Beyond Models and Decisions: Situating Design through generative functions

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Beyond Models and Decisions: Situating Design through generative functions

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This paper aims to situate Design by comparison to scientific modeling and optimal Decision. We introduce "*generative functions*" characterizing each of these activities. We formulate inputs, outputs and specific conditions of the generative functions corresponding to modeling (G_m), Optimization (G_o) and Design (G_d): G_d follows the classic view of modeling as a reduction of *observed* anomalies in knowledge by assuming the existence of *unknown* objects that may be *observed* and described with *consistency and completeness*. G_o is possible when *free parameters* appear in models. Gd bears on recent Design theory, which shows that design begins with *unknown* yet *not observable* objects to which *desired properties* are assigned and have to be achieved by design. On this basis we establish that: i) modeling is a special case of Design; ii) the definition of design can be extended to the simultaneous generation of objects (as artifacts) and knowledge. Hence, the unity and variety of design can be explained, and we establish Design as *a highly general generative function* that is *central to both science and decision*. Such findings have several implications for research and education.

1 INTRODUCTION: THE NATURE OF DESIGN THEORY

1. *Research goals*: in this paper, we aim to situate Design theory by comparison to Science as a *modeling* activity and to Decision as an *optimization* activity. To tackle this critical issue, we introduce and formalize *generative functions* that characterize these three activities. From the study of these generative functions we show that: i) modeling is a special case of design; and ii) Design can be seen as the simultaneous generation of artifacts and knowledge.

2. *Research motivation and background.* Contemporary Design theories have reached a high level of formalization and generality (Hatchuel et al. 2011). They establish that design can include, yet cannot be reduced to, classic types of cognitive rationality (problem-solving, trial and error, etc.) (Dorst 2006; Hatchuel 2002). Even if one finds older pioneers to this approach, modern attempts can be traced back to Yoshikawa (1981) and have been followed by a series of advancements which endeavored to reach a theory of design that *is independent of what is designed*, and that can rigorously account for the generative (or creative) aspects of Design (Hatchuel et al. 2011). General Design Theory (Yoshikawa 1981), Coupled Design Process (Braha and Reich 2003), Infused Design (Shai and Reich 2004), Concept-Knowledge (C-K theory) (Hatchuel and Weil 2009) are representatives of such endeavor. The same evolution has occurred in the domain of industrial design where early esthetic orientations have evolved towards a comprehensive and reflexive approach of design that seeks new coherence (Margolin 2009). Such academic corpus opens new perspectives about the situation of Design theory within the general landscape of knowledge and science: *the more Design theory claims its universality, the more it is necessary to explain how it can be articulated to other universal models of thought well known to scientists.*

Still the notion of "Design theory" is unclear for the non-specialist: it has to be better related to standard forms of scientific activity. To advance in this direction this paper begins to answer simple, yet difficult, questions like: *what is different between Design and the classic scientific method? Why design theory is not simply a decision theory?* In this paper we focus on the relation between design, modeling and optimization; the latter are major and dominant references across all sciences.

3. *Methodology.* Authors (Cross 1993; Zeng and Cheng 1991; Horvath 2004) have already attempted to position Design in relation with Science. Rodenacker (1970) considered that Design consisted in: i) analyzing "physical phenomena" based on scientific modeling; and ii) "inverting" the logic by beginning with selecting a function and addressing it by using known physical models of the phenomena (see p. 22 in(Rodenacker 1970)). After WW2, Simon's approach of the artificial proposed a strong distinction between science and design (Simon 1969). However, Simon's Design theory was reduced to problem solving and did not capture specific traits of design (Hatchuel 2002; Dorst 2006). Farrell and Hooker (2012) criticized the Simonian distinction, considering that design and science have a lot in common. Still science and design are not specified with enough rigor and precision in these comparisons. Our aim is to reach more precise propositions about "scientific modeling" and "optimal decision" and to establish similarities and differences with design theory, at the *level of formalization* allowed by recent design theories.

The core of this paper is the analysis of modeling, decision and design through *generative functions*. For each generative function we define its *inputs* and *outputs*, as well as the *assumptions* and *constraints* to be verified by these functions. This common formal language will help us establish the relations and differences between design theory, modeling theory and decision theory.

4. *Paper outline*. *Section 2* presents a formal approach of classic modeling theory and decision theory. *Section 3* shows why Design differs from modeling and decision theory. *Section 4* outlines differences in the status of the "unknown" in each case. We show that modeling can be interpreted as *the design of knowledge*. It establishes that science and decision are centrally dependent of our capacity to *design*.

