed methods either pursue the purpose of optimization or constraint satisfaction. Most of the considered methods use mixed numeric and symbolic relations due to reasoning methods that are based on symbolic relations, as well as the use of numeric optimization methods. However, Jin and Li [2007], Kurtoglu and Campbell [2009] and Hoisl and Shea [2013] apply only spatial relations for representation. Whereas Hoisl and Shea [2013] focus on 3D spatial design including function only implicitly, the other approaches focus on functional synthesis where numeric evaluation is often not feasible [Jin and Li 2007]. Regarding the spatial aspects of the treated design tasks, one can see that methods considering spatial aspects make up about 50 percent. However, multiple different categories of tasks can be identified within these two sets: first, tasks where functional synthesis for conceptual design is performed and components are assigned to functions, i.e. methods by Jin and Li [2007], and Kurtoglu and Campbell [2009]. Next, tasks where system architectures are designed by means of functional building blocks, however, intrinsic variables are assigned in order to meet performance criteria. Methods belonging to this criterion comprise Wyatt et al. [2012], Moullec et al. [2013] and Bayrak et al. [2013]. Building upon the FBS methodology [Gero and Kannengiesser 2004], Helms can be seen as belonging to both functional and system architecture design since system design requires precedent functional synthesis. Additionally, methods that map components to existing functional models and optimize corresponding variables, Hutcheson et al. [2006], or only perform optimization of design variables for a given system architecture, Wu et al. [2008], can be identified as system architecture optimization tasks. The method by Münzer et al. [2013], [Münzer and Shea 2015] both generates system architectures and performs optimization of the corresponding variables, hence, lies on the interface of both categories. To summarize, categories of non-spatial design tasks comprise functional synthesis, system architecture design and system architecture optimization.

For tasks where spatial relations are the focus, Lin et al. [2009] apply a spatial representation for solving of both a spatially and functionally constrained design task. The methods by Bolgnini et al. [2007], Baldock et al. [2005], Shea and Smith [2006] and Coorey and Jupp [2014] focus on structural and architectural design where functions are implicitly fulfilled by the overall topology of the design. Hence, Lin et al. [2009] is categorized separately for tasks with both focus on spatial and performance constraints. Hoisl and Shea [2013] consider solely spatial aspects in order to solve a 3D embodiment design task where function is only implicit. To summarize, tasks considering spatial aspects can be solved by usage of spatial representations and are distinguished by type of usage for solving both spatially and functionally constrained tasks, topology optimization problems or pure embodiment design tasks.

Four of the methods also evaluate time-dependent behavior of generated solutions, i.e. Münzer et al. [2013], [Münzer and Shea 2015], Moullec et al. [2013], Bayrak et al. [2013] and Bolognini et al. [2007]. Whereas Moullec et al. [2013] use simplified models for performance assessment of design, the other methods apply advanced simulation techniques for performance evaluation. Considering structural simulation models, both Baldock et al. [2005] and Shea and Smith [2006] integrate automated structural simulation for performance evaluation.

Regarding the type of input parameters, Moullec et al. [2013] propose a method to account for uncertainties within parameter values. Similarly, Hutcheson et al. [2006] assume uniform distribution of parameter values when generating design alternatives.
Having a look at the used types of variables, most methods consider both discrete and continuous variables. The only exceptions are the methods by Jin and Li [2007] and Kurtoglu and Campbell [2009], who consider functional building blocks only, and Baldock et al. [2005] and Helms [2013], which use fixed building blocks, i.e. seat types for Helms [2013] or trusses for Baldock et al. [2005].

