Models in Engineering Design. Generative and epistemic function of product models

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Abstract

Engineers interact with their products and processes largely through models, however rarely reflect about the nature of these models and how technical possibilities and actions are affected by the models' properties and characteristics. Models in engineering describe the product, but at the same time also shape and create them. This clearly distinguishes them from scientific models that primarily aim to describe a certain target system. While over the last decades or so, there has been a growing body of literature on models in the sciences, much less research has been done on models in engineering design. In this chapter we aim to fill this gap by looking at the epistemology of design from the model point of view. In particular we suggest a classification of different types of models used in engineering design and compare them to models used in scientific research. This is not an encompassing map of models in engineering practice, but we aim to identify key categories of models with regards to their relationship to their targets. We contend that the function of models in design cannot be fully captured when focusing on the representative aspects of models alone as is usual in contemporary philosophy of science.

Keywords

Models; models in science; engineering design; representation

1 Introduction

In engineering design, engineers interact with their products and processes largely through models, but they rarely reflect about the nature of these models and how technical possibilities and actions are affected by the models' properties and characteristics. The design process is largely a process of creating, manipulating and using models during which the models themselves evolve and are repurposed multiple times. Both design and model are ambiguous terms in a very similar way (Poznic, in press). Both terms can be used to mean a thing (designed artefact/design or model) or a process (design*ing* or modell*ing*). This paper focusses on product models used in the design of physical engineering products, where often very complex physical products are created to meet physical requirements. By contrast software design is not concerned with a physical product unless it is embedded in one, so that some of the arguments discussed in the paper don't quite fit software engineering. While process models play an important role in design and raise interesting epistemic questions (see Eckert and Stacey, 2010) they are beyond the scope of this paper. However unlike the science community[1], the engineering design community has a strong interest in process models (see for example Browning and Ramasesh (2007); Wynn, 2007).

Divergent interpretations of the context, content, purpose or role of models is a significant cause for (sometimes unnecessary) iterations in design processes; and therefore has a profound effect on both the product and effectiveness and efficiency of the process. Iteration plays an important part in exploring design alternatives and to resolve problems arising in the design process. For example designers create multiple models of the shape of a consumer product like a vacuum cleaner to discuss alternatives with each other. These may be in the form of sketches, technical drawings, computer aided design (CAD) models, or so-called blue foam models that are rapidly cut out three-dimensional shapes. Designers run focus groups with users to understand their responses to the product and potential requirements they might have overlooked. However, iterations take time and resources and can jeopardize refining the design at the end of the process. Such iterations often arise from incomplete or ambiguous information contained in the models (Stacey and Eckert, 2003), as well as a lack of understanding of the nature of models and the relationship a model has to reality (Eckert and Stacey, 2010). Hence there is some hope that a closer look and better grasp of the modelling involved improves the whole design process.

Models also play a fundamental role in the sciences. They are central epistemic and pedagogical devices in the process of scientific discovery. For example, the standard model of particle physics provides the current standard explanation and understanding of the most fundamental physical processes at subatomic scale. It is thus today an important epistemic device.[2] Bohr's model of the atom, on the contrary, which describes the motion of the electrons around the nucleus in analogy to the motion of the planets around the Sun, is clearly outdated. However Bohr's model still proves useful in teaching science and thus even today fulfils a pedagogical function. It helps to understand, for example, as to how the subatomic movement distinguishes itself from the classical planetary motion, i.e. that electrons do not move on fixed orbits.

While over the last few decades a growing body of literature on models in the sciences has emerged, much less research has been done on models in engineering design. In this chapter we make a first step to bridge this gap by looking at the epistemology of design

[1] The philosophical literature does not dwell on the details of modelling scientific practice. Scientific processes are discussed today rather in the context of the sociological study of science and technology. An example provides the actor-network theory that originally aims to describe processes of innovation and knowledge-creation in science and technology (e.g. Latour 1987). Psychological studies of scientific processes, e.g. Dunbar (1997) has been picked up in the artificial intelligence literature and in creativity research (e.g. Sawyer, 2011; Holyoak and Thagard, 1997).
[2] Notwithstanding its name, the standard *model* is often seen also as a *theory.* We will briefly turn to the intricate relationship between model and theories in the following section

from the model point of view. We ask what the engineering design literature can learn from the models in science debate and how, vice versa, philosophy of science can learn from design. In science as well as in engineering, various different objects function as models: From concrete material objects like scale models or animal models in the life sciences, where living special-breed animals are used to test drugs in place of the human organism, to abstract models that make use of mathematical equations or computer simulations. However there are also seeming differences between models in science and in engineering design. For example, engineering models typically model specific designs. Only rarely are engineering design models created with the intention of reusing them. Nonetheless, in practice the models will often be re-used in different circumstances. This may lead to problems and iterations in the design process. At first glance, models in the sciences seem to be of a different sort. They often model repeatable and repeated phenomena, such as gravitational forces between two massive bodies, and are usually on a rather high level of abstraction. However these are only one type of models used in the sciences. Other models exist of very specific phenomena at a much lower level of abstraction. These models are often not intended to be reused. Examples can be found, for example, in the geosciences with models to explain specific rock formations or models for climate change. Just like in engineering practice, these models can get reused despite not being set up for reuse.

Philosophy of science has traditionally been very strongly influenced by physics as many of the philosophers of science themselves have a background in physics. However, in recent years the interest of philosophers in other sciences has grown and in particular climate science with its mixed methods and clear societal need has brought new issues into focus. The physics focus of philosophy of science suits reflection on the aspects of product models in engineering which are concerned with the physical properties and behaviours of products and their components. Modelling of physical properties of products have become a mature area and is now well supported with computer tools and modelling techniques. In recent years there has been a shift from thinking of engineering products only as physical product to thinking of them as socio-technical systems, which interact with humans and the environment. The behaviour of both humans and environment is increasingly modelled explicitly and often simulated in computer systems.