2 MODELING AND DECISION: UNKNOWN OBJECTS AS OBSERVABLES

2.1 Modeling: anomalies and unknown objects

The classic task of Science (formed in the 19th Century), was to establish the "true laws of nature". This definition has been criticized during the 20th century: more pragmatic notions about Truth were used to define scientific knowledge, based on falsifiability (Poincaré 2007; Popper 1959); laws are

interpreted as provisional "scientific models" (Kuhn 1962; McComas 1998; Popper 1959). The conception of "Nature" itself has been questioned. The classic vision of "reality" was challenged by the physics of the 20th century (Relativity theory, Quantum Mechanics). The environmental dangers of human interventions provoked new discussions about the frontiers of nature and culture.
Yet, these new views have not changed the scientific *method i.e. the logic of modeling*. It is largely shared that Science produces knowledge using both *observations* and *models* (mostly mathematical, but not uniquely). The core of the scientific conversation is focused on the consistency, validity, testability of models, and above all, on how models may *fit* existing or experimentally provoked *observations*. To understand similarities and differences between Design theory and modeling theory, we first discuss the assumptions and *generative function* that define modeling theory.

2.1.1 The formal assumptions of modeling

Modeling is so common that its basic assumptions are widely accepted and rarely reminded. To outline the core differences or similarities between Modeling theory and Design theory, these assumptions have to be clarified and formalized. We adopt the following notations:

- X_i is an object *i* that is defined by its name "X_i" and by additional properties.
- $K_i(X_i)$ is *the established knowledge about* X_i *(e.g.* the collection of its properties). Under some conditions described below, they may form *a model* of X_i
- $K(X_i)$ is the collection of models about all the X_i*s*. At this stage we only need to assume that K follows the classic axioms of epistemic logic (Hendricks 2007) (see section 4).

Still, modeling theory needs additional assumptions (these are not hypotheses; they are not discussed):

A1. *Observability of objects and independence from the observer*. Classic scientific modeling assumes that considered objects X_i are *observable*: it means that the scientist (as the observer) can perceive and/or activate some *observations* x_i about X_i. The quality and reliability of these observations is an issue that is addressed by statistics theory. These observations may impact on what is known $K_i(X_i)$ and even modify some parameters of X_i i.e. some subsets of $K_i(X_i)$ but it is usually assumed that observations *do not provoke the existence of* X_i, i.e. the existence of the X_is is *independent* of the observer. For instance in quantum mechanics, the position and momentum of a particle are dependent of the observation, not its existence, mass or other physical characteristics. (Here we adopt what is usually called the positivistic approach of Science. Our formalization also fits with a constructivist view of scientific modeling but it would be too long to establish it in this paper.)

A2. *Model consistency and completeness*: $K(X_i)$ is a model of the X_is if two conditions defined by the scientist are verified:

- *Consistency*: the scientist can define a consistency function $\boldsymbol{H}$, that tests $K(X_i)$ (no contradictions, no redundant propositions, simplicity, unity, symmetry etc…):

  $\boldsymbol{H}(K(X_i))$ *true means* $K(X_i)$ *is a consistent model.*
- *Completeness*: we call $\boldsymbol{Y}$ the collection of observations (or data coming from these observations) that can be related to the X_is. The scientist can define a completeness function $\boldsymbol{D}$ that checks ($K(X_i)$-$\boldsymbol{Y}$):

  $\boldsymbol{D}(K(X_i)\text{-}\boldsymbol{Y})$ *holds means that* $K(X_i)$ *sufficiently predicts* $\boldsymbol{Y}$.

Obviously, there is no universal formulation of $\boldsymbol{H}$ and $\boldsymbol{D}$. Scientific communities tend to adopt common principles for consistency and completeness. For our research, what counts is the logical necessity of some $\boldsymbol{H}$ and $\boldsymbol{D}$ ***functions*** to control the progress of modeling.

Notations: For the sake of simplicity, we will write: $\Delta\boldsymbol{H} > 0$ (resp. $\Delta\boldsymbol{D} > 0$) when consistency (resp. completness) of knowledge has increased.

A3. *Modeling aims to reduce knowledge anomalies.* The modeling activity (the research process) is stimulated by two types of "anomalies" that may appear separately or together:

- $K(X_i)$ seems inconsistent according to $\boldsymbol{H}$. For instance $K(X_i)$ may lack *unity or present contradictions.* For instance Ockam's razor is a criterion of economy in the constitution of K.
- New observations $\boldsymbol{Y}$ appear or are provoked by an experiment, and do not fit, according to $\boldsymbol{D}$**,** with what is described or expected by $K(X_i)$. Or $K(X_i)$ predicts observations $\boldsymbol{Y}^*$ that still never happened or are contradictory with available ones. For instance Higgs's Boson was predicted by the standard theory of particles and was observed several decades after its prediction.

A4. *Hypothesizing and exploring unknown objects*. Facing anomalies, the scientist makes the *hypothesis* that there may exist an ***unknown object*** $\boldsymbol{X_x}$, *observable but not yet observed*, that would reduce the anomalies if it verifies some properties. Anomalies are perceived as signs of the existence of X_x, and the modeling process will activate two interrelated activities.