Table 3. Categorization of design automation methods

Case	Objective	Relations	Parameters	Variables	Approach	Simulation
Baldock et al. [Baldock et al., 2005]	Optimization	Numeric / symbolic; spatial; static	det	dis	Bracing topology / deterministic & stochastic pattern search	yes
Shea and Smith [Shea and Smith, 2006]	Optimization	Numeric / symbolic; spatial; static	det	dis / con	Spatial graph grammar / simulated annealing	yes
Hutcheson et al. [Hutcheson et al., 2006]	Optimization	Numeric / symbolic; non-spatial; static	sto	dis / con	Model-based / Genetic algorithm	-
Bolognini et al. [Bolognini et al., 2007]	Optimization	Numeric / symbolic; spatial; dynamic	det	dis / con	Graph grammar / multi-objective burst optimization	yes
Jin and Li [Jin and Li, 2007]	Optimization	Symbolic; non-spatial; static	det	dis	Frame-based / genetic programming & genetic algorithm	-
Wu et al. [Wu et al., 2008]	Optimization	Numeric / symbolic; non-spatial; static	det	dis / con	Bond graph / genetic algorithm	yes
Lin et al. [Lin et al., 2009]	Optimization	Numeric / symbolic; spatial; static	det	dis / con	Spatial grammar / simulated annealing	-
Kurtoglu and Campbell [Kurtoglu and Campbell, 2009]	Constraint satisfaction	Symbolic; non-spatial; static	det	dis	Graph grammar /breadth first	-
Hoisl and Shea [Hoisl and Shea, 2013]	Constraint satisfaction	Symbolic; spatial; static	det	dis / con	Spatial grammar / randomized generation	-
Wyatt et al. [Wyatt et al., 2012]	Constraint satisfaction	Symbolic; non-spatial; static	det	dis / con	Model-based / depth-first search	-
Helms [Helms, 2013]	Constraint satisfaction	Numeric / symbolic; spatial; static	det	dis	Object oriented graph grammar / stochastic search	-
Münzer et al. [Münzer et al., 2013], [Münzer and Shea, 2015]	Optimization	Numeric / symbolic; non-spatial; dynamic	det	dis / con	Graph-based object oriented metamodel/ SAT solver & simulated annealing	yes
Moullec et al. [Moullec et al., 2013]	Constraint satisfaction	Numeric / symbolic; non-spatial; dynamic	sto	dis / con	Bayesian network / heuristics	-
Bayrak et al. [Bayrak et al., 2013]	Optimization	Numeric / symbolic; non-spatial; dynamic	det	dis / con	Bond graph / heuristics	yes
Coorey and Jupp [Coorey and Jupp, 2014]	Optimization	Numeric / symbolic; spatial; static	det	dis / con	Model-based / random generation & physics based	-

As shown in Table 3, the entire set of methods considers tasks containing implicitly dependent variables, e.g. mutually dependent building blocks. Thus, a categorization similar to the one performed by Amen et al. [1999], which categorizes design tasks according to dependence of design variables, is not feasible for a distinct mapping of design task characteristics to methods. Alternatively, in this study a categorization according to the abovementioned spatial characteristics of design tasks is proposed.

3.2 Benefits of Application of Design Automation

Prior to implementing design automation in industry, companies need to estimate the potential benefits resulting from the application of design automation. Amen et al. [1999] conducted a survey within twelve companies to determine motivating factors, i.e. objectives for implementation of design automation, specifically, of rule-based systems. A more recent study [Cederfeldt and Elgh 2005] confirms the primary objectives which are:

- *Quality assurance*: reduction of error rates in the design process
- *Lead time minimisation*: reduction of time needed for development of a new design, i.e. reduction of time to market
- *Establishment of knowledge base*: storage of product and process knowledge in the computational model

- *Need for highly optimized designs*: computational optimization is required; due to the wording, this metric is further referred to as *Optimal design* and denotes whether optimization algorithms are used or not
- *Laborious design task*: automation of cumbersome tasks, e.g. including large numbers of design variables and a highly constrained design space.

Another objective, *Generation of alternatives,* is added, since it is a major goal of methods associated to the field of computational design synthesis primarily motivated as a means to support ideation of designers [Chakrabarti et al. 2011]. These objectives are used in the following for qualitative analysis of the experienced benefits of method application. Gained results are listed in Table 4.

