On AI Adoption Issues in Architectural Design

Identifying the issues based on an extensive literature review.

Mateusz Zwierzycki

1 Brandenburg University of Technology Cottbus-Senftenberg
1 mateuszzwierzycki@gmail.com

An analysis of AI in design literature, compiled from almost 200 publications from the 1980s onwards. The majority of the sources are proceedings from various conferences. This work is inspired by the Ten Problems for AI in Design (Gero 1991) workshop report, which listed the problems to be tackled in design with AI. Almost 30 years since the publication, it seems most of the Ten Problems cannot be considered solved or even addressed. One of this paper's goals is to identify, categorize and examine the bottlenecks in the adoption of AI in design. The collected papers were analysed to obtain the following data: Problem, Tool, Solution, Stage and Future work. The conclusions drawn from the analysis are used to define a range of existing problems with AI adoption, further illustrated with an update to the Ten Problems. Ideally this paper will spark a discussion on the quality of research, methodology and continuity in research.

Keywords: artificial intelligence, review, design automation, knowledge representation, machine learning, expert system

INTRODUCTION

In 1991, during the Twelfth International Joint Conference on Artificial Intelligence, a workshop led by John S. Gero took place to identify possible research avenues for AI in design. The result of that meeting is a report titled Ten Problems for AI Design (Gero 1991). This concise publication identifies and describes the following list of problems:

1. Representation in Design
2. Design Semantics-Coding and Decoding
3. Inference in Design
4. Combinatorial Explosion in Design
5. Indexing in Design
6. Dynamic Modification-Learning in Design
7. Generalisation in Design
8. Situation in Design
9. Creativity in Design
10. Evaluation in Design

The author relates the problems of AI with the problems of design, understanding that some parts of the list are more coincided with AI when others are general design problems. For instance: Representation in Design is said to be a problem both in AI and Design when Creativity in Design mostly yields deeply philosophical questions about the creativity of computers and algorithms. Even though the list is almost 30 years old, it seems some of the problems remain unsolved. An update on the Ten Problems is the main
Definitions
Artificial Intelligence. In the nature of all man-made tools is the desire to either replace or aid the human in his/her activities in changing the environment. While a simple tool such as a fork aids very simple tasks, more complex human actions require more advanced objects or methods. The complexity at which the necessity for intellect arises is reached whenever any information processing has to be done before, during or after the action taken. This is where the term Artificial Intelligence emerges - a tool which can help humans by performing a part of intellectual work (Bellman 1978) or tools which require some intellect to perform physical work (Kurzweil 1990) - i.e. recognizing objects in an image to navigate the environment or scheduling a plan to run a complex system.

Design. The definition of design according to the Cambridge Dictionary [1] is: “to make or draw plans for something, for example clothes or buildings”. “To design” is “to plan” - to foresee the future and the consequences of an item or action being planned, be it a building, computer system or a fork. A typical design is composed of information research, analysis and compilation of the processed information in the synthesis (Ullman 2010, p.17-19). The information is then used to prognose and decide the expected outcomes of the design. Auxiliary information is sourced through mid-process evaluation of selected design parameters. It is clear that design “foreseeing” feeds on information. A complementary response to the question “why to design?” is given by (Gero 1990), stating that the designer’s role is to “change the world through the creation of artifacts.” so that the world suits the human better.

Design Automation. Design can be bounded together with AI to accomplish Design Automation. This process requires Artificial Intelligence which is an aid or replacement of the human in the act of processing information. The indispensable presence of information both in AI as well as in Design is the reason this paper focuses as much on AI as it does on Knowledge Representation.

One example of Design Automation is Layout Generation, which in this text is referred directly to accentuate the popularity of this topic. Layout Generation is an act of creating or refining a building’s spacial configuration - either a 2D plan or a simplified 3D model.

Expectations
The first eCAADe proceedings were published in 1983 - during that time the Expert Systems were one of the most proliferated AI tools (Nilsson 2010, p. 291) - and this AI approach continued to be explored in the 80s by architectural design researchers. Throughout the next 37 years, different tools and techniques appear in the field: artificial neural networks, fuzzy logic, genetic algorithms, recommendation systems, clustering, and more recently convolutional neural networks and generative adversarial networks. The question arises - why in the most popular CAD packages currently available in the market, the only widespread AI tools are based solely on optimization? (Nagy et al. 2017, Autodesk Generative Design [2], Galapagos [11]) In the big picture, this paper tries to analyse existing research to find the answer to this question. The assumption is made that given a large enough sample of research papers, it will be possible to learn about the macro-scale characteristics of the research spectrum and draw conclusions.