In studying models in design, the paper is organized as follows. In Section 2 we give a short overview over the philosophical discussion on models in science. Section 3 reviews the literature on models in design and tries to draw a first comparison to models in sciences. In Section 4 we develop a classification of models in design and zoom in on differences and commonalities between models in design and models in the sciences. Just as in the sciences, models in design represent a certain target system. However in design, models fulfil also other central purposes that cannot be reduced to their representative function alone. We refer to this as the generative function of models. Quite generally, however, most of the seeming differences between models in science and models in design prove on close inspection to be differences in degree rather than differences in principle. Nonetheless awareness about these differences help to understand both design and sciences better. The paper finishes with a conclusion in section 5.

Before we begin our discussion, let us allow a word of caution. With this paper on models in design we want to reach two rather disjoint communities: philosophers of science working on models as well as design scholar. Much of what we say about models will thus remain cursory or introductory for one of the audiences.

2 Models in the sciences

In the 1930s Carnap (1938) still famously remarked that 'the discovery of a model has no more than an aesthetic or didactic or at best heuristic value, but it is not at all essential for a successful application of the physical theory'. Understanding of the importance of models in scientific reasoning and scientific theories has developed slowly over the past several decades in the philosophy of science. At the same time the use of computers and other technologies in scientific research has increased the range and power of different types of model.

2.1 Different types of models in science

We can find a whole plethora of models in the sciences, whereby the individual models seem to fulfil various functions. Hesse (1963), for example, distinguishes between *material models* and *formal models*, where the latter can be *analytic* or *constructive* models. Examples of material models range from Watson and Crick's original tangible metal stick model of the DNA as a double helix, to animal models as used in the life sciences. Analytic models are mainly mathematical models. Examples comprise the standard model in particle physics, or the Black-Sholes model of the evolution of asset (e.g. stock) prices over time. Though of course here the mathematical equation is essential, most authors do not equate the model with the mathematics, i.e. the equations, alone (e.g. Frigg 2010). These analytic models are contrasted by constructive, i.e. computational models. Today, Hesse's two-fold distinction is sometimes replaced by a threefold one where computer simulations are explicitly distinguished from mathematical models (e.g. Weisberg 2013). A lot of the models that are implemented on a computer are first formulated as continuous mathematical equations. Take as an example the origins of lattice gauge theory. It originated in the differential equations of quantum chromodynamics. Computational models, however, often refer to those models that are first formulated in a discrete way, apt for direct numerical implementation. Paradigm example are the Schelling's Segregation Model. Models that are first formulated in a discrete way are referred to as "discrete" models, while models consisting in differential equations that are then implemented numerically are referred to as "continuous models" (Hartmann, 1996). Note that in Weisberg's or Hartman's sense, *simulation* models do not have to be do not have to be numerical or implemented on a computer.. What is at the heart of a simulation model is that it mimics *dynamical* aspects. For example, the FloWave Ocean Energy Research Facility at the University of Edinburgh is a large scale testing facility with a physical machine that simulates waves and currents for marine energy devices. Models may be used in more than one category. For example the theories of elementary particles, for discretized spacetime, originates from the mathematical model in particle physics. Due to their importance both in the contemporary sciences and in design, we will devote a whole subsection to simulation models (2.4).

2.2 Models in the philosophy of science

While models have always been part and parcel of scientific reasoning, it took the philosophy of science a long time to recognize the importance of models in the scientific process. One reason for this may be philosophers' preoccupation with the context of justification. This detracted attention from the actual scientific practice in which models are central both in theorizing as well as in experimenting. Moreover philosophers of science usually focused for a long time on those natural sciences where we find elaborate theories. For long, it was that (theoretical) physics seemed philosophers' favourite pet. Unsurprisingly, theories and often natural laws were seen to be at the centre of scientific activities, while models were treated merely as orphans. In the few exceptions in which classical philosophy of sciences discusses models, mechanical as well as mathematical models were seen as inferior to theories and even as a disturbance of scientific reasoning (e.g. Duhem 1954).

Arguably this changed at least for abstract models with the so-called semantic view of scientific theories. While the alternative conception of theories, the so-called syntactic view of the logical empiricists, perceived theories as axiomatizations in first-order logic, the semantic view interprets a theory as the sum of all its models, where a model is an interpretation on which all the axioms of the theory are true. This notion of a model derives from mathematical logic, and in this sense a model represents a particular theory. Consider as an example Newton's laws and theory of gravitation. Then the model of the Earth moving around the Sun can be seen as one instantiation of this theory. Note that the semantic account of model coming from a mathematical understanding of models may seem far off the way scientist themselves use the term model. But in this way, the shift to a theory's models still allows for the axiomatization of a theory just as in the syntactic view, while at the same time it solves certain problems that plagued the syntactic account. For example, the sentences that form the theory in the syntactic interpretation are uninterpreted and need to supplemented by so-called correspondence rules. These assign empirical meaning to the theory's theoretical terms. These correspondence rules, however, may not be uniquely defined nor can they be specified in every context. For the semantic view, on the contrary, the theory is a set of its models as the structure is already interpreted. One and the same theory may be formulated in different languages as long as its models are the same. There is hence no need for correspondence rules.

The semantic view was developed by Suppes (e.g. 1961, 1962) and later Suppe (1977) and has many followers. Though they all defend various different versions of the semantic view of theories and as such also different notions as to what a model is exactly, they all agree that models are the central unit of scientific theorizing. As a logic notion, the term model is defined in terms of truth here: A model of a theory is defined in such a way that all the theory's axioms are true. In these accounts models are seen to derive (more or less) straightforwardly from some overarching theory (e.g. Suppes, 1962, Mayo, 1996). For example, the model of the Earth's motion around the Sun is seen as the interpretation of an abstract calculus, in this case Newton's theory and Newton's law of gravitation. The model is then interpreted as a realization of the more general theory, and the set of all its models is the theory. All proponents of the semantic view agree that models are as a whole non-linguistic entities, but what they are exactly varies. For Suppes, whose approach we mainly followed in this short sketch of the semantic view, models are set theoretical structures, while for example van Fraassen (1980) views them as possibilities of how a possible state space evolves.

