Performative design strategies: the synthesis process of a woven complexity

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Introduction

The design of buildings that perform well is a challenging task, which combines the careful blending of architectural form-finding with technical considerations of structural behaviour, building science aspects, economic considerations, and others. It involves the specification of a product that meets a wide range of performance requirements. At the same time buildings are complex, and by nature positioned at a specific location and context. Most buildings are unique, bespoke products with a custom-designed geometry, and consist of many parts and (sub)systems, which broadly can be categorized as building structure, façade, infill, and building services. The needs of the client are typically formulated in a design brief or architectural programme that varies from project to project. Mostly client needs are only general statements and need to be developed into more formal technical performance requirements. For instance, a client may ask for an office environment without glare. A technical performance requirement would express the lighting conditions in the office in terms of a Daylight Glare Index (DGI) and stipulate under what sky conditions this DGI needs to be studied; the requirement will also define exactly what level of DGI is still acceptable for this client, where a DGI of 16 is just perceptible, 20 is just acceptable, 22 is the borderline between comfort and discomfort, 24 is uncomfortable, and 28 intolerable. Obviously, the definition of such technical performance requirements needs to be based on in-depth expertise of the subject. The design process then needs to create building proposals that meet the requirements; in the specific example this will be the spatial definition of office space, complete with window openings, artificial lighting systems, daylighting and shading systems, and definition of the properties of all surfaces inside the space. Building design thus is a highly unique process which needs to be customized to the specific conditions of each individual case.

In the design stage, there is no actual building yet that can be studied in order to observe or measure performance; therefore, the only way to predict performance is to employ computational tools or to rely on extrapolation of previous experiences of the design team. As many tools relate to specific performance aspects such as thermal, lighting or acoustic performance, approaches have been developed that allow the sharing of information between tools; this ability of tools to share data is named interoperability. An initial framework for sharing data was the use of a common 'product model' for the storage of building information, with interfaces to specific performance analysis tools. Over the years this has grown into a wider, all-encompassing digital approach which is commonly known as building information modelling (BIM). In current practice, BIM tools such as Revit are now the mainstream technology used to define and capture building geometry and properties such as the cost of building elements, material properties, and order of construction. However, in the field of building performance prediction, many challenges remain. For instance, while thermal analysis is arguably one of the most developed fields of building performance simulation, there often is a significant discrepancy between predicted performance and measurement results once a building has been constructed and occupied.

Various actors may be involved in a design project, from a single designer/architect to a large design team that involves structural engineers, building science consultants, building services engineers, fire safety experts and others. Design teams may comprise different companies and may be globally dispersed, especially for large and prestigious projects. Within teams, there may be different organizational structures; for instance, Negendahl (2015) discerns between situations, where an architect is assisted by an engineer, where architect and engineer are partners, and situations where a hybrid practitioner emerges that blends the disciplines of architecture and engineering.

Architects are still following apprenticeship models when learning about design and in a way digital design tools do not really change this paradigm. Despite being focused on functionality, engineering design processes did get updated in relation to design thinking because of manufacturing processes and mass production demands. On one hand, one can argue that architects do not have to respond to these types of pressure but on the other hand, the level of requirements imposed in relation to the various aspects of building performance and behaviour cannot be addressed anymore through the use of Renaissance design methods.

Whilst design thinking has been somehow discussed in relation to manufacturing processes through digital fabrication and BIM, the decision-making process related to considerations of the different and interwoven aspects related to building performance still need further thinking. Functionality was condemned by the post-modernism movement but building technology and the sustainability movement made legislation, client and user requirements to evolve in the opposite direction. Designers now have to reconcile with the fact that they have to produce buildings that work, and in the future even behave according to predictions. Design-thinking and design processes need to be prepared to cope with this or they will be subject to embracing engineering design methods or deterministic decision support systems to quantify behaviour taking design control out of the hands of the architects.

This chapter invites designers to reflect on how they work, particularly exploring different types of design decision-making models available, which could be used in the different stages of the design process to better cope with addressing technological and sustainability requirements related to building performance. It critiques and situates the appropriateness of the different types of decision-making methods within the different design stages and highlight gaps to invite the community to further reflect upon.