Quality assurance hereby refers to generation of validated designs. In particular, the studies using simulation techniques can be considered especially suitable for accurate and early evaluation of design candidates. Thereby, the risk of pursuing an infeasible solution candidate after computational generation can be avoided that is considered as error reduction within the design process. Further, through the encapsulation of design knowledge in the design automation system, once the system has been validated, only correct solutions are generated. This can reduce errors in design.

With respect to methods aiming at lead time minimisation, tasks where the number of variables and solution alternatives exceeds a possible manual exploration are tackled, e.g. by means of the method developed by Baldock et al. [2005]. Further, strongly time constrained tasks in early conceptual design are dealt with in the methods by Jin and Li [2007] and Wyatt et al. [2012]. More indirectly, Münzer et al. [2013], [Münzer and Shea 2015], Moullec et al. [2013], Bayrak et al. [2013] and Helms [2013], who all address knowledge intensive design tasks, similarly allow increasing the speed of product development, since reuse of knowledge as well as the use of simulation techniques have been shown to reduce development time [Thomke and Fujimoto 2000]. Thus, these studies not only reduce lead time, but also establish a formalized knowledge base.

Methods with the objective being optimization provide optimized designs as output. The method by Jin and Li [2007] is one of the only that aims at optimization of early conceptual designs, however, quantification of the design's performance is not possible at that early stage of the design process. Hence, they use qualitative measures for evaluation of results.

Table 4. Benefits gained through application of design automation solutions

Case	Quality assurance	Lead time minimisation	Establish knowledge base	Optimal design	Laborious design task	Generation of alternatives
Baldock et al. [Baldock et al., 2005]	-	x	-	x	x	x
Shea and Smith [Shea and Smith, 2006]	-	-	-	x	x	x
Hutcheson et al. [Hutcheson et al., 2006]	-	-	-	x	x	x
Bolognini et al. [Bolognini et al., 2007]	-	x	-	x	x	x
Jin and Li [Jin and Li, 2007]	-	x	-	-	x	x
Wu et al. [Wu et al., 2008]	x	-	-	x	x	-
Lin et al. [Lin et al., 2009]	-	x	x	x	x	x
Kurtoglu and Campbell [Kurtoglu and Campbell, 2009]	-	-	x	-	x	-
Hoisl and Shea [Hoisl and Shea, 2013]	-	-	-	-	-	x
Wyatt et al. [Wyatt et al., 2012]	-	x	-	-	x	x
Helms [Helms, 2013]	x	x	x	-	x	x
Münzer et al. [Münzer et al., 2013], [Münzer and Shea, 2015]	-	x	x	x	x	x
Moullec et al. [Moullec et al., 2013]	-	x	x	-	x	x
Bayrak et al. [Bayrak et al., 2013]	x	x	-	x	x	x
Coorey and Jupp [Coorey and Jupp, 2014]	-	-	x	x	x	x

Considering generation of solution alternatives, as stated above, a goal of CDS methods refers to creation of alternative designs. Additionally, stochastic optimization techniques are applied to generate multiple solution alternatives when searching optimal solutions. All methods considered in the selection

of this paper provide this benefit with exceptions being Kurtoglu and Campbell [2009] who use deterministic search for solution space exploration as well as Wu et al. [2008], who perform optimization for a design that is initially provided by the designer.
All methods treat laborious design tasks that involve intensive solution space exploration, e.g. Baldock et al. [2005], or require interdisciplinary domain knowledge, for instance Bolognini et al. [2007]. The method by Hoisl and Shea [2013] is used for creation and exploration of three-dimensional solution alternatives, thus rather aiming at enhancing ideation instead of automating a laborious design task since evaluation of performance of generated solution alternatives is neglected.

4. Linking design tasks, design automation methods and objectives

Combining now the findings of Section 3.1 and Section 3.2, a 2D map relating design tasks and objectives of automation can be created. This allows to map the introduced methods and relate the tackled type of design task to the experienced benefits.
As indicated in Section 3.1., a measure for categorizing the design task is the type of variables that are dominating the design task, i.e. whether spatial or functional aspects are in focus. Thus, the abscissa of the chart shown in Figure 1 ranges from pure abstract conceptual design to embodiment design tasks that focus on geometrical aspects of design including the subcategories of Section 3.1. Following Table 4, benefits that resulted from the design automation methods' applications are listed on the ordinate. This allows to locate the introduced methods in the chart and gives an overview what might be achieved by applying a specific method for a given design task.