2.3 Models after the practice turn

The semantic concept of a model carries over directly from logic and seems to not be apt to accommodate all the various ways in which scientists use the term model. First of all, it seems impossible to extend it to concrete models like the mouse model, i.e. using standardised lab mice as a model for humans. But even for abstract models the semantic view seems sometimes far from the lab practice. For example, unlike in the semantic view often models do not derive in a straightforward way from theories. Further specifications are needed. This even holds true for the aforementioned and seemingly simple model of the Earth's movement around the Sun. In applying theoretical knowledge to the planetary system, a lot of simplifying assumptions have to be made: Other gravitationally interacting bodies (e.g. planets, the Earth's moon, asteroids) are neglected; the bodies are assumed to be perfectly spherical; and the mass distribution inside Earth and Sun is assumed to be homogenous. All these assumptions do not follow in any straightforward way from the theory. They are additional modelling assumptions, independent from the theory. One example is the assumption that the mouse model, the actual mice used in a laboratory experiment, indeed mimics human bodies well enough so that they can be used to predict human responses to the tested drug. No theory supports this claim.

With the so-called practice turn, which began in philosophy of science round the 1980s or so, philosophy of science got more attentive to the actual practices with their fields of studies. Arguably this turn led philosophers to more caution about theorizing what scientists actually do. For sure, this turn let philosophers to engage more with the actual practice of scientists and a reconstruction for their actual work. This case studies gained more centre attention and with them next to physics also various other areas of science, from the Life sciences to economics, got centre attention. As a consequence, many contemporary philosophers of science turned away from this interpretation of models of the semantic view. It got acknowledged that in many scientific contexts models are central epistemic tools that may not be subordinate to theories (e.g. Hughes 1999, Morrison 1999, Cartwright, 1999, Suárez, 1999, Bailer-Jones, 2003). We follow these authors of the practice turn. Thus, unlike in the semantic interpretation, we see models (also) as non-linguistics entities. We will use the notion model of theory for the models of the semantic interpretation and now turn to what is known as *models of phenomena.* Such phenomena are "relatively stable and general features of the world that are interesting from a scientific point of view and for empiricists have to be observable" (Frigg and Hartmann, 2012). A typical phenomenon is the motion of the Earth around the Sun, but as philosophy of science after the practice turn opened up to various areas of sciences, such phenomena do not have to be repeatable or naturally repeated events, but may also be singular phenomena like the world's climate, a specific rock formation or the extinction of the dinosaurs.

Though this last sentence may be not worth much more than a footnote for philosophy of science, it becomes crucial when comparing models in design to models in science: at first glance there seems a difference between the universal models in science and the apt-for-purpose models in design. Indeed, design models are most often constructed with one particular design in mind, without the idea of re-using the model when constructing it. However, in practice they can often get reused later on. Models in science seem to be designed in an already universal way, for example the models of Newton's laws and his theory of gravitation. A rather high level of abstraction assures here a kind of universality, a readiness to be re-used. But closer inspection reveals that also the sciences know models that are much less universal than the standard example of Newton's gravitation and much less aimed at generalization and in this sense closer to models in design.

Next to models of phenomena, *models of data* are distinguished. Models of data transform the raw experimental data into interpreted data. Important steps are here the transformation of the so-called raw data by eliminating outliers due to disturbed or faulty observations etc. This step is referred to as 'data reduction' and essential in most experimental processes. The other essential step is `curve fitting.' For example when observing planetary motions, first points that seem to be based on flawed measurements as they lie outside the range of all other data points are eliminated, then a smooth curve, e.g. an ellipse, is fit to the remaining observational points (cp. Frigg and Hartmann, 2012). Often the data models are much more sophisticated and particularly for complex experimental setups also entail what Morrison refers to as the experimental model, containing at least a model of the measuring apparatus. In the end scientists do not compare a theory to an observation, but models with models (Morrison 2009, p. 49): The model of a theory is tested against a data model.

Morgan and Morrison (1999) developed the influential "models as mediators" account. It contends that models are autonomous agents in that "(1) [they] function in a way that is partially independent of theory and (2) in many cases they are constructed with a minimal reliance on high level theory" (Morgan and Morrison, 1999, p. 43). Models here can mediate between theory and the real world by virtue of their partial independence from high-level theory. The model of the Earth moving round the Sun illustrates this lucidly. As already pointed out, many assumptions, simplifications and idealizations enter the model that do not derive from the theory (Newtonian mechanics and Newtons' theory for gravitation) itself. Moreover, models are also partially independent from the raw data. Through this mediating role, models function as tools or instruments that enable us to learn more about both theories and the real world. With respect to computer simulations, Morrison (2009) argues that simulation models can function as "measurement instruments" that enable one to extract information from the apparatus under consideration in an experiment. In this sense, simulation models function as "mediators" between the theory and the material system.

As will become clear in the following sections, we hold that the more vague use of the term model of philosophers of science after the practice turn, as depicted above, is not only more adequate for models actually used in the sciences, but also for models in design. Nonetheless the semantic view in which models foremost represent theories has contemporary followers. For example Fraassen (1980) or Giere (1988) defend a special versions of the semantic approach. As they are also philosophers who have made the practice turn, their views on models may be seen as a way to combine the more formal approach to models of the semantic view with the more recent discussion on models. That sometimes models of theory as well as models of phenomena or data are combined in a single model, is illustrated nicely by global climate models that project the Earth climate over the course of the 21st century. Parts of these multi-modal models are derived in a more or less straightforward way from underlying theories, like the thermodynamics of the atmosphere. Other model part like modelling cloud formation and their interactions in the atmosphere are much more heuristic.

2.4 Models and representation

With the above reconstruction of scientific practice as a model-based endeavour, it seems time to come back to the original mistrust that philosophers had in models. Some of their intuitions seem to be hard to deny. Models in some sense or another seem to be inferior to theories: They sometimes contradict accepted knowledge, they can be internally inconsistent, etc.

In order to capture how models can be more than merely heuristic devices despite all their shortcomings, the term representation was introduced into the model discussion. Models represent a phenomenon, some experimental data, or even a theory.

Models fulfil various different aims (Morgan and Morrison 1999), though the representation of some target system seems to be the unifying feature of all concepts of models we encountered: The target system may be a theory, a set of data, or a phenomenon. Let us now focus on models of phenomena. These represent some phenomenon as being a system with particular components and properties. Such models are not only of instrumental use, but they want to mimic some aspect of reality in a certain way. Thereby a model's target system most often is not the whole system under consideration, but only a certain aspect of it. Consider again the model of Earth around the Sun. The simple two-body model discussed above represents well the day–night cycle, but cannot account for some of the seasonal variation. Note that in representing a target system, models of phenomena just as models of data make use of idealization and abstractions. In the Earth-Sun model we can explicitly formulate these assumptions and explain why these are valid, i.e. the forces exerted on the Earth by all other celestial bodies are smaller by several orders of magnitude than the force exerted by the Sun (cp. Hillerbrand 2015).