- The elaboration of $K(X_x)$ will hopefully provide a definition of X_x and validate its expected properties. Optimization procedures can routinize such elaboration (Schmidt and Lipson 2009).
- The expansion of $\boldsymbol{Y}$, i.e. new provoked observations (experimental plans) may also increase information about $(X_x, K(X_x))$.

Ideally, the two series should converge towards an accepted model $K_x(X_x)$ that increases $\boldsymbol{H}$ and $\boldsymbol{D}$. . This process may also provoke a revision of previous knowledge $K(X_i)$ that we will note $K'(X_i)$ in all the paper (revised knowledge on X_i).

2.1.2 Some examples of scientific modeling

Example 1 *X-Rays*. When the story of X rays begun, many objects were already known (modelled): electricity, light, electromagnetic waves, photography where common $K(X_i)$ for scientists. Research was stimulated by the formation of a photographic anomaly $\boldsymbol{Y}$: a photosensitive screen became fluorescent when Crookes tubes were discharged in a black room. Roentgen hypothesized the existence of an unknown radiation, X_x, that was produced by the Crookes tube and could produce a visible impact on photographic screens. It took a long period of work combining hypothesis building and experimental testing before **X rays** were understood and the photographic anomaly reduced.

Example 2 *New planets*. We find a similar logic in the discovery of Neptune and then Pluto, the "planet X". In the 1840s, astronomers had detected a series of irregularities in the path of Uranus, an anomaly $\boldsymbol{Y}$ which could not be entirely explained by Newton gravitational theory applied to the then-known seven planets (the established $K(X_i)$). Le Verrier proposed a new model with *eight* planets ($K'(X_i)$, $K(X_x)$) in which the irregularities are resolved if the gravity of a farther, unknown planet X_x was disturbing Uranus path around the Sun. Telescopic observations confirming the existence of a major planet were made by Galle, working from Le Verrier's calculations. The story followed the same path with the discovery of Pluto, which was predicted in the late 19th century to explain newly discovered anomalies in Uranus' trajectory (new $\boldsymbol{Y}$). For decades, astronomers suggested several possible celestial coordinates (i.e. multiple possible $K(X_x)$) for what was called the "**planet X**". Interestingly enough, even today astronomers go on studying other models $K(X_x)$ to explain Uranus trajectory, integrating for instance new knowledge on Neptune mass, gained by Voyager 2's 1989 flyby of Neptune.

2.1.3 Corollary assumptions in modeling theory

Modeling theory is driven by the criteria of consistency $\boldsymbol{H}$ and completeness $\boldsymbol{D}$ that allow detecting anomalies of knowledge *before any explanation* has been found. Hence, modeling needs *the independence between X_x and the criteria that judge the consistency and completeness of $K(X_i)$*: $\boldsymbol{H}$ and $\boldsymbol{D}$. This assumption is necessary because $\boldsymbol{H}(K(X_i)$ and $\boldsymbol{D}(K(X_i)\text{-}\boldsymbol{Y})$ have to be evaluated when X_x *is still unknown* and its existence not warranted (only $K(X_i)$ and $\boldsymbol{Y}$ are known). Still, as soon as $(X_x, K(X_x))$ are formulated, even as hypotheses, $\boldsymbol{H}$ and $\boldsymbol{D}$ can take into account this formulation.

Finally, modeling can be described through what we call a *generative function* $\boldsymbol{G_m}$.

Definition: in all the following, we call *generative function* a transformation where the output contains at least one object $(X_x, K(X_x))$ that was unknown in the input of the function (Hatchuel et al. 2011) and which knowledge has been increased during the transformation.

In the case of modeling, this generative function can be structurally defined as:

$$\boldsymbol{G_m}: (K(X_i), \boldsymbol{Y}) \rightarrow (K(X_x), K'(X_j))$$

under the conditions that:

- $\boldsymbol{D}(K(Xi)\text{-}\boldsymbol{Y}))$ *does not hold* (i.e. there is an anomaly in the knowledge input of G_m)
- $\boldsymbol{H}(K'(X_j) \cup K(X_x)) - \boldsymbol{H}(K(X_i))>0$ or $\Delta\boldsymbol{H}>0$ (i.e. the new models are more consistent than the previous ones)
- $\boldsymbol{D}((K(X_i) \cup K'(X_j) \cup K(X_x))\text{-}\boldsymbol{Y})$ *holds* or $\Delta\boldsymbol{D}>0$ (i.e. the new models better fit with the observations)

The generative function $\boldsymbol{G_m}$ *only acts on knowledge* but not on the existence of modeled objects. It helps to detect the anomalies and reduce distance between knowledge and observations.