Building Performance: Definition and tools

Building performance is a concept that is used by many authors, yet also one that often remains undefined. It has been noted that often '*technical articles of research tend to use the term "performance" but rarely define its meaning'* (Rahim, 2005: 179); this tends to apply to the building discipline but also to many other fields that use performance, such as the automotive, engineering, medical and sport sectors.

However, there is a body of work that defines system performance as an attribute that measures how well a system is able to meet intended system functions. Taking this definition further, one may look at building performance in three categories: performance of building as an object/system, performance of building as a construction process, and aesthetic performance. For each of these categories, a number of performance categories may be defined. For buildings as an object, building performance can then be defined as quality, resource saving, workload capacity, timeliness, or readiness. Examples in each of these categories would be thermal comfort (quality), efficient use of water (resource saving), number of passengers an airport can process per hour (workload capacity), ensuring heating/cooling schedules meet room use (timeliness) or reaction time of a lift system (readiness). For building as a process, typical categories will be cost, time, quality, safety, waste reduction and customer satisfaction. Building performance in terms of aesthetics is a category that needs further work, but typically relates to attributes such as creativity, interpretation and enchantment (de Wilde, 2018: 111). The building design process has to cater for all of these dimensions of performance.

Figure 1: three views of building performance (object, process and aesthetics)

- ***Building Performance Simulation***
  A key prerequisite for the design of buildings that perform well is the ability to predict future building performance. Instruments to do this are provided in the form of building performance simulation tools. In principle, these are computer programs that carry out advanced engineering calculations which in turn represent physical processes. These tools emerged in the 1960s and 1970s with the introduction of personal computing, and in response to concerted efforts in the field of building energy efficiency since the first energy crisis. General overviews of the development of the field are provided by Clarke (2001) and Augenbroe (2003); a genealogy of more specific thermal simulation tools is provided by Oh and Haberl (2016). These overviews show that simulation tools have evolved over the years and are often subject of continuous development rather than step changes. Some of the original engines like TRNSYS are still around today; others like DOE-2 and BLAST have morphed into the EnergyPlus simulation engine. More recent developments focus on the development of 'shells' around simulation engines, which make it easier for the tool user to enter geometry details and help modelling efforts through extensive defaults; examples of these are DesignBuilder, IES, OpenStudio and Safaira. More fundamental work looks at the Modelica programming language, and the reuse of building system models on the component level. Overall it can be observed that building simulation tool development is a rather slow process, mostly consisting of gradual improvement rather than step changes, and that the driving force is evolution rather than clean-slate design based on specific software development requirements (de Wilde, 2018).

  The science and application of building performance simulation is advanced and promoted by the International Building Performance Simulation Association (IBPSA). Similarly, the symposium series on Simulation for Architecture and Urban Design (SimAUD), an offshoot of the Society for Modelling and Simulation International, promotes the use of simulation amongst architecture researchers. Some of the other organisations that influence the development and application of simulation are the Chartered Institution of Building Services Engineers (CIBSE) and the Royal Institute of British Architects (RIBA) in the UK, and the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE).

- ***Building Information Modelling and Interoperability***
  Building information modelling (BIM) is the process or activity of generating and managing digital representations of buildings, including their geometry, physical and functional characteristics. From a buzzword around ten years ago (Eastman *et al*., 2011), this now has become a leading principle in the construction industry; in for instance the USA, UK, Singapore, Sweden and Finland the use of BIM is mandatory for all public sector projects. The underlying technology has grown from early efforts in building product models and building process models, where the product models describe the properties of the building as an object, whereas the process models describe the activities that are carried out with those objects. BIM fuses product and process models together in a joined-up digital environment. Early seminal work on this area is Eastman (1999). Typically, one will employ different applications within a design process, thus leading to a need for data exchange between these applications; the capability to do this is named interoperability.