In contemporary philosophy, two accounts of how models represent can be distinguished: informational and pragmatic views. While informational views point to similarities between the model and the target system and put the relation between the model and target, understood as some structural similarity, at the centre, pragmatic account of representation holds that the (intended) use of the model by the scientists is prior to any established relation of representation (e.g. van Fraassen 2008). Note that informational and pragmatic views are not mutually exclusive but can be seen as complementing each other (cf. Chakravartty 2010). As to what exactly this structural similarity is, there is no consent in the literature. Formal notions of isomorphism, partial isomorphism, homomorphism, or other mathematical mappings have been suggested just the same as less formal types of similarity such as analogies, similes, or resemblances (cp. Poznic, in press). Hesse (1963), for example, has developed an account of how analogies can prove useful for modelling. She distinguishes between positive, negative and neutral analogies between model and target systems. Consider the mouse model. Then the positive analogies are the known similarities between target and model, i.e. a similar hormonal cycle between mice and humans. The negative analogies are those where we know that the model does not represent well the target system, i.e. when the mice in the lab experiments do not develop AIDS like humans do. Following Hesse, the really interesting things for scientific progress are the neutral analogies. These comprise all properties or relations of the model of which it is not known yet whether they indeed have a correspondence in the target system.

2.4 Computer simulations in the sciences

Computers takes centre stage in many areas of modern life, so also in sciences and engineering. So let us turn to this specific type of modelling in more detail. To distinguish simulations from calculations or equations used in analytic models Weisberg, Hartmann and others use the term simulation to denote the imitation "of one process by another" (Hartmann, 1996, Weisberg, 2013; Parker, 2009). Here, 'process' refers to some temporal sequence of states of a system, thereby stressing the dynamic aspects of (not only computer) simulations. By contrast, Humphreys (1991) adopts a broader notion of computer simulations: "A computer simulation is any computer-implemented method for exploring the properties of mathematical models where analytic methods are unavailable". But computer simulations may be of great value even where analytic solutions are known, for example via computer aided visualizations. However, in design, the term "simulation" is mainly reserved for mimicking dynamic processes and we thus follow Hartmann's definition given above.

Note that not all numerical investigations aim at "simulations" in the strict sense that refers to genuine dynamical aspects. But generally at least within the sciences, the most interesting computer experiments, however, are simulations in the sense that they mimic a dynamic sequence of states. Note moreover that most scientific investigations seem to be concerned with dynamic processes. Even when explaining such stationary phenomena like rock formation, for example, one often falls back on dynamic explanations and thus simulations in Hartmann's sense.

Computer simulations are used for various different purposes and we want to distinguish different epistemic aims that computer models commonly fulfil in the sciences. These different epistemic aims are not limited to computer simulations, but can be extended to abstract or concrete models as well and parallel to some extent the distinction of structure, function, and behaviour we will distinguish for engineering design models in the following sections. Following Hillerbrand (2012), we distinguish three types of computer models as regards their epistemic content or aim.

'Proof' by simulation: This refers to simulations that aim at information about abstract, most often mathematical systems. Often the systems under investigation are differential equations that cannot or cannot yet be solved analytically. The search for finite-time singularities in the three-dimensional incompressible Euler equations provides an excellent example where the numerical investigation of an abstract system, i.e. the Euler differential equation, is of practical importance for research in the empirical sciences, in this case fluid dynamics (e.g. Grauer et al. 1998). In this first sense, simulations yield a (possibly preliminary) alternative for a lack of theoretic understanding.

Proxy-experiment: Other simulations provide information on systems that cannot or cannot yet be accessed experimentally or are simply very hard to access in real laboratory or field experiments. Examples here are very diverse. (a) Physicists may use this type of simulation for analyzing turbulent flows on scales too small to access in laboratory experiments, but information on the behaviour on these small scales is very important for refining or testing existing theories. (b) In numerical experiments, certain aspects can be singled out that cannot be untangled in material experimenting. When analyzing inertial particles in any sort of flow, for example, the numerical simulation has the advantage that one may focus on the particles' inertia only while neglecting aspects like gravitational interaction or the particles' finite-size effects cannot be decoupled in real experiments. Moreover (c) the analysis of some real, i.e. material experimental data may rely on simulations, usually on the form of Monte Carlo simulations. In this sense, simulations may be seen as a (possibly preliminary) replacement of experiments.

Prognosis: These third type of simulations may be seen as a kind of instrument for prognosis or forecasting. Here, simulations are used for predicting the behaviour of real, usually complex systems for which (a) no accepted analytic description exists, or for which we are (b) certain that the theoretical description implemented numerically is correct (within the desired precision). Typical examples for the former arise in the engineering sciences, in weather and climate predictions; while the latter type is often studied in astrophysics (cp. Morrison 2009) or engineering sciences (see next section). Note that often scientists use the very same simulation for various purposes. Practically in applied sciences the aims of "proof by simulation" and "proxy experiment" seem to mix fairly commonly.

3 Models in Design

Engineers in all fields, from nanotechnology and household appliances to nuclear technology, use a huge variety of models in the process of defining and evaluating a new product. They create models of components, of sub-systems, and of entire products: from sketches to computer models of parts, from scale models in a wind tunnel over prototypes to the actual industrially manufactured product. Throughout the design processes the models become closer to the final product as the process progresses. Models are fundamental epistemic tools for designers and engineers without which modern engineering would not be possible. While engineers use models all the time, they rarely theorise about models or modelling as such, however some sub-communities with a more mathematical background have engaged more than others. In the modelling and simulation community Tolk and Turnitsa (2012) see "Modelling is the purposeful process of abstracting and theorizing about a system, and capturing the resulting concepts and relations in a conceptual model" (p.2), while Pidd (1999) defines a model in operations research as: "A model is an external and explicit representation of a part of reality as seen by the people who wish to use that model to understand, to change, to manage, and to control that part of reality in some way or other" (p.120). Both of these definitions assume that the target of the model either exists or is well into development and highlight that both abstraction and selection of relevant features as vital aspects of representation.