2.2 Decisions and decidable parameters: models as systems of choice

The output of a modeling process is a transformation of $K(X_i)$ that includes a new model $K_x(X_x)$ that defines an observable X_x and captures its relations with other X_is. A decision issue appears when this new object X_x can be a potential instrument for action through some *program* about X_x.

2.2.1. Models as programs

The path from the discovery of a new object to a new technology is a classic view (yet limited as we will see in later sections) of design and innovation. This perspective assumes that $K(X_x)$ can be decomposed into two parts: $K_u(X_x)$ which is invariant and $K_f(Xx)$ which offers *free parameters* (d_1, d_2,..,d_i) that can be decided within some range of variation.

Example 3: X rays consisted in a large family of electromagnetic radiations, described by a range of wavelengths and energies. The latter appeared as free parameters that could be controlled and selected for some purpose. The design of specific X-rays artefacts could be seen as the "best choice" among these parameters in relation to specific requirements: functionality, cost, danger, etc.

The distinction between K_f and K_u clarifies the relation between the discovery of a new object and the discovery of a *decision* space of free parameters where the designer may "choose" a strategy. Decision theory and/or optimization theory provide techniques that guide the choice of these free parameters.

2.2.2 Optimization: generating choices

The literature about Decision theory and optimization explores several issues: decision with uncertainty, multicriteria or multiple agents decision making, etc. In all cases, the task is to evaluate and select among alternatives. Classic "optimization theory" explores algorithms that search the "best" or "most satisficing" choices among a decision space which contains a very large number or free possibilities - a number so large that systematic exploration of all possibilities is infeasible even with the most powerful computers. In recent decades optimization algorithms have been improved through inspiring ideas coming from material science (simulated annealing) or biomimicry (genetic algorithms, ant based algorithms…). However, from a formal point of view, the departure point of all these algorithms is a decision space ($K(X_x)$, $D(d_j)$, $O(d_i)$), where:

- $K(X_x)$ is an established model of X_x,
- $D(d_j)$ is the space of acceptable decisions about the d_js, which are the free parameters of X_x
- $O(d_j)$ is the set of criteria used to select the "optimal" group of decisions $D^*(d_j)$.

The task of these algorithms can be seen as a generative function $\boldsymbol{G_o}$ that transforms the decision space into $D^*(d_j)$, which is the optimal decision.

$$\boldsymbol{G_o}: (K(X_x), D(d_j), O(d_j)) \rightarrow D^*(d_j) \quad (1)$$

so that $D^*(d_i) \in D(d_j)$ and $O(D^*(d_j))$ holds.

From the comparison of $\boldsymbol{G_m}$ and $\boldsymbol{G_o}$, it appears that they both *generate new knowledge*, but in a different way. Modeling may introduce new X_x when optimization only produces knowledge on the structure of $K(X_x)$ from the perspective of some criterion O (If O was independent of X_x (for instance, if O is a universal cost function), it could be possible to integrate both functions in one unique modeling function including optimization $\boldsymbol{G_{m,o}}$: ($K(X_i)$, $\boldsymbol{Y}$) $\rightarrow$ ($K'(X_j)$, $K(X_x)$, $D^*(d_j)$) where $\boldsymbol{H}$**,** $\boldsymbol{D}$ and O hold. Yet, in most cases, O may depend on the knowledge acquired about X_x).

We now compare these structural propositions to the generative function associated to Design theory.

3 DESIGN: THE GENERATION OF NEW OBJECTS

Intuitively, Design aims to define and realize an object X_x that does not already exist, or that could not be obtained by a deduction from existing objects and knowledge. This intuition has been formalized by recent design theories (Hatchuel et al. 2011). However, it mixes several assumptions that imply, as a first step of our analysis, strong differences between Design and modeling and need to be carefully studied. In the next developments we will follow the logic of C-K design theory to formalize the generative function of Design (Hatchuel and Weil 2003; Hatchuel and Weil 2009).

- ***Unknowness, desirability and unobservability***

Unknown objects X_x are necessary to modeling theory. Design also needs unknown objects X_x. According to C-K design theory, these objects do not exist and hence are not *observable* when design begins. They will exist only if design succeeds. Actually, when design starts, these objects are unknown *and only* desirable. How is it possible? They are *assigned desirable* properties $P(X_x)$ and they form a *concept* (X_x, $P(X_x)$), where P is the only proposition that is formulated about the specific unknown X_x that has to be created by design. Similarly to the O of G_o, P refers to a set of criteria to be met by X_x. Moreover, within existing $K(X_i)$, the existence of such concept is necessarily undecidable (Hatchuel and Weil 2009). X_x is not assumed as an observable object like in modeling, thus it can be viewed as an imaginary object. In design, X_x is only *partially* imagined: design only needs that we imagine the concept of an object, but its complete definition has to be elaborated and realized. This has important consequences for the generative function of Design.