  Typical BIM authoring software (tools that support the digital design of buildings) are for instance Autodesk Revit, Graphisoft ArchiCAD, and Bentley Architecture. The data exchange with building simulation software, mostly Building Energy Modelling or BEM tools, typically takes place via an intermediate format named gbXML. The name gbXML stands for green building XML and this is an industry supported schema for sharing building information.
  While BIM is clearly changing the way industry works, with many tasks now carried out in a digital environment, BIM also is subject to an element of hype. Ideas like intelligent BIM where there is seamless collaboration between actors and tools within one environment have significant hurdles to overcome and existing systems fall short of being able to deliver these ideas in practice, especially where building performance analysis is at stake.

In other disciplines, such as economics, the 'performativity thesis' is the concept that models and theory cannot only explain reality, but that their use also may shape and form that reality (Santos and Rodrigues, 2009; Vosselman, 2014). Translated to buildings, '*performative building design'* then becomes a building design process where one expects that the focus on building performance and the use of building simulation tools will lead to buildings that perform better. This idea of performative building design has a long tradition in the world of building research; see for instance Markus *et al.* (1972) or Clarke (2001). However, the collection of hard evidence for the impact of building performance theory and tools on resulting building performance is extremely difficult, as this would require the comparison of measured building performance data from a set of buildings designed with such theory and tools with similar data from a control group that did not have this intervention. While this type of data is very hard to obtain in the first place, further complexity arises from the potential noise in such an experiment: Improvements attributed to theory and tools may also stem from other influences, such as financial incentives, building regulations, or attitudinal shifts amongst various actors.

Performative Design

There is a significant number of efforts that aim to contribute to performative building design. These efforts are mostly embedded in a wide range of approaches such as green building design, eco-house design, sustainable buildings, although many of these remain relatively open-ended. Other approaches that are more specific on the role of performance, tools and building science knowledge are Passivhaus design (Feist, 1996), performance-based building (Bakens et al., 2005; Jusuja, 2005), performance-based building design (Becker, 2008) and high-performance building design as per ASHRAE certification. Another work emphasizes the need to consider a wide range of performance aspects, typically by bringing together actors with different contributing expertises early in the design process; this is often advocated under the term integral or integrated design; see for instance Glicksman (2008) or Pelken et al. (2013).

A wider discussion of design for performance takes place in the adjacent fields of product and systems engineering (INCOSE, 2015; Gilb, 2005). However, translation of ideas and concepts of those areas to that of building design needs extreme care: there are fundamental differences between these other fields and buildings in terms of product series, system longevity, upgrade/renovation, product transportability, and fabrication conditions. Some developments such as the use of robots in construction (Bock, 2015) or automated additive manufacturing (Labonnote et al., 2016) may be reducing some of these differences but change of the construction industry typically is a slow process.

In performative building design strategies, a crucial issue is the framing of the interaction between design process with theory and tools (Bleil de Souza, 2013; de Wilde, 2018). There are three main interpretations of this framing:

(1) The view that design takes place by a number of design experiments (exploration of different design options) which special characteristics distinct from scientific experiments (systematic variation of independent parameters);
(2) The view that design is essentially a process of finding solutions to design problems;
(3) The view that design can be seen as a series of decisions which depend on the type of problem and the knowledge of the decision maker.

Interestingly, this issue seems to be under-explored by most of the existing literature on performance-based building design (from aesthetic to building physics), with most work emphasizing a range of performance aspects that needs to be considered and then moving straight into claims about design support and optimization. As a consequence, the literature on the subject seems rather biased towards normative decision making for design, where authors describe how design ought to take place. This fits well with the knowledge base on decision making (Jordaan, 2005) and approaches such that of Utility Theory and Multi Criterion Decision Making (MCDM). In contrast, there is a very limited literature on design observations, with the work of Struck et al (2009), Harries et al. (2013) or Zapata-Lancaster and Tweed (2016) being some of the exceptions. There seems to be little reflection on the theory of naturalistic decision making (Klein et al, 1993), which focuses on a series of decisions as made by experts and where context awareness is crucial issue; yet it may be argued that this maps well to what actually happens in building design processes.