Design is often described as the co-evolution of problem and solution (see Wynn and Clarkson (2006) for an overview of general design models). While many design and in particular engineering processes start with a clear statement of the problem or specific requirements, the co-evolution paradigm captures the fluidity of many design processes. Only by looking at a potential solution, it is possible to understand whether the problem has been posed in a suitable way, which makes design processes highly iterative. At the same time only by externalizing and reflecting over a potential solution it is possible to distance oneself sufficiently from an existing and just conceived idea to see another potential design in an ambiguous or incomplete representation (Schön, 1983). This notion of design puts representation at the heart of design as cognitive activity. This not only includes the representations designers actively generate, such as sketches, but also other products or past designs that act as models for products that are being designed. Designers frequently draw analogies to other designs or natural phenomena, that they are familiar with. In this case designers make a choice to use something as a model. As the target is often only emerging, we argue that rather than something being a model of its target, it is people who decide that something acts as a model.

In industry this fluidity has to be managed, and design processes are structured, for example, into stages, work packages or milestones often associated with particular deliverables. These prescribe activities to be carried out and models generated through them (e.g. French, 1999; or Pahl and Beitz, 1996). These processes are adapted for individual companies and typically disseminated throughout an organisation through high level process models to the become the "official process". These are typically complemented by Gantt charts of the specific process activities and a multitude of plans generated by individual designers and team leaders (see Eckert and Clarkson, 2010). The overall logic of most engineering processes is one of fixing the overall design and concentrating on details as the design process progresses. However in practice both requirements and solutions change throughout the entire design process (Eckert et al., 2004). The options for designers to make changes become increasingly limited as key parameters or components are frozen to fix dependencies between different parts of the design or to accommodate long lead times (Eger et al. 2005). Thereby the epistemic status of the model changes through the decisions that people take.

Models thus take centre stage**:** Consider for example a scale model of a car in a wind tunnel. This model is not meant to represent all aspects of the car on the street: It aims to represent the air flow around the real car, while other features like its driving characteristics or the noise inside the driver's cabin are not targeted. Modelling involves a selection of the aspects of reality that are represented. This example hints that though models in engineering may have a more instrumental character, also here the representative function is essential in order to ensure the models achieve their instrumental purposes.
Unlike science, engineering design research does not have a large body of literature reflecting on the nature of models in design. Visser (2006) sees design as the construction of internal and external representations, which is influenced by the structure of the representations and the actions they afford. This point is also argued by Galle (1999), who rejects the view of design representations as descriptions of possible or future things to avoid the implying the existence of such non-existent things. Design representations frequently have a dual role as a means of communication and a vehicle of exploration. The interpretations of representations depends on the viewpoint and background of individuals (Bucciarelli 1994). Other authors, such as Schön (1984) or Ferguson (1994), highlight the role of representations in the idea generating processes of individuals.

Models of the product, are classified in the literature in many different ways according to their purposes. The classification of design model we want to suggest follows a classical distinction of aspects of a design into *structure, function*, and *behaviour* (Gero and Kannengieser, 2004; Umeda et al, 1996; Goel, et al. 2009). Here structure represents the physical elements of a product and the relations between them; function is the product's purpose; behaviour refers to the actual behaviour of the product, irrespective of whether this is desired or not. These terms are interpreted in different ways (see Vermaas, 2013) that in itself can cause problems in using models (see Eckert, 2013). For example function can be seen as the purpose of a product, e.g. the purpose of a hairdryer is to dry hair or to bring in profit, but its main action is to heat up air. However this discussion is beyond the scope of this paper.

We use the distinction between function, structure and behaviour to distinguish different design models. Models of the *structure* of the product range from simple product sketches to CAD models of parts to physical and virtual prototypes of the entire product. Models that express the *function* of the product usually try to avoid presuming the product's structure. For example a functional model for a car would include a function to "propel the car", without making assumptions whether the car is an electric car or has an internal combustion engine[3]. Models of the *behaviour* of the product include simple performance equations, virtual analysis models, such as finite element models to carry out a stress analysis, as well as detailed physical or virtual models to test the behaviour of the system. Many of the simulation models used in engineering model the structure of product in different circumstances to assess the behaviour of the product before it is built.

Note that the classification into one type of model is not necessarily unique. For example, during later stages of the product development process when the product is more or less defined, the same models can be use to describe and analyse structure and behaviour. Just as in the sciences we find concrete, mathematical, and computational models of designed artefacts. Since the introduction of computers, the increasing number of more and more sophisticated simulation models tends to reduce the number of physical 3D models. 2D technical sketches, for example, have all but disappeared in favour of 3D computer aided design models. Numerical models often reduce costs of building and testing when compared to physical prototypes; as well as the cost of rework to other parts which are affected by changes due to test results. One numerical model often represents both the structure and the behaviour of the product. Companies sometimes express this aspiration of not building multiple physical prototypes under the catchy, usually not quite accurate slogan of "right first time".

Let us turn to computer or simulation models in design. The academic research around the use of computer models in design currently concentrates on several different angles. Industrial need drives discussions about the extent simulation models can replace physical testing and failure mode analysis of products (e.g. Tolk, 2012). Engineering simulations are most often a combination of proxy-experiments and prognosis as defined in subsection 2.5, because they typically vary input conditions or use simulations of real use conditions to predict the performance of products or components over the life of the product. Rapid prototyping, which allows the creation of parts from three dimensional computer aided design data usually using 3D printing or additive layer manufacturing, has begun to blur the boundaries between physical and virtual models. Over the last few years the technology has sufficiently improved that it can be used to create production parts, making the transition between virtual models, prototypes and final design seamless, so that regular production examples of individual components' become indistinguishable from their prototypes unless their role is known.

More academic research addresses the generation of structure. There is a debate around the role of computers in design synthesis, where computers are used to create new designs according to certain prescribed rules or heuristics or by inference from similar designs. In some areas such as the design of electronic chips, this is now nearly fully automated. Some computational approaches, such as shape grammars (Stiny, 1980), which encapsulate rules of designed based on analogous designs, aim at understanding how designed objects are influenced by the structure of the representations through which they are generated. Other research is interested in studying human creative processes by building computational models of them.