- ***Design as decided anomalies***

Like in modeling, we again assume $K(X_i)$. Now, Design is possible only if between the concept (X_x, $P(X_x)$) and $K(X_i)$ the following relations hold:

- $(K(X_i) \rightarrow P(X_x))$ is wrong (i.e. what we know about X_is cannot imply the existence of X_x)
- $(K(X_i) \rightarrow (\text{non } (P(X_x))$ is wrong (i.e. what we know about the X_is cannot forbid the existence of X_x).

These relations mean that $K(X_i)$ is neither a proof of the existence of X_x, nor a proof of its non-existence. Hence, the existence of (X_x, $P(X_x)$ is *undecidable*, yet desirable, under $K(X_i)$.

Remark: undecidability can be seen as the *anomaly specific to Design*. It is not an observed anomaly, a distance between observations and $K(X_i)$; it is *a decided anomaly* created by the designer when she builds the concept (X_x, $P(X_x)$). This makes a major difference between modeling and design.

- ***The generative function of design: introducing determination function***

Design theory is characterized by a specific generative function $\boldsymbol{G_d}$ that aims to build some $K(X_x)$ that proves the existence of X_x, and $P(X_x)$. As we know that $K(X_i)$ cannot prove this existence, Design will need new knowledge. This can be limited to $K(X_x)$ or, in the general case, this can require, like in modeling, to revise (X_i, $K(X_i)$) into (X_j, $K'(X_j)$) *different from* X_x. These (X_j, $K'(X_j)$) were also unknown when design began, thus design includes modeling. The generative function of design $\boldsymbol{G_d}$ is:

$$\boldsymbol{G_d}: (K(X_i), P(X_x)) \rightarrow (K'(X_j), K(X_x))$$

with the following conditions (two are identical for modeling and the third is specific to design):

- $\Delta \boldsymbol{H} \geq 0$ which means that Design creates objects that maintain or increase consistency
- $\Delta \boldsymbol{D} \geq 0$ which means that Design maintains or increases completeness
- $(K(X_i) \cup K'(X_j) \cup K(X_x)) \rightarrow ((X_x \text{ exists}) \text{ and } (P(X_x) \text{ holds}))$

The third condition can be called a *determination function* as it means that Design needs to create the knowledge that *determines* the realization of X_x and the verification of $P(X_x)$. This condition did not appear in the generative function of modeling. We will show that it was implicit in its formulation.

- ***Design includes decision, yet free parameters have to be generated***

Design could appear as a special case of decision theory: it begins with a decided anomaly and it aims to find some free parameters that, when "optimized", will warrant $P(X_x)$. However, the situation is different from the decision theory analyzed previously: when design begins *the definition parameters of* X_x *are unknown,* they have to be generated before being decided.

- ***Design observes "expansions" i.e. potential components of*** $\boldsymbol{X_x}$

As mentioned earlier, when Design begins, X_x is *not observable*; it will be observed *only when its complete definition will be settled,* its existence warranted and made observable. So what can be observed during design if X_x still does not exist? We may think that we could observe "some aspects" of X_x. This is not a valid formulation as it assumes that X_x is already there and we could capture some of its traits. But X_x cannot be "present" until we design it and prove its existence. What can be, and is, done is *to build new objects* that could *potentially* be used as components of X_x. These objects can be called *expansions* $C_i(X_x)$ (we use here the language of C-K design theory). Their existence and properties cannot be deduced from $K(X_i)$, they have to be observed and modeled. Obviously if one of these expansions $C_j(X_x)$ verifies P, it can be seen as a potential design of X_x. Usually, these expansions only verify some property P' that is a necessary (but not sufficient) condition for P. By combining different expansions, X_x will be defined and P verified. The notion of "expansion" unifies a large variety of devices, material or symbolic, usually called *sketches, mock-sup, prototypes, demonstrators, simulation* etc. These devices are central for Design practice and are well documented in the literature (Goldschmidt 1991; Tversky 2002; Subrahmanian et al. 2003). Still they received limited attention in science (except in experimental plans) because they were absent of Modeling or Decision theory.

Observing expansions generates two different outputs: i) some "building bricks" that could be used to form X_x; ii) new knowledge that will stimulate modeling strategies or new expansions. Thus, $\boldsymbol{G_d}$ can be formulated more precisely by introducing expansions in its output:

$$\boldsymbol{G_d}: (K(X_i), P(X_x)) \rightarrow (K'(X_j), C_i(X_x))$$

and some subgroup C_m of the expansions is such that $X_x = \cap\, C_m(X_x)$ and verifies P.

- ***G_d does not generate a pure combination of X_{is} : design goes out of the box***

This is a corollary of all previous findings. Because X_x is unknown and undecidable when related to $K(X_i)$, if a successful design exists, it will be composed of expansions that are different from any of the X_is (and outside the topology of the X_is). Hence, there is no combination of the X_is that would compose X_x. $\boldsymbol{G_d}$ goes necessarily out of the X_is' box! Creativity is not something added to design. Genuine design is creative by definition and necessity.