METHODS
The collection of analysed papers was done manually by browsing the series of papers in the CumInCAD database [12]. Overall, 370 papers were selected. 332 papers were manually searched for existing keywords, out of which 148 had such data. 180 papers were used in the analysis of the tools used and problems approached. Narrowing the selection from 370 to 180 was done in a pseudo-random fashion. The following is a list of sources for the 180 papers used for in-depth analysis:
• 85 from eCAADe (Education and research in Computer Aided Architectural Design in Europe)
• 53 from ACADIA (Association for Computer Aided Design in Architecture)
• 12 from IJAC (International Journal of Architectural Computing)
• 9 from CAAD Futures Foundation
• 17 from various other sources

It is important to note that there might be more publications related to AI in the listed events/journals as the initial selection process was based on title, keywords or the author. The browsing process is measured in days, if not weeks, as a lot of time was spent on formatting the entries.

**Examination criteria**
The papers were analysed to obtain the following data: Problem (the general research Area of the approached problem in the paper), Tool (the class of the tool proposed to solve the problem), Solution (the solution to the Problem which uses the Tool), Stage (the stage of the works presented), Future work (the outlook for the Solution), Keywords and overall Paper Count. Obviously, not all the papers fit the evaluation criteria in the same manner. While most of the publications follow the Problem-Tool-Solution pattern, there is a significant amount of texts about other people's work or describing the history or properties of existing tools. These "meta-papers" are also included in the analyzed sample to cover a broader perspective of the field. It is assumed the Problem-Tool-Solution papers are usually closer to applied research, while the rest represents the basic research in the field.

**RESULTS**
The results are compiled in two parts: Quantitative Analysis and Qualitative Analysis. In the first part the analysis is used to reveal: the overall interest of AI in design research, the most popular research areas in the field, the most popular tools used by researchers and the occurrence of the keywords. The second part is a list highlighting the common qualitative issues identified in the study. Quantitative Analysis is based on the number of occurrences of specific Problems, Tools etc., and Qualitative Analysis discusses the content of particular papers.

**Quantitative analysis: Paper count, Areas, Tools and Keywords**

**Paper count.** Figure 1 shows the number of AI-related papers published each year. The total amount of found texts is 370 over the last 39 years. The first paper (Cullen 1983) appeared in the 1983 eCAADe proceedings, treating on Expert Systems for the teaching/tutoring process. In the proceeding years AI research efforts kept intensifying, with a growth peak around 1995-2005 when the number of papers published yearly remained on the same level. In the next decade (2010-2020) there seems to have been another growth period in the field. It is hard to pin down the exact reason why AI became more popular in the recent years, yet it is possible to write down a speculative list of incentives:

- AI becomes popular thanks to the maturity of Internet applications and data-oriented services like social media; research interest transpires to the architectural domain.
- Parametric modelling becomes widespread within academia with the popularity growth of software such as Grasshopper, Generative Components etc.
- Architectural research oriented academia grows
in size, which increases the number of publications overall, including the AI-related ones.

Within the eCAADe proceedings, there were 103 papers submitted in 2003, 117 in 2008, 149 in 2013 and 181 in 2018. ACADIA proceedings usually count around 60 papers in each edition.

**Areas.** This part of the analysis was focused on identification of research areas in the field - or in other words, what seemed the most interesting AI-related topic for the architectural design community. Looking at the Figure 2 it is quite evident there are 3 key research subjects, that is:

- **Knowledge Representation [KR]**
- **Design Automation [DA]**
- **Layout Generation [LG]**

While Layout Generation is in fact a task of automation, the amount of research done around this topic is so significant (Calixto and Celani 2015) it requires a category on its own.

The Knowledge Representation area leads the chart and it seems the activity of this research is constant. The range of tools used for KR covers: graphs, grammars, symbolic notations, databases, languages, discrete models, explicit models, frames, parametric models. There is a reason (Gero 1991) puts the problems of Representation and Semantics first on the list.