- ***Design Experiments***

  Under this view, each piece of design is treated as a ‘universe of one’ and problem and solution co-evolve through the ‘conversation’ the designer develops with the materials of the situation (Schon 1991). Designers engage in a process of testing and developing ideas (Coyne and Snodgrass 1991) through a cycle of move – appreciation – move, either using paper-based sketches or by manipulating form and exploring parametric changes using 3D digital models.

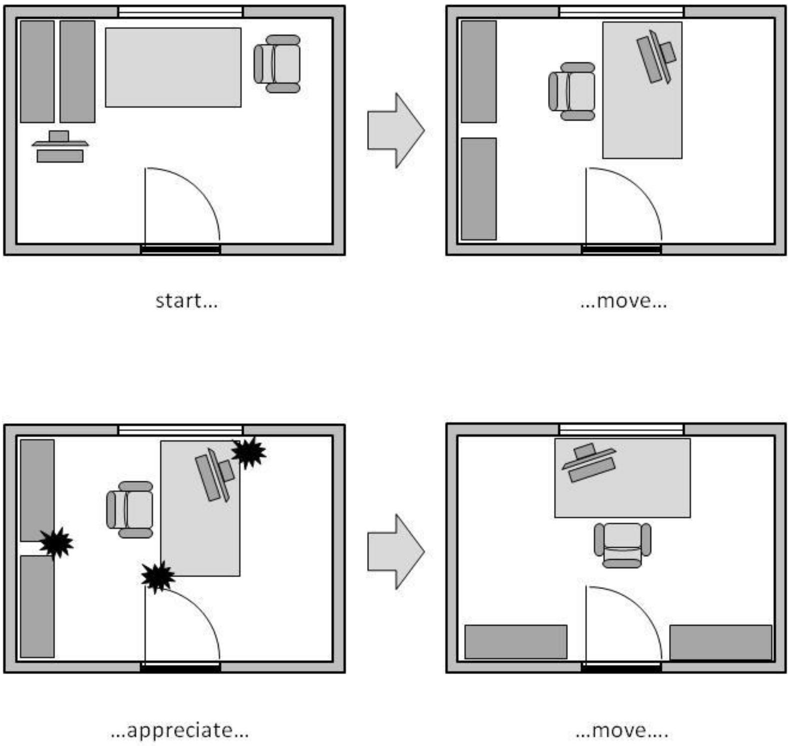

Figure 2: design experiments

“In order to formulate a design problem to be solved, the designer must frame a problematic design situation: set its boundaries, select particular things and relations for attention and impose on the situation a coherence that guides subsequent moves” (Schon 1988). “To frame a problem, you have to begin with a ‘what if’ situation to be evaluated” (Schon 1991). These ‘What if’ situations are actually experiments which according to Schon (1991) can be of three different types:

1. *Exploratory experiments (open-ended ‘what ifs’)*, experiments of exploratory nature in which actions/moves are undertaken without specific predictions or expectations associated to them but simply used to explore new options in terms of their outcomes. They are important types of experiments for designers to acquire new knowledge, build up repertoire, and gain insights.
2. *Move-testing experiments (simplified ‘what ifs’),* experiments undertaken with and end in mind with consequences judged in terms of achieving or not achieving this end. They are normally used for designers to affirm or negate moves in relation to the type of changes they produce. “Moves that get intended consequences are affirmed, whereas moves that do not get intended consequences are negated. At the same time, the practitioner appreciates the value of the situation, judging if (s)he likes what (s)he gets from the action undertaken in terms of local and global consequences” (Bleil de Souza and Tucker 2014).
3. *Hypothesis-testing experiments (quasi-scientific ‘what ifs’),* experiments used to confirm or disconfirm a hypothesis proposed by designers. “The best alternative is defined based on confirmations of the consequences of a given hypothesis together with predictions derived from alternative hypothesis that conflicted with observations. In hypothesis-testing experiments designers are constantly reframing the problem through a new hypothesis to be tested” (Bleil de Souza and Tucker 2014) but contrarily to scientific experiments, designers “seek to exert influence in such a way as to confirm not refute their hypothesis (Schon 1991).