Example 4: *the design of electric cars.* The use of electric power in cars is not a design task. It is easy to compose an electric car with known components. Design begins for instance with the concept: "*an electric car with an autonomous range that is not too far from existing cars using fuel power*". Obviously, this concept was both highly desired by carmakers and undecidable some years ago. Today, it is easy to observe all the new objects and knowledge that have been produced in existing electric cars that are now proposed, thus observable: new architectures, new batteries technologies and management systems, new car heating and cooling systems, new stations for charging or for battery exchange… New types of cars have been also proposed like the recent Twizzy by Renault who won the Red Dot best of the best design award in 2012. Still, commercialized cars could be seen as only *expansions of the concept* as none of them has reached the same autonomy as existing fuel cars (circa 700km). From a theoretical point of view commercial products are only *economic landmarks* of an ongoing design process. This example also illustrates the variety of design propositions, predicted by the theory.

4 COMPARISON AND GENERALIZATION: DESIGN AS THE SIMULTANEOUS GENERATION OF ARTEFACTS AND MODELS

Now we can compare similarities and differences between Design, modeling and Decision theories. Table 1 synthesizes what we have learned about their generative functions.

Table 1 : Comparison of generative functions

Generative function	Modeling: $\boldsymbol{G_m}$	Decision: $\boldsymbol{G_o}$	Design: $\boldsymbol{G_d}$
Status of the unknown	X_x is unknown, yet observable and independent, $\boldsymbol{Y}$ forms an anomaly	X_x presents free parameters to be decided, optimum is unknown	X_x is unknown, assigned properties desirable, not observable,
Input	$(K(X_i), \boldsymbol{Y})$ $\boldsymbol{Y}$ not explained by X_is	$(K(X_x), D(d_i), O(D^*(d_i)))$	$(K(X_i), P(X_x))$ $P(X_x)$ undecidable / $K(X_i)$
Output	$K'(X_j), K(X_x)$	$D^*(d_i)$	$K'(X_j), K(X_x)$
Conditions	- consistency $\Delta\boldsymbol{H} > 0$ - completeness $\Delta\boldsymbol{D} > 0$	$O(D^*(d_j))$ holds.	$\Delta\boldsymbol{H} \geq 0$ $\Delta\boldsymbol{D} \geq 0$ Determination: (X_x exists) and ($P(X_x)$ holds)

4.1 Discovery, invention and the status of the unknown

One can first remark the *structural identity* between the outputs of $\boldsymbol{G_d}$ and $\boldsymbol{G_m}$. It explains why it is actually cumbersome to distinguish between "invention" and "discovery": in both cases, a previously unknown object has been generated. Yet this distinction is often used to distinguish between science and design. The difference appears in the assumptions on the unknown in each generative function: in modeling, the unknown is seen as an "external reality" that may be observed; in design, it is a desirable entity to bring to existence. The structure of the generative functions will show us that these differences mask deep similarities between modeling and Design.

4.2. Modeling as a special form of Design

We can now reach the core of our research by examining how these generative functions can be combined. Three important findings can be established.

Proposition 1: Design includes modeling and decision. This is obvious from the structure of G_m.

Proof : Design needs to observe and test expansions as potential components of X_x:

$\boldsymbol{G_d}$: $(K(X_i), P(X_x)) \rightarrow (K'(X_j), C_i(X_x))$ so that $X_x = \cap\, C_m(X_x)$ and verifies P.

If for some $X_u = \cap C_m(X_x)$, $P(X_u)$ does *not* hold, *(non-$P(X_u)$)* can be interpreted as an observed anomaly. Let us set: $\boldsymbol{Y}$=*non-$P(X_u)$*, $\boldsymbol{Y}$ appears as a provoked observation; if $K(X_u)$ is the available knowledge