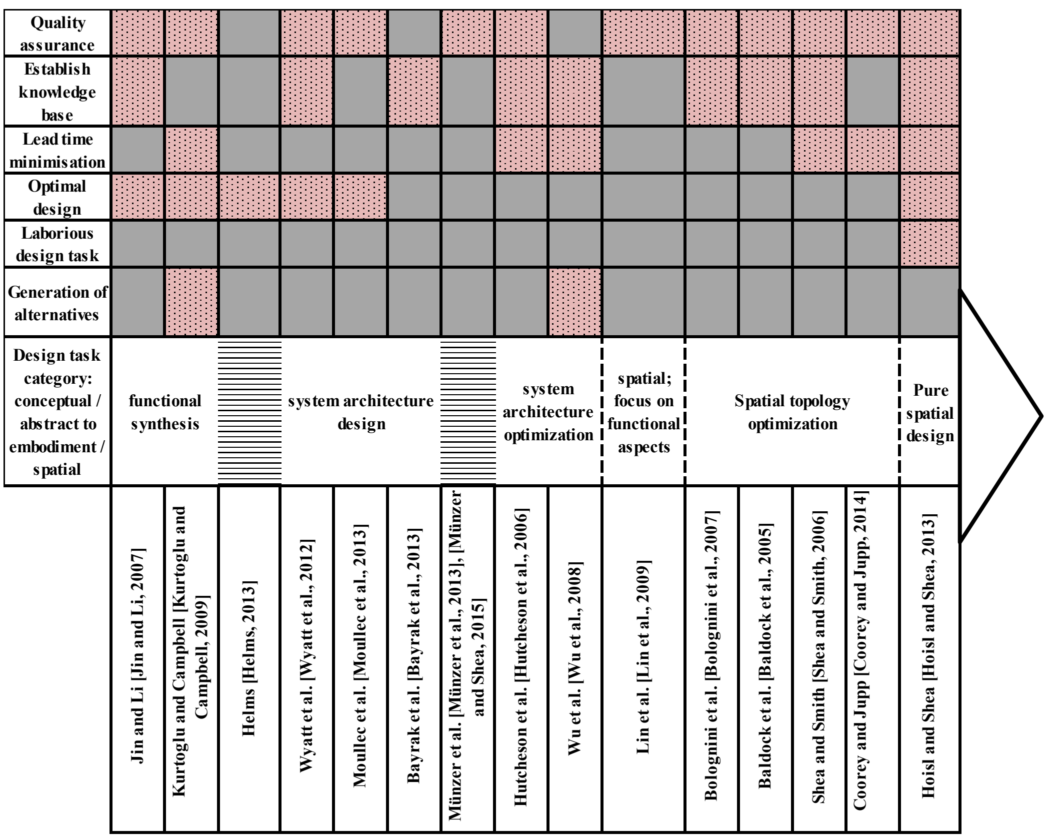

Figure 1. Mapping of design automation methods to design tasks and associated benefits. Abscissa refers to spatial aspects of the design task, whether it can be categorized to being conceptual or embodiment design, respectively. Categories based on spatial design task characteristics help to further differentiate the methods. The ordinate lists benefits experienced when applying the introduced methods. Areas highlighted in grey show where the methods have proven to be effective