Notably, design experiments have a particular characteristic: they are always related to “transforming the situation from what it is to something [the designer] likes better” (Schon 1991). Contrarily to scientific experiments which aim to add to the body of knowledge in a field by producing reliable and reproducible results and therefore provide evidence for technological or knowledge development, design experiments are assessed in terms of how desirables are their outcomes in relation to design intentions as well as how much they conform to or violate implications set up by earlier moves and how these moves fit into the designer's appreciation of the new problem created.

This dictates how the design process proceeds as "the perceived changes produced by earlier moves determine the need for and the direction appropriate to reflection in action" (Schon 1991). "The process is stopped when changes in the whole are satisfactory or when new features which give the situation new meanings and affect the nature of questions to be explored are discovered" (Bleil de Souza and Tucker 2014). Objectivity and distance are not mandatory, the results are biased and the progress is defined and controlled by designers while creating a large part of what they are trying to understand.

- ***Design Problems***
  Heavily based on the works of Simon (1973 and 1996) and Rittel and Webber (1974), this view proposes design is essentially a process of finding solutions to design problems either through simply pairing problems with solutions (Alexander 1977) or through the co-evolution of problem and solution (Cross 2001).

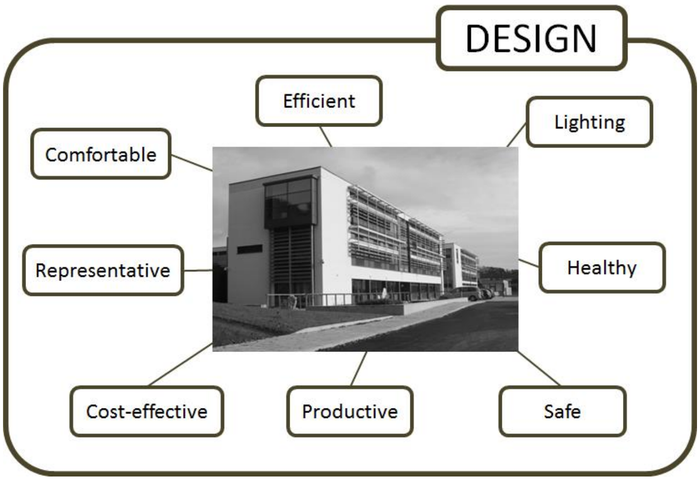

Figure 3: Sub-problems within the design process

The design process can be seen as a collection of sub-processes in which the type of problem definition evolves gradually from ill-defined or wicked to well-defined (Jones 1981, Cross 2001, Goldschmidt 2001, Harfield 2007, to cite a few). To rationalists, the concept generation stage can be seen as ill-defined as the problem is open to constant redefinition, have loose criteria and boundary conditions, and no clear aims making it impossible to define the means to achieve them. A more comprehensive view (Buchanan 1995, Zimring and Craig 2001, Coyne 2005, to cite a few) considers the conceptual generation stage as actually 'wicked' expanding the concept of ill-defined problem to acknowledge the social forces involved in shaping any kind of problem structure. Contrarily to Simon (1973), who proposes ill-defined problems can be decomposed into self-contained parts to become well-defined problems, with clear solution criteria and desired states to be achieved through potentially scientific means, wicked problems will "depend on the abilities and priorities of a problem solver not necessarily by a problem given" (Zimring and Craig 2001) to become well-defined. i.e. they would depend on designer's decisions about shifting the whole problem framing from constant problem restructuring to only discrete restructuring.