Design Automation is the second most popular research area, with multiple papers published each decade. While this might be the ultimate task for AI in architecture, problems with KR stay in the way. In this scope there are solutions using genetic algorithms, shape grammars, expert systems, genetic programming, self-organizing maps, cellular automata and most recently generative adversarial networks.

Layout Generation popularity earns a category of its own. A multitude of tools used for LG spans between genetic algorithms, spring systems, convolutional neural networks, generative adversarial networks and self-organizing maps. It is quite surprising that such a complex topic stays on top of the chart, given the collateral problems still unsolved - lack of semantically rich KR for layouts and most importantly, the problem of metrics and evaluation.

**Tools.** There seems to exist a range of sentiments in the Knowledge Representation area. Grammars (including Shape Grammars, but not exclusively) are
certainly a tool attractive for researchers for a long time having a constant number of papers published (Figure 3). There are more than 15 papers in the analysed texts using shape grammars one way or another, published in every decade. The popularity of this method probably roots in the simplicity of notation which makes it readable both for computers as well as humans (as compared with big databases or complex semantic networks).

Another favourite KR tool is Graph representation. Widely used for decades, KR emerges as a natural choice for researchers. One can speculate that floor plans are easiest to represent using adjacency matrices/graphs. While this representation carries only a small fraction of information about a floor plan, there seems to be no more popular representation.

When it comes to Design Automation and Layout Generation, the most popular AI-related tools used in those scopes are genetic algorithms (Calixto and Celani 2015). There is a peak of research papers on genetic algorithms between 2010-2015, which might be suggesting the rising popularity of Galapagos solver available in Grasshopper. This impression is quickly overturned with a look at the publications around that time (ACADIA 2012, eCAADe 2012 proceedings), which reveal the tools used by the researchers were mostly bespoke solvers.

**Keywords.** Finally the keyword analysis reveals a number of trends. From a list of 525 unique keywords, Figure 4 presents the 25 most popular ones with a number of occurrences. The most frequent keywords “parametric design” and “generative design” reflect the field interest in KR and information encoding. Right after these, the ubiquitous term “artificial intelligence” emerges together with “machine learning”. The rest of the keywords show a balance between the research areas and the variety of methods and problems. The higher amount of keywords found in the papers after the year 2000 might indicate the popularization of the Internet and search engines.

**Qualitative analysis**

Following is the classification of AI adoption obstacles. The causes are divided into two groups: endogenous and exogenous. Endogenous obstacles arise from the way the research is done - issues directly under control of the researchers. Exogenous obstacles will classify the issues induced by the research environment and practical limitations. It is an approach to write a comprehensive list of issues, even if some of them might not have a major influence on the AI adoption rate.
Endogenous issues

Lack of methodological consistency. Assuming architectural design is not a scientific discipline which follows the scientific method [5], it is irrational to require every paper to be guided by a purely logical thought process. Yet, within this field there exists a number of clear and logical problems. The papers which address these have to be scrutinized under the same requirements as publications in scientific disciplines.

Another methodological problem is the lack of means for evaluation (lack of good metrics), which in scientific disciplines is usually solved by a comparison against an existing solution. A quick glimpse at the Layout Generation research papers shows that these could greatly benefit by using that evaluation method. Tolerance for such methodological deficiencies may lead to a headache, similar to the Reproducibility Crisis [4].

The next methodological issue visible in the field is the lack of a proper evaluation of subjective properties, be it architectural or referring to UI etc. A sample size of 20 (a common size for a group of students), gives a 20% margin of error with 95% confidence level. With a sample size of 30 and a confidence level of 90%, the margin of error equals 15%. While (Lenth 2001) shows that those numbers are acceptable, the same text argues for a higher number of samples in long term experiments (how “long-term” is the design process?). Sample randomization can be an issue whenever the students are asked to evaluate part of the research.

Finally, a common issue with the majority of the analysed papers is the overly elaborate descriptions of the used methods. This can be simplified by referencing the paper which describes the method used and extending the description only to put it into the context of the presented research. While this does not directly influence the quality of the research, it greatly lowers the text comprehension for other researchers.