The left denotes methods focusing on synthesis of functional models and assignment of conceptual models. Whereas Jin and Li [2007] focus on lead time minimisation of this time-constrained task, Kurtoglu and Campbell [2009] aim at establishment of a knowledge base for the early stages of design rather than time reduction or generation of alternatives. Methods regarding system architecture design focus on lead time minimisation, generation of solution alternatives, as well as automation of laborious design tasks. Bayrak et al. [2013] developed a case specific method, hence a generic knowledge base is not established. However, in contrary to the other approaches of this category, they applied genetic algorithms in order to yield optimized designs and apply simulation in order to guarantee quality assurance. Following the system architecture design, Hutcheson et al. [2006] and Wu et al. [2008] aim at optimization of already defined designs. Whereas Hutcheson et al. [2006] aim at generation of optimized solution alternatives, Wu et al. [2008] target at generation of one optimal solution by means of simulation, thereby guaranteeing the quality of the solution. Regarding design tasks focusing on spatial aspects, a method aiming at both functional and spatial design by means of full spatial representation is Lin et al. [2009]: spatial grammars and simulated annealing allow generation of optimized solution alternatives, storage of corresponding design knowledge and lead time minimisation. Next, methods focusing on structural and architectural optimization can be identified. Whereas Baldock et al. [2005] aim at lead time reduction, generation of alternatives and optimal design, Coorey and Jupp [2014] aim at establishment of a knowledge base. Bolognini et al. [2007] applies full simulation models for generation of validated designs. The set of methods apply stochastic algorithms in order to produce optimized solutions. Lastly, Hoisl and Shea [2013] treat pure spatial design, where function is integrated implicitly, without consideration of numeric evaluation of design. The major focus is on generation of solution alternatives to support ideation.

To summarize, one can observe that the type of yielded benefits is dependent on the type of algorithms applied, i.e. generation vs. optimization, deterministic vs. stochastic, as well as the integration of advanced simulation techniques.

5. Discussion

This paper provides a mapping between approaches in design automation, distinguished by the importance of functional and spatial aspects, and possible benefits. Therefore, given a design task with fitting characteristics, a suggestion can be provided, which approach could yield which benefits.

In contrast to the presented literature, this paper provides a categorization based on design task characteristics in order to provide less abstract measures for categorization that are suitable for practical use in industry and allow identification of similar design tasks. Furthermore, the created mapping is related to methods reflecting current state of the art of design automation.

Considering the entire set of methods examined in this paper and experienced benefits one can see that multiple methods aim to achieve different objectives even for similar tasks. This gives rise to an overview containing a design task categorization according to key characteristics, an overview of recent methods for design automation as well as objectives that can be gained through application of specific methods. To the best of the authors' knowledge, this is the first mapping of this type, where design task characteristics, automation methods and potential benefits of application are interrelated.

The mapping is proposed to ease the understanding in industry with respect to what type of tasks can be automated. Thereby, the introduced categorization according to spatial aspects should support identification of similarities. Further, the mapping of tasks to methods and objectives aims to increase the understanding of potentials of design automation application.

Still, it has to be mentioned that the investigated selection of papers solely represents a small part of methods developed in the field of design automation. A more comprehensive review is needed, also considering methods from other fields investigating design automation, such as knowledge-based engineering and configuration systems. Further, field tests and interviews to investigate suitability of the proposed mapping for practical use is needed.

6. Conclusion

By means of existing design task characterizations, metrics for potential of design automation application as well as a set of recently developed methods, a mapping relating the three aspects has been

introduced. Analysis of recently developed design methods according to an established set of design task characteristics is performed. Spatial aspects of the design task have been shown to be useful for mapping of design task characteristic to methods due to the manifold properties of automation tasks with this respect. The investigated methods range from automation of conceptual design tasks neglecting any spatial aspects to automation of generation of 3D designs, representing embodiment design.
Investigation of benefits experienced through application of the methods have shown that multiple methods satisfying different objectives for a similar task exist. Benefits of application range from pure solution alternative generation to satisfaction of all listed objectives, namely, quality assurance, lead time minimisation, establish knowledge base, optimal design, laborious design task and generation of alternatives. The type of benefits experienced strongly depend on the type of algorithms applied as well as the integration of advanced simulation techniques.
The contribution of this paper is a mapping from design task characteristics to potential benefits via design automation methods. This is expected to be a first step to mitigate obstacles for industrial application of design automation that exist due to uncertainties with respect to types of tasks that can be automated and what methods exist for automation. Future work includes validating the mapping by means of industrial case studies.

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