Thinking in terms of generic types of problems is useful because well-defined problems can be rewritten consciously into known structures, are likely to have specific constraints and can be set to follow predefined rules. They can be mapped into a familiar structure, previously defined by the design community, and the problem-solving activity is subsumed to a search through a solution space with clearly defined boundaries. The problem structure tends not to be questioned and the whole design activity becomes mainly a matter of optimisation. For wicked problems, the interpretation of the problem is up to the designer to handle which implies the discovery of a strategy to invent an appropriate problem structure to be used when formulating a design hypothesis. The problem space is explored from a particular perspective “in order to frame the problem in a way that stimulates and pre-structures the emergence of design concepts” (Cross 2004). Designers impose their views, positions and preferences in seeing the brief and in constructing the problems to be solved, defining and limiting the solution possibilities available to them (Harfield 2007). “Designers formulate a partial structuring of the problem space and then transfer that partial structure into the solution space, and so develop both problem and solution in parallel (…) or [they] first identify a partial structure in the solution space, such as a preferred shape or form, and then use that to structure the problem space” (Kruger and Cross 2006).

Thus, the conceptual design stage can be seen a stage in which problem and solution tend to co-evolve. I.e. the designer tries to understand the problem by attempting to solve it and solves the problem by attempting to understand it (Cross 2001) whereas the detailed design stage can be seen as well defined, meaning goals can be clearly set together with an action plan to achieve them.

- ***Design Decision-making***

  The predominant work in this view is concerned with normative theory which prescribes how design ought to take place, and how to select the best solution from a set; see for instance the paper by Becker (2008). The design process emphasizes another avenue of thought stemming from the work of Simon (1996: 118): that where design is in essence a process of making ‘rational choices among given alternatives’. This view goes back to the early theory of performative building design, with Markus et al (1972) already dedicating a full chapter of their seminal book to ‘design as a special kind of decision making’. The concept of rational decision making is well-established in engineering and supported by mathematics (Hazelrigg, 2012). It leads to a significant attention for the use of optimization techniques as exemplified by Machairas et al (2014) or Nguyen et al (2014). Yet Simon (1996: 27) already noted that one may opt to decide on an alternative that is ‘good enough’ rather than ‘best’ and introduced the verb ‘satisficing’ to indicate this type of decision-making. The aforementioned theory of naturalistic decision-making again emphasizes decisions but takes a longitudinal view where there are chains of decisions rather than single choices, and where expertise and situational awareness play important roles (Klein, 1993).

  The way decisions are made in itself is the subject of debate. Kahneman (2011) distinguishes between two systems, and intuitive and an analytical one, which help humans making decisions in different contexts. Hammond (1988) contents that these two systems are ends of a continuous system in which analysis and intuition alternate in cycles depending on changes to task characteristics over time. In his earlier work, Hammond (1988) relates the decision-making process to the type of problem interwoven with the knowledge of the decision maker. Dynamic decision making is examined based on a theory of task characteristics and task conditions in which the following well established types of judgement and cognitive activities are applied:

  - Intuition vs. analysis, opposite types of judgement
  - Patterns and Functional relationship seeking, cognitive activities not mutually exclusive.

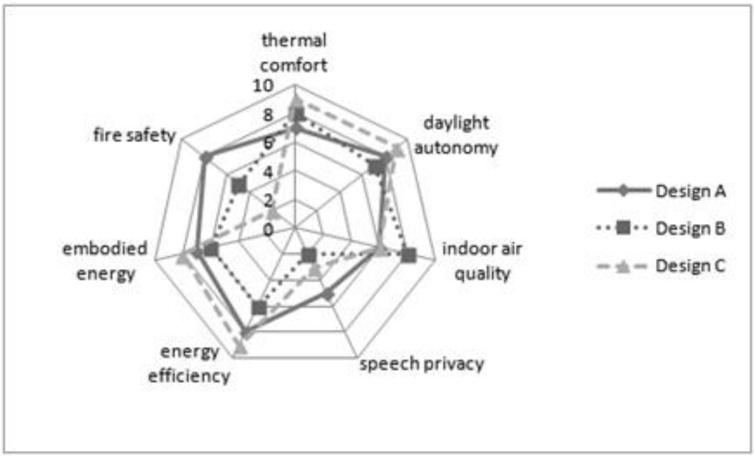

Figure 4: design decisions

When exploring task conditions in relation to the type of cognitive activity they induce, Hammond (1988) notes that pattern seeking is predominantly used with information prone to high degrees of conceptual organisation requiring coherent explanations. Patterns are commonly associated with visual image formation and pattern seeking implies data matching with a template acquired by training and/or experience. Functional relationship seeking is predominantly used with information which requires description and prediction, with no easy formation of visual images associated to them. Seeking also implies data matching with a template acquired through training and/or experience.