Wrong prioritization of the existing problems. Similar observations about generative design as pointed out by Davis [6] can apply to the more general field of AI in architectural design. For instance: prioritization of Layout Generation or Optimization, might introduce new (and more costly) problems to the process - a person has to review hundreds of options or set up a complex optimization solver routine (and run it multiple times to get a good understanding of a problem). The benefits of those new activities seem to not cover the additional costs.

As suggested by Davis “a more fruitful path seems to be taking the existing process and finding ways to enhance it with algorithmic smarts”. The author suggests tackling smaller problems with the example of spell-checkers and other typing aids. Based on the analysis of the AI-related papers it seems to be the successful path for some architects (Fagerström et al. 2012).

Overly ambitious projects. This was a problem back in the early 90s, during what could be considered an “early stage” of AI-oriented architectural design research. An appropriate illustration of the attitude towards AI in design is demonstrated by (Bayazit 1992), which shows the high hopes put in AI during that time. In the most recent years, the problem seems marginal.

Existing AI concepts are not applicable in design. Plenty of research done reuses the tools developed by computer scientists who made them to solve a particular problem. Is a design problem similar to any of those problems? This question currently remains unanswered and certainly needs more research.

The recent spawn of generative adversarial network research in design is of particular concern (Figure 3) Are GANs able to learn well enough to generate floor plans of human-like quality? That is a binary decision - anything of lower quality will be considered a failure and will prevent the designers from using such a tool.

A majority of papers reuse tools like neural networks, clustering methods etc., but maybe some architectural problems require new kinds of tools, specific for this discipline. Basic research needs to be done.
Lack of representation methods. The representation problem emerges any time a researcher tries to use machine learning methods. Just as good BIM and parametric models are for general representation, these models might not be equipped with the information necessary for machine learning. The example of Topologic (Aish et al. 2018) models for structural analysis and energy simulation shows that in some cases, a new type of representation might be the easiest way to utilize new tools. The need for better representation methods is visible in the popularity of Knowledge Representation research (Figure 2).

Innovation. How innovative is another paper on daylight optimization or layout generation? It seems the major focus in such research is put on the part of basic research. Accordingly to (Edison et al. 2013), the process of innovation is:

“...implementation of a new design, analysis or development method that changes the way how products are created”

Which accents the product as the final outcome of innovation. There are 31 papers listed in (Calixto and Celani 2015) using GA for layout optimization (and the GA is the most common tool used - see Figure 3), yet no CAD package comes with an integrated out-of-the-box tool based on that research. The solutions exist, what is left is to develop the product - which requires innovation in developing other parts of the workflow - user interface, representation methods etc. This is reciprocal with the wrong prioritization of the research problems.

Exogenous issues

Interface problem. With AI working with big amounts of data, the interface problem appears as one of the main issues with AI adoption. This was partially solved with the introduction of parametric modelling (which enabled optimization solvers), yet it seems other AI tools can’t benefit much from the new representation method. The key concern for research on UI and representation methods should therefore be the amount of information humans can transfer to a computer within a finite amount of time.
search environment seems rich and on the right track to solve the Ten Problems listed in (Gero 1991). As will be described in this part, it appears there must be some adjustments made in the research to overcome all of the problems. The listing below scrutinizes the current state of each one of the Ten Problems.

**Representation in Design / Design Semantics--Coding and Decoding.** The problem of representation and design semantics is widely researched by multiple teams and institutions. With the introduction of Parametric Modelling and BIM, there now exists multiple ways of getting the computer to “know” what there is to be known. Knowledge Representation is the most popular research area among the researchers with 47 papers found as shown in Figure 2; “parametric design”, “generative design” are the most popular keywords (Figure 4). Even with the current interoperability issues (tackled for instance by Speckle [1] and projects such as Complex Modelling [10]), it appears that the research on those 2 problems is either done or underway. Missing is the representation methods developed especially for AI applications - e.g. GAN (Newton 2019) encodes floor plans as semantically poor bitmaps (which, according to “scruffies” might be the right way to use AI (Nilsson 2010, p.416-417)).

**Inference in Design.** The Inference problem seems to be currently neglected. Some basic research on symbolic approaches exists (Cha and Gero 1999), yet it’s far from a real-world application. This is reflected in the sudden loss of popularity of Expert Systems (Figure 3), which are tightly bounded with the Inference problem.