[3] However this example also shows that in practice it is almost always unrealistic to assume that at least the basic structure remains unspecified, as no car company begins this process without knowing what type of car they will build.

4 The relationship between models and their targets in design and in science

The relationship between the models and representations and their target systems is more problematic in design, as they bring the product into being (e.g. Galle 1999). This section unpacks this relationship between model and target system arguing that in design the target systems of models are frequently other models.

Regarding representations, a first difference between design models and scientific models is the direction of fit (Poznic, in press): While in the sciences the fit is from the target to the model and hence in Searle's (1983) words a world-to-model fit, for design it is the other way round as the future designed artefact has to fit the model and not the other way round, as illustrated in **Error! Reference source not found.**~~Figure 2~~. Here the direction of fit is therefore from the model to the world. This can be illustrated through the relationship between an architectural drawing and the building. The building is built in such a way that the building corresponds to the technical drawing. The technical drawing is derived from the earlier sketches. There will be many sketches that show alternative designs that have never been built. Rather than the models being fitted to the world, as in science, in design the world is fitted to the model (cf Poznic, in press). The scientific phenomenon usually exists before it is being modelled, whereas an engineered artefact is brought into being through a sequence of models[4]. Engineering models often need to fit ideas that engineering designers have in their mind; however the nature of that fit is very different as mental models tend to be fluid and can change without the person being aware of it (Kosslyn, 1994). At the same time phenomena can appear in models that engineers then become interested in.

Two different directions of fit hints at a central function models play in design. In design models are used to generate another model or the final artefact. At the same models are used to analyse the properties of a target system, in a similar way to how models are employed in science. Again the example of the model of a car in the wind tunnel highlights these two aspects of design models. The wind tunnel models serve the overall purpose of analyzing the properties of the new car. The results might lead to a modification of the shape of the car and further testing.

4.1. Classification of models in design

However, not all models in design have model-to-world type of fit. Some models are there to evaluate or test another model, a specific prototype or design. We thus propose to distinguish in design between *generative* and *evaluation* models.

Generative models describe aspects of a potential product or process during the design process. The generative model can describe the function, behaviour, or structure of a product. Throughout the design process the product is defined through a series of generative models. However not every generative model leads directly to a product or part of the product. For example an architect might make multiple drawing, cardboard or computer models of an office building or a school. Many alternative potential products, which might be represented by alternative models, are considered in the course of the product development. The same model can be used to represent different design ideas, for example different colours or scales; or models can be combined in different ways to

[4] In software design there is often no distinction between the model and final design.

form various products. This can be illustrated with the card board models for buildings, where parts of the building would be scaled, added or repeated. Generative models can be seen as suggestions for a potential product. Whether they become an eventual product is down to decisions taken by the designers in the course of the design process.

Evaluation models are used to analyse the behaviour of a design defined by a generative model. Their closest parallel in the sciences are the models of phenomena. The design literature (see for example Eppinger and Ulrich 1995) distinguishes between three different forms of evaluation: analysis, verification and validation. Analysis investigates the properties an emerging design has. Verification addresses whether the design meets the requirements and validation makes sure that the product addresses the underlying need or opportunity. For example wind tunnels models were traditionally used during the analysis phase to learn about aerodynamic properties. This role is now largely taken over by computer models. However a physical model in a wind tunnel is still used to validate the computer analysis. For design we can divide evaluation models into *analysis models*, which are typically mathematical and aim at analysing the behaviour of the product or component, e.g. stress analysis on a beam; *simulation models*, which are computational, often probabilistic and address different conditions and circumstances, e.g, simulate different load conditions and environmental conditions on a beam; and *physical prototypes*, which can be tested on a test rig or in the "the field", e.g. loading a beam to breaking point.

The issues of validation and verification come to prominence in the context of reliability of simulation (for a review see e.g. Sargent, 2005); and have recently received some attention within the philosophical literature on simulations (see, e.g., Klein and Herskovitz, 2005; Küppers and Lenhard, 2005). Note that in the science, design or philosophical literature, the terms "validation" and "verification" are not used unequivocally. Within science or philosophy of science, "verification" often refers to the process of ensuring whether or not the simulation program of the real system under consideration is executed correctly on the computer. "Validation" refers to the process of substantiating whether the simulation program is an adequate representation of the real system. Here an adequate representation means that the simulation results mimic closely enough the features of the real system. In design, however, it is typically the final product that is being verified and validated. Here verification tests whether the final product indeed meets the requirements, while validation asks whether the product solves the problem the requirements tried to encapsulate. Verification can be done through simulation or physical testing. Evaluation activities occur throughout the design process. However the large cost commitment involved in formal validation only makes sense when a commitment has been made to the final design. For simulation, design engineers talk about fidelity.

Analysis and validation can give rise to changes in the product definition. Analysis models are typically numerical models set up to understand the behaviour of the design either through calculations or through simulation methods such as finite element analysis. Engineering companies often use the analysis models as a starting point for simulation models, which aim to understand how a product or component would behave under different conditions of use. For example when a truck company is designing a new suspension, they start with calculations to understand the properties of a particular configuration. When they have a preliminary geometry they carry out a finite element analysis to assess whether this design could meet the requirements. Later they use simulation to assess whether the design can operate safely under all load conditions and road conditions. In a simulation the engineers also check for misuse situations, for example if the load in a trucks shifts and or the truck is overloaded. Simulations enable them to understand the point of failure, whereas in physical tests they make sure that the product meets the requirements.

4.2. Reuse of models in design

Design models usually have a primary purpose of being a generative model or an analysis model; however the distinction can be difficult to draw. Generative models allow designers to evaluate and reflect about their design as a form of informal analysis or evaluation. Many analysis models are based on generative models. For example the scale model of a car in a wind tunnel has been generated based on the geometry created in a CAD model to define the product. With some features added and subtracted for the wind tunnel analysis it is retested, and the analysis will lead to modifications to the product.