Both cognitive activities can match arbitrary, non-arbitrary or both types of templates. Arbitrary templates are mainly empirical (empirical patterns or empirically justified functional relations), normally lacking theoretical basis. Non-arbitrary templates are usually derived from theory, forming a coherent whole with elements inter-related by causal explanations (patterns) or containing rules which fit within a network of laws not necessarily empirically justified (functional relationships). Templates which are both (arbitrary and non-arbitrary), theoretically and empirically justified are normally considered the ones providing soundest basis for decision making.

Interestingly, Hammond notices that seeking for patterns and functional relations can be pursued either through intuition or analysis, depending on a set of 11 task characteristics mainly related to task cues (number, metrics, distribution, redundancy and display) and their relationships in the model, the nature of the task (prone to decomposition or not, prone to imposition of organising principle or not, degree of uncertainty) and the time period allowed for the task to be completed. Most of task characteristics listed in this model do resemble Simon's classification of well-defined vs. ill-defined problems. However, Simon missed details in relation to availability or not of organising principles, display of cues and time available for the task to be completed. Details which are well taken on board by Schon on his model of the practitioner conversing with the materials of the situation.

Hammond finishes his report on the use of judgement and decision making in dynamic tasks by relating intuition and analysis with a set of properties which have to do not only with the task but also with the decision maker's knowledge and understanding of the situation. He connects analysis with expert knowledge, cognitive control, awareness and high level of confidence in the method, and intuition with common sense knowledge, low cognitive control and low confidence in the method but high confidence in the answer. "Intuition (…) is generally considered to be an unconscious, implicit, automatic, holistic, fast process, with great capacity, requiring little cognitive effort. By contrast, analysis (…) is generally characterised as conscious, explicit, controlled, deliberative, slow process that has limited capacity and is cognitively demanding" (Dhami and Mumpower 2018). "...the key wisdom lies in being able to match modes of cognition to properties of the task" (Dhami and Mumpower 2018).

Challenges and Complexity

Exploring the 'fit' between the three main views of the design process and existing building performance simulation tools and digital support environments, we can make the following observations:

- ***Computational support for doing design experiments:***
  Digital representations of buildings are an excellent tool for undertaking design experiments once the building is already defined. They allow designers to explore and manipulate building representations in a simulated environment and study their consequences without having to invest in changes to an actual building, i.e. consequences of design experiments for building performance can be predicted. However, there is one important caveat: the analysis tools need to have the capacity to simulate the relevant systems and changes. This is a non-trivial issue; most models are simplifications of reality within one or two domains (e.g. thermal reality, lighting reality) meaning changes outside the simulated domain will not show an effect as manipulations may introduce systems or features that the analysis tool cannot handle, either because these tools normally have a series of limitations or because the changes produce effects outside the domain they deal with. Think of adding triangular geometries to a tool that is designed to only handle

rectangular geometries or adding acoustic panels to thermal simulations – the thermal effect will be assessed but the acoustic one will not.

Hypothesis-testing is arguably one of the main drivers for commercial building performance analysis; this is essential for ensuring that a design meets performance standards as mandated by building regulations or required to get certain certification levels in schemes like LEED and BREEAM. However, similar caveats arise: hypothesis-testing will be limited by domain being investigated and the assumptions and capabilities that are inherent in the analysis tool that is being used.