about X_u, then $\boldsymbol{G_d}$ leads to a modeling issue corresponding to the following generative function: $(K(X_u), \boldsymbol{Y}) \rightarrow (K'(Xj), K(X_z))$ where X_z is a new unknown object that has to be modeled and observed.
Example 5: Each time when a prototype ($\cap C_m(X_x)$) fails to meet design targets, it is necessary to build a scientific modeling of the failure. One famous historical example occurred at GE Research in the 1920s where Langmuir study of light bulb blackening led to the discovery of plasma, which owed him Nobel prize in 1932 (Reich 1985).
Proposition 2: Modeling needs design. This proposition seems less obvious: where is design in the reduction of anomalies that characterizes modeling? Actually Design is implicit in the conditions of the generative function of modeling: $\boldsymbol{D}((K(X_i) \cup K(X'_j) \cup K(X_x))\text{-}\boldsymbol{Y})$ holds.
Proof: This condition simply says that adding $K(X_x)$ to available knowledge explains $\boldsymbol{Y}$**.** Now to *check* this proposition may require *an unknown experimental setting* that should desirably fit with the requirements of $\boldsymbol{D}$**.** Let us call E_x this setting and $D_r(E_x)$ these requirements. Hence, the generative function of modeling $\boldsymbol{G_m}$: $(K(X_i), \boldsymbol{Y}) \rightarrow (K(X_x), K'(X_j))$ is now dependent on a *design function:* $\boldsymbol{G_d}$*:* $(K(X_i), D_r(E_x)) \rightarrow (K'(X_j), K(E_x))$
Example 6: There are numerous examples in the history of science where modeling was dependent on the design of new experimental settings (instruments, machines, reactors,…). In the case of the Laser, the existence of this special form of condensed light was theoretically predicted by Einstein as early as 1917 (a deduction from available $K(X_i)$). Yet, the type of experimental "cavity" where the phenomena could appear was unknown and would have to meet extremely severe conditions. Thus, the advancement of knowledge in the field was dependent on Design capabilities (Bromberg 1986).
Proposition 3: Modeling is a special form of Design
This proposition will establish that in spite of their differences, modeling is an implicit Design. Let us interpret modeling using the formal generative function of Design. Such operations are precisely those where the value of formalization is at its peak. Intuitively modeling and Design seem two logics with radically different views of the unknown; yet structurally, *modeling is also a design activity*.
Proof: we have established that the generative function of modeling $\boldsymbol{G_m}$ is a special form of $\boldsymbol{G_d}$.
$\boldsymbol{G_m}$: $(K(X_i), \boldsymbol{Y}) \rightarrow (K'(X_j), K(X_x))$ with the conditions :

- ***a.*** $\boldsymbol{D}(K(X_i)\text{-}\ \boldsymbol{Y})$ does not hold
- ***b.*** $\boldsymbol{H}(K'(X_j) \cup K(X_x)) - \boldsymbol{H}(K(X_i))>0$
- ***c.*** $\boldsymbol{D}((K(X_i) \cup K'(X_j) \cup K(X_x))\text{-}\boldsymbol{Y})$ holds.

Now instead of considering an unknown object X_x to reduce the anomaly created by $\boldsymbol{Y}$, let us consider *an unknown knowledge* K_x (note that we do not write $K(X_x)$ but K_x). In addition, we assume that K_x verifies the following properties **b'** and **c'** which are obtained by replacing $K(X_x)$ by K_x in conditions **b** and **c** **(**remind that condition **a** is independent of K_x and thus is unchanged**)**:

- ***b':*** $\boldsymbol{H}(K'(X_j) \cup K_x) - \boldsymbol{H}(K(X_i))>0$
- ***c':*** $\boldsymbol{D}((K(X_i) \cup K'(X_j) \cup K_x))\text{-}\boldsymbol{Y})$ holds.

Remark that K_x, like X_x, is unknown and not observable, it has to be generated (designed). If we set a function $T(K_x)$ that is true if "(**b'** and **c'**) holds" then $\boldsymbol{G_m}$ is equivalent to the design function:

$$\boldsymbol{G_d}: (K(X_i), T(K_x)) \rightarrow (K'(X_j), K_x)$$

Proof: if design succeeds then $T(K_x)$ is true; this implies that **c'** holds i.e. K_x *reduces the anomaly* $\boldsymbol{Y}$. Thus, modeling is equivalent to a design process *where the generation of knowledge is designed*.
Conditioning the "realism" of K_x: with this interpretation of modeling, we miss the idea that K_x is about an observable and independent object X_x. Design may lead to an infinite variety of K_x which all verify $T(K_x)$. We need an additional condition that would control the "realism" of K_x. "Realism" was initially embedded in the assumption that there is an observable and independent object. Now assume that we introduce a new design condition $\boldsymbol{V}(K_x)$ which says: K_x should be designed *independently* from the designer. This would force the designer to only use observations and test expansions (for instance knowledge prototypes) that are submitted to the judgment of other scientists. Actually, this condition is equivalent to the assumption of an *independent* object X_x. Proof: to recognize that X_x exists and is independent of the scientists, we need to prove that two independent observers reach the same knowledge $K(X_x)$. Conditioning the design of K_x by $\boldsymbol{V}(K_x)$ is equivalent to assuming the existence of an independent object. This completes our proof that modeling is a special form of Design.