A special case of design models worth considering in this context are past designs that designers often use as generative models. The overwhelming majority of designs are generated by modification from existing designs or based on other designs as inspirations. In fact it is extremely difficult to find an example of a design that is not based on a predecessor of some kind. Think for example of a car that was originally based on a horse drawn carriage which had existing over many years. Now cars are based on their predecessor versions, the newest technology used in the company and competitor products. Designers use references to past designs to communicate with each other, and to generate ideas, but also to test designs or parts of designs (Eckert et al. 2005). For example to test the emissions of a diesel engine, engineers modify existing engines to run tests (Tahera et al., 2014). Thereby the company's own existing designs are used as models. This also has the advantage that many of the models used in the design process of the starting design still exist and can be reused. Designers are therefore using models that more detailed and exact than the skeletal or underspecified or provisional designs they represent This is another example of the fluid repurposing of models by designers. Designers opportunistically reapply models. Our classification therefore refers to the intended purpose rather a property of the model.

This re-use of models in a different context may at first glance seem alien to the sciences. After all, here a model often aims to represent a phenomenon and thus often a naturally re-occurring natural event. However we also observed in section 2 that in the data generation process, models are often needed to make sense of the experimental data. They may include models of the experimental setup. A case at hand are complex high energy physics experiments. Here a simulation simulates the real detector and determines what, following the underlying theory of particle physics, the detector is to see. These so-called event generators (and other simulations) are used to gauge the real detector and as such have a somewhat evaluative function as well. Moreover, for years, an event generator originally developed at CERN was reused for a wider range of high energy physics experiments all over the world.

4.3 The relationship between model and target

As already noted, in the design process, decisions are being taken that finalize part of the design and thereby change the epistemic status of models. Only once such a decision is taken to keep an aspect of a design it makes sense to think about the mapping between the model and reality, as opposed to the mapping between the model and the design it represents. However, there is a considerable amount of uncertainty and provisionally associated with design decisions. Some parts of the design are considered to be fixed from the beginning as components are reused, others are frozen through the design process. However many decisions are undone in the course of a design process due to iteration and change propagation. While many aspects of a design are explicitly decided others are the results of other design decisions that are taken; for example when components are reused they strongly influence the overall architecture, the choice of materials and the manufacturing processes. Only once the design is completely finished there can be a product against which the model can be compared. Therefore the action lies in correspondences between models, as the design can change until it is handed over to manufacturing or the end customer. Before this point the relationship between the models and the target depends on the state of the design and the decisions the designers have taken. Still we can say that for generative models designers decide whether the whole model or part of it will be built.

Let us now turn to evaluation models. For analysis models the target of the model changes throughout the design process, as changes occurs and decisions are finalised in the design process. For example the shape of the car is repeatedly tested in a wind tunnel because engineering decisions can affect the aerodynamics of the car. While in that example the engineers are not allowed to change the external appearance of the car after the design freeze, the configuration of the parts behind the grill can still change affecting the aerodynamics. Initially analysis models analyze or simulate the behaviour of generative models. The results are compared both to the requirements and to experience from the past.

For simulation models, designers are largely concerned with the fidelity of models as a measure for their validation. Tolk (2012) for example defines fidelity of a simulation thus: 'is the accuracy of the representation when compared to the real world system represented. A simulation is said to have fidelity if it accurately corresponds to or represents the item or experience it was created to emulate: How realistic does the simulation react?' As monitoring real live systems such as traffic flow can require a lot of effort, often real live systems are used to calibrate the simulation model, where the simulation model is tweaked until the snapshot of the simulated processes meets the observed snapshot of reality. In engineering processes simulation models are calibrated against the results of physical tests of prototypes, unless companies are extremely confident about the quality and accuracy of their simulation models.

Companies still create some physical models of the product or parts of their products as soon as possible to compare the results of the analysis and simulation against test results from physical model to validate the design and calibrate the model, and to assess properties of the product that require physical interaction. At the beginning of the process, the physical models can be very crude or they are versions of the previous design; later they are prototypes of the later product, which can be parts of the final product or be produced with different manufacturing technology. This also applies to highly complex products, like oil platforms, which cannot be prototyped in their entirely. Here companies would aim to reduce the risk by building physical models of components and systems and testing these to assure that key functional components are working. For example companies would not build prototype of entire buildings or ships, but key components such as lifts or engines would be thoroughly tested.

Both physical tests and simulations test product behaviour against a set of requirements under a small number of predefined conditions typically covering both normal use and some extreme conditions. However, products are used and sometimes misused in a large number of situations making it impossible to validate the design against all these possible scenarios. To broaden the range, companies increasingly carry out so-called hybrid tests where the product or part of it is tested physically using test conditions generated by a computer simulation of different environmental or use conditions. The range of test conditions is usually tailored to the specific markets and customers that the company has. In highly regulated industries like the automotive industry the products are specifically tested against a set of explicitly described and standardised test conditions predefined by the regulator that apply to all companies selling in the same market, which the product needs to meet.