- **Computational support for solving design problems:**
  The notion of problem solving is more challenging in terms of computational support. Tools cannot cope with wicked or ill-defined problems as they are normally domain specific and rely on a series of input parameters specified by designers, so rules and equations can be applied to compute the effect of changes. The essence of simulation tools is based on modelling already well-defined problems, decomposed by the user into a series of known domain specific templates that can be solved by using existing programmable solutions and then recombined into a large system to assess its response to a series of domain specific criteria. Tools like TRNSYS and EnergyPlus include predefined models for a series of these templates which can be toggled 'on' or 'off' according to user needs. However, these predefined models severely limit the solution space. An alternative is the use of the Modelica to combine templates, with full access to model equations and interlinkage; imposing higher levels of computer literacy on the users.

  The idea of well-defined problems can also be extended to parametric design, where the computer generates design solutions by running many permutations of design parameters, capitalizes on the ability of the computer to handle large amounts of data; however, such approaches are limited to the predefined parameter range and hence 'think inside the box', even though they may outperform human creativity. To a certain extent, this idea also fits with BIM when seen as strictly a 'product modelling'. If seen as a 'process modelling', BIM can potentially open up other avenues where software may indeed support 'out of the box' thinking and where the ability of computers to handle countless building alternatives in parallel may yield surprising results.

- ***Computational support to design decision making***
  Simulation tools fit well with analytical judgement and are suitable to be applied to tasks after functional relations to assess performance are identified. They provide lists of domain specific templates for either theoretically and/or empirically justified relationships (e.g. fluid flow, thermodynamics) bringing computational support to expert knowledge through well accepted methods promoting controlled environments for domain specific experiments to be undertaken. By contrast, they are normally unsuitable to intuitive judgement, lacking 'the big picture' by being domain specific, forcing the explicit declaration of variables and demanding high cognitive effort to be operated.

  However, this should not exclude them to assist in pattern seeking, an under explored field which could bring benefits to certain domains as well as to non-expert users. Simple algorithms for template matching could be embedded in simulation tools to support pattern seeking in performance queries and performance assessment (Bleil de Souza and Tucker 2015). Machine learning techniques could be used to implement knowledge management schemes for design decision making by aiding designers to abstract real problems into domain specific templates facilitating modelling activities, supporting simulation settings and the application of analysis processes to assess performance as well as the understanding of limitation and uncertainties associated with results, facilitating knowledge transfer and knowledge sharing (Tucker and Bleil de Souza 2016).

Conclusions

Considering that none of the interpretations of framing interactions between the design process with theories and tools are mutually exclusive, opens a wider discussion in terms of the roles of analysis and creativity in design.

Performative design requires both creativity and analysis. Many efforts in the field fail to span the wide area that needs addressing, and take very simplified views of that is needed on the other side, ignoring some of the deep complexity that needs to be taken into account:

- Architects who do not want to do analysis, architects who cannot do analysis because they don't have enough knowledge, architects who think relying on consultants is enough, architects who do want to do analysis, architects who are full of intentions but cannot at all transform their ideas into practice, etc.
- Engineers who focus on analysis and optimization, investing a lot of time and energy to explore a specific problem/issue while the overall design process may move on and render all efforts redundant, and who may show a lack of creativity and tendency to stick with known solutions.

However, in designing buildings that meet the performance requirements of the client, both creativity and analysis are needed. This limits the prospects of cook book recipes that fail to allow for innovation and iteration. The need to combine creativity and analysis leads to a need for deep subject knowledge in areas such as building science; without mastering of the basics this is hard to implement. Unfortunately, the typical design curriculum and the amount of technical knowledge that it contains falls short of what is needed. At the same time engineering are overly based on scientific analysis, and need more constructivist teaching, teaching of using fundamentals in design, and student engagement with experimentation in loose and creative way.

Existing analysis tools are typically not designed to support building design; they are suitable for checking whether designs meet regulatory targets but should be redeveloped to allow designers to learn and experiment. Data transfer as inherent in interoperability approached and deeply embedded in current BIM technology is useful but does not solve deeper issues that are related to the role that tools play in design. Schon experiments may be a good starting point for revisiting the tools used in the industry. These experiments are powerful generic descriptors for how decisions are made regardless of a decision-making classification system; they encompass normative as well as naturalistic decision-making process all in one in terms of the rationale and types of actions proposed.

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