**Combinatorial Explosion in Design.** With the popularization of parametric modelling, combinatorial explosion is one of the problems most widely addressed by the researchers. There now exists a strong suite of optimization solvers [11] (Cichocka et al. 2017) (Vierlinger and Hofmann 2013) and solution space analysis methods (Harding 2016) (Stasiuk and Thomsen 2014) which tackle the combinatorial explosion using different strategies. Genetic algorithms are the most popular tool in the analysed papers with 25 occurrences (Figure 3).

**Indexing in Design.** While there is some common ground with the Combinatorial Explosion problem, the accent should be probably put more at existing databases and database querying. The only found example of a solution addressing this issue is Autodesk Design Graph [8], which uses shape-recognizing artificial neural networks to categorize geometries and put them in a relational database which the authors describe as a “design graph”.

**Dynamic Modification-Learning in Design / Generalisation in Design.** Just as with the Inference problem, there seems to be no major research on the problems of Dynamic Modification and Generalization in Design. Again, this is reflected in the disappearing popularity of Expert Systems.

**Situation Recognition in Design.** An interesting approach to Situation Recognition was recently presented in (Peng et al. 2017), where the authors used neural networks to classify various architectural spaces. No real-world software application currently exists which could guide the architect in the design process by recognizing problems and suggesting solutions.

**Creativity in Design.** This topic is common for almost all disciplines using AI (not just architecture). There seems to be some movement with Reinforcement Learning in computer science (Baker et al. 2019), yet none of it transpires to architectural research yet. Creativity is visible in the way researchers use the AI tools, yet the AI tools still lack creativity. None of the papers considered Creativity important enough to add a related keyword (Figure 4).

**Evaluation in Design.** None of the above mentioned problems can be considered relevant without an appropriate way to measure architectural qualities. Some advances were made by (Wilkinson and Hanna 2015) where the author used neural networks to speed up the wind turbulence pattern estimation. There still seems to be a long way to go for addressing the socio-ethical values and other “soft-values” of design as proposed by (Gero 1991).
Main Findings
Quantitative analysis revealed a range of problems, tools and solutions researchers used or worked on so far. A range of research areas and problems are presented and then evaluated against the Ten Problems in the Discussion. This comparison highlights a number of problems which are not yet approached by the research community.

Quantitative analysis identifies a range of issues with the existing research, which are divided into Endogenous and Exogenous groups. Endogenous issues are identified as: lack of scientific methodology, wrong prioritisation of the existing problems, overly ambitious projects, wrong application of the existing AI concepts, lack of representation methods and lack of innovation. Exogenous issues are identified as the interface problem, lack of computation power and institutional problems (funding and education).

Conclusions
The performed evaluation was driven mostly by the interest in AI, current stage of the research field and how it affects the design practice. This interest was additionally fueled by the (Gero 1991) Ten Problems for AI in Design and a sudden realization that a big part of the listed problems remain intact.

Thanks to the in-depth analysis of close to 200 papers, an update on the (Gero 1991) could be performed. Problems missing satiating solutions were helpful in finding the possible issues with adoption of AI in design, highlighting the research spaces requiring more attention.

It is in the best interest of the research field to self-reflect and question the current status - which this publication intends to motivate.

Future work
The list of analysed papers serves as an entry point in the research. Tackling one of the Ten Problems with the knowledge gained from the identified adoption issues will now serve as a reference for future steps. A self-evaluation is possible to be performed - first by questioning the research problem, then by questioning the importance of it for the field, finally ensuring the identified adoption issues can be addressed.

REFERENCES
Cichocka, JM, Migalska, A, Browne, WN and Ramirez, ER 2017, 'SILVEREYE - The Implementation of Particle Swarm Optimization Algorithm in a Design Optimization Tool', CAAD Futures, 724(June), pp. 151-169

Gero, JS 1991 ‘Ten Problems for AI in Design’, *Workshop on AI in Design*, IJCAI-91


Nagy, D, Villagi, L, Zhao, D and Benjamin, D 2017 ‘Beyond Heuristics A Novel Design Space Model for Generative Space Planning in Architecture’, ACADIA


[1] https://speckle.systems/