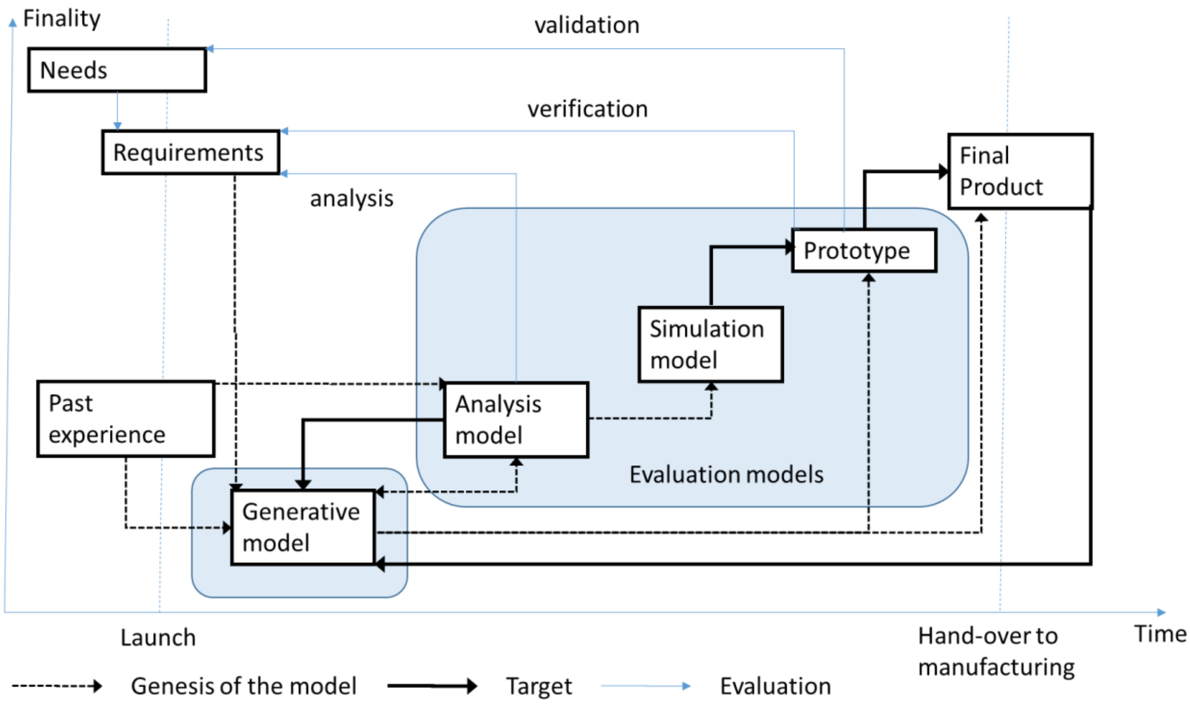

Figure 1 relationships of fit between different models through the design process (black lines), the genesis of models (dashed line) and the evaluation criteria (thin grey lines)

In design the artefact fits to the models through which it is generated, whereas in science the model is fitted to a pre-existing reality. Figure 1 depicts the relationship between model and target in design. Here the black arrows show the directions of fit between models and targets; the dashed lines show the generation of models based on each other. The generative model is the target of first the analysis model and later the final design. However the target of the simulation model is the prototype, that is generated based on the generative model.

However on closer inspection this relation is even more complex than the figure shows. Before a design process officially starts, the organisation typically has identified the needs for a new product. These needs are then translated into requirements[5]. The improvements to generative models. Analysis models are developed into simulation models. The final design is created from the generative models. The grey arrows show the evaluation processes going on. Analysis models are used to analyse a design against the requirements. The target of simulation models are physical prototypes. The target of the prototypes is the final product. Standing in place of the final product they are verified against the requirements. Towards the end of the processes, when the engineers are fairly confident of the product, it is validated against the original needs.

Just like models of data and of phenomena in the science, models in design are partially independent from the target system they are meant to represent. As the design process is highly iterative, the product or process models devised in the design process do not follow directly from a given design problem. Rather they elicit outside input and can lead to reformulation or refinement of the original design problem. For example car designers like to maintain stylistic continuity across models, but might realise through wind tunnel experimentation or simulation, that they need to radically redesign the front of the car. Also neither the available design methods, like a failure mode and effect analysis, nor the underlying scientific models, such as thermodynamics of heat flow, determine in a unique way what the solution to a given design problem should look like.

Just as in the sciences the design models take a central role here in mediating between the artefact to be designed on the one hand, and on the other hand the available design methods and resources, including past designs, relevant scientific theories and models. The models also mediate between the different agents involved in the design process, the organisations that design the product and often also the customer. Without models design would not be possible.

5 Conclusion

While models in the sciences have attracted the interest of philosophers for quite some time, models in design are rarely reflected upon. This paper aimed at a meta-level reflection on models in the design process trying to use the knowledge and insight gained from the philosophy of science debates on models. We tried to compare models in design and models in science and, though differences remain, some of the seemingly obvious differences could not sustain a closer look at scientific reality. Models in science not only aim to represent repeatable phenomena like the interaction of gravitationally interacting bodies, but also aim at target systems that are much more concrete, such as specific rock formations or the evaluation of the Earth's climate system. These models are much less aimed at generalization, and in this sense are closer to models in design where models are tools for that particular design, only rarely created with the purpose of reusing them. Nonetheless generally science often has more claim to generality than design.

Based on this, we aimed at a classification of models as they are used in design. A first distinction separates models of the designed artefact from models of the design process.

[5] Models of requirements can be thought of as part of the design models, however as they are often provided by customers or other teams outside the design organisation they are treated as external.

Overlapping with this distinction we can in both categories distinguish generative and evaluative models. Note that the term "generative" was chosen deliberately as the models are not quite as prescriptive as they may seem at first glance. The fit is from model to target, i.e. the designed product is to resemble in some sense the model (unlike in the sciences where the fit is the other way round: from the phenomena to be modelled to the model). But, the propositions following from the models are not prescriptions in a strict sense. Note furthermore that generative models are generative as regards the designed artefact, but also more generally regarding the ideas of the designer who creates and shapes the final product as the models stimulate or narrow down her imagination.

Just as in the sciences, design product models as well as process models act as mediators. However in design, models fulfil various central purposes that cannot be reduced to their representative function alone as becomes clear in our distinction between generative and evaluative models. We hold that this is one of the major difference between the modelling in the sciences and modelling in design. In engineering the same models are often used for multiple purposes over time due to the effort involved in modelling, however engineers are necessarily aware of the influence that the purpose of the model has on the details in the model. In the absence of reflection about the nature of models, engineers think of models as positive analogies of their target systems to their products, when in reality many models have other models as target systems.

With its classifications this paper hopefully helps to identify hot spots for future research, particularly in those areas where design studies can profit from the model debates within philosophy of science and vice versa. More generally, we hold that the view, prominent in philosophy of science, of models as epistemic tools – that is, as conceptual equipment for constructing knowledge – may also be a useful perspective for design where models are not seen as tools but as products of tools. Here for example, CAD systems are seen as tools that create models. This is undoubtedly a valid picture, but we think that also viewing the model as a tool can help to better understand the limits and potential of the use of models in design.

On the other hand the debates on models and simulations in philosophy of science may learn from studies of design as well. Design researchers and practitioners often aim at a very detailed picture of a complex design process and have a clear awareness that the process and their understanding of the process can have a profound effect on the product that it generates. By contrast philosophy of science, even after the practice turn, has a tendency to abstract away from a lot of possibly equally relevant features of the scientific process.

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