4.3 Generalization: design as the simultaneous generation of objects and knowledge

Design needs modeling but modeling can be interpreted as the design of new knowledge. Therefore we can *generalize* design as a generative function that simultaneously applies to a couple (X_x, $K(X_x)$):

- Let us call, $Z_i = (X_i, K(X_i))$, $Z_x = (X_x, K(X_x))$,
- In classic epistemic logic, for all U: $K(K(U))= K(U)$ this only means that we know what we know; and as $K(X_x) \rightarrow X_x$ then $K(X_x, K(X_x))=(K(X_x), K(K(X_x))$ according to the distribution axiom (Hendricks 2007), which means that K is consistent with implication rules.
- Then, $K(Z_i) = K(X_i, K(X_i)) = (K(X_i), K(K(X_i)) = (K(X_i), K(X_i)) =K(X_i)$; and similarly $K(Z_x) =K(X_x)$
- the generalized generative function $\boldsymbol{G_{dz}}$ can be written with the same structure as $\boldsymbol{G_d}$:

$$\boldsymbol{G_{dz}}: (K(Z_i), L(Z_x)) \rightarrow (K'(Z_j), K(Z_x))$$

Where $L(Z_x)$ is the combination of *all desired properties related to the couple* $(X_x, K(X_x))$:
  - Assigned property to X_x: $P(X_x)$
  - Conditions on $K(X_x)$: consistency $\Delta \boldsymbol{H} > 0$; completeness $\Delta \boldsymbol{D} > 0$

Example 7: there are many famous cases where new objects and new knowledge is generated, e.g. the discovery of "neutral current" and the bubble chamber to "see" them at CERN in the 1960s (Galison 1987), or DNA double helix and the X-ray diffraction of biological molecules, needed for the observation (Crick 1988).

This result establishes that the generative function of design is not specific to objects or artefacts. The standard presentations of modeling or design are partial visions of Design. Confirming the orientation of contemporary Design theory, our research brings rigorous support to the idea that Design is a generative function that is independent of what is designed and simultaneously generates objects and the knowledge about these objects according to the desired properties assigned to each of them.

5 CONCLUDING REMARKS AND IMPLICATIONS.

1. Our aim was to situate design and design theory by comparison to major standard references like scientific modeling and Decision theory. To reach this goal, we have not followed the classic discussions about science and design. Contemporary design theory offers a new way to study these issues. It has reached a level of formalization that can be used to organize a rigorous comparison of design, modeling and optimization. We use this methodology to reach novel and precise propositions. Our findings confirm previous research that insisted more on the *similarities between Design and Science*. But it goes beyond such general statements: we have introduced the notion of *generative functions* which permits to build a common formal framework for our comparison. We showed that design, modeling and decision correspond to various visions of the unknown. Beyond these differences, we have established that modeling (hence optimization) could be seen as special forms of design and we have made explicit the conditions under which such proposition holds. Finally we have established the high generality of Design that simultaneously generates objects and knowledge.

These findings have two series of implications, which are also areas for further research:

2. On the unity and variety of forms of design: tell us what is that unknown that you desire…

Establishing that design generates simultaneously objects and knowledge clarifies the unity of design. Engineers, Scientists, Architects, product creators are all designers. They do not differ in *the structure of their generative functions*, they differ in *the desired properties* they assign to the objects (or artifacts) *and* in the knowledge they generate. Scientists desire artefacts and knowledge that verify consistency, completeness and determination. They tend to focus on the desires of their communities. Engineers give more importance to the functional requirements of the artefacts they build; they also design knowledge that can be easily learned, transferred and systematized in usual working contexts. Architects have desires in common with engineers regarding the objects they create. But they do not aim at a systematized knowledge about elegance, beauty or urban values. Professional identities tend to underestimate the unity of design and tend to overemphasize the specificity of their desires and to confuse it with the generative functions they have to enact. This has led to persistent misunderstandings and conflicts. It has also fragmented the scientific study of design. It is still common to distinguish between "the technology and the design" of a product – as if generating a new technology was not the design of both artefacts and knowledge. Our research certainly calls for an aggiornamento of the scientific status of Design where its unity will be stressed and used as a foundation stone for research and education.

3. *On the relations between Science and Design*

In this paper we avoid the usual debates about the nature of Science, knowledge and Design. We add nothing to the discussions on positivist and constructivist conceptions of reality. Our investigations focus on the operational logic and structure of each type of activity. We find that the status of the unknown is a key element of the usual distinction between design-as-artifact-making and Science-as-knowledge-creation. Still we also establish that Design offers a logic of the unknown that is more general and includes the logic of scientific Knowledge. Design makes explicit what it desires about the unknown. We establish that Science also *designs knowledge according to desires* but they are implicit or related to a community (not to the unique judgment of one researcher). Obviously, these findings should be better related to contemporary debates in epistemology and philosophy of Science. This task goes largely beyond the scope of this paper.

Finally, our main conclusion is that Design theory can serve as an integrative framework for modeling and decision. By introducing desirable unknowns in our models of thought, Design does not create some sort of irrationality or disorder. Instead it offers a rigorous foundation stone to the main standards of scientific thinking.

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