Models that Include Cows: The Significance of Operational Thinking

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Abstract

The unconscious application of sophisticated tools, and in particular the popular reverence to data as the source of knowledge, seems to be the rule in many scientific activities, in which the application of tools replaces thinking and data analysis replaces understanding. In this respect, system dynamics has much to offer. One of its trademarks is known as "operational thinking". This paper demarcates operational thinking as a distinct epistemic posture that, unlike popular scientific practice that seeks to explain the world by means of data analysis, intends to understand the world in terms of its operations. I explore the significance of such a posture for the domain of human systems and its epistemic value in particular with respect to the prevalent observational approach to science, the Humean problem of induction and determinism. Operational thinking means to recognize that human systems do not obey laws to be discovered by data-analysis, instead, it acknowledges *agency*, that is, the fact that a social system is the result of the consequences of actions taken by free decision-makers. Operational thinking fits these ontic commitments by providing intelligible explanations that acknowledge responsibility and freedom as characteristic attributes of human systems, whose redesign requires then the capacity to recognize and transform operational arrangements, that is, the intervention in the very decision processes that the systems' constituents carry out.

Keywords: modeling, operational thinking, induction, uniformity, data, epistemology.

> *A popular economic journal published the research of a noted economist who had developed a very sophisticated econometric model designed to predict milk production in the United States. The model contained a raft of macroeconomic variables woven together in a set of complex equations. But nowhere in that model did cows appear. If one asks how milk is actually generated, one discovers that cows are absolutely essential to the process.*
>
> (Richmond, 1993, p. 128).

Barry Richmond, engineering professor and an inspirational system dynamics educator, used the previous statement to show what he labeled as "operational thinking", which he described as to think in terms of "how things really work", as opposed to "how things would theoretically work, or how one might fashion a bit of algebra capable of generating realistic-looking output" (1993, p. 127). Richmond associated such operational thinking with the identification of key material

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arrangements of the modeled system, “getting down to the physics… the core stock-and-flow infrastructure that lies at the heart of a system…with an occasional wire thrown in to make an information link” (Richmond, 1994, pp. 141, 143). In this paper I expand this notion and explore the significance of thinking in terms of *operations*, which in a social system means to think in terms of actual decision making processes driven by actors of a specific system. From this perspective, the performance of a social system is understood as the result of the intricate complex of decision processes continuously carried out by inter-acting free actors.

My impression is that the epistemic value of such a way of thinking is unrecognized or underestimated. This paper claims that operational thinking opposes to mere theorizing activities based on data-analysis, which happens to be the fashionable way (and the “scientific” style in many cases) to study social systems. Instead of developing knowledge by observation to generate general statements through induction, the production of knowledge through *operational* modeling does not rest on data in order to bring understanding or explanation. Rather, it relies on the generation of dynamic hypotheses that explain the performance of a system in function of its structure that is generated by its operations. Such an approach recognizes human systems as systems that change through time according to free actions of decision makers.

The paper develops as follows. First, I summarize a system dynamics view of operational thinking. I concentrate on Jay Forrester’s writings in order to highlight the foundational nature of this discussion for system dynamics. The following section contrasts operational thinking with data-based approaches; this discussion is illustrated with different ways to model milk production in order to highlight that data-based science excludes the notion of decision-making actors as essential constituents of social systems whose actions drive the performance of such systems. The next section shows why such exclusion, based on a notion of a world driven by hidden laws that are discoverable via data-analysis, requires the assumption of uniformity of nature which, in turn, implies a determined world with no room for moral responsibility or freedom. The following section articulates the possibilities and the significance of thinking and modeling in terms of operations for designing and transforming social systems. The final section recapitulates the discussion.

1. Operational Thinking: A Foundational Issue

Richmond felt that operational thinking, as a thinking skill, remained very underappreciated in the system dynamics field. The reason for this, according to him, is that such skill “is so much a natural part of the way Jay Forrester sees the world that he doesn’t (or didn’t) recognize it as anything separable. Instead, it simply became rolled into the essence of system dynamics―so obviously true that it didn’t require any particular distinguishing” (Richmond, 1994, p. 140). I agree with Richmond. Operational thinking is a distinctive building block of system dynamics modeling, but somehow it is taken for granted, many times inadvertently. Yet, it can be traced back to the initial writings of Forrester.

Jay Forrester wrote in 1956 a “note” to the M.I.T. Faculty Research Seminar in which he sketched the elements of what would be known as “System Dynamics” (Forrester, 2003). He imagined *a new kind of models* that would include various aspects from which I want to highlight the next three: dynamic structure in terms of sequences of actions, explicit information flows along with decision criteria, and correspondence with modeled counterparts.

Dynamic structure**:** detailed attention to the *sequences of actions* which occur in the system being studied and to the *forces* which trigger or temper such actions. Forrester’s example:

> Consumers do not purchase (as implied by most past models) from producers of goods. They buy from retailers, who buy from wholesale distributors, who draw goods from factory warehouses which are stocked by factory production. Such a distinction and stress on reality can have a first-order effect on the degree to which a model matches the real system in performance (p. 337).

Information flow and decision criteria**:** explicit recognition of information flow channels and information transformation with time and transmission, which requires a re-examination of the proper decision criteria used by decision makers. Such criteria must not be defined as depending only on current values of gross economic variables. Instead, Forrester suggested that such criteria must be traced to the motivations, hopes, objectives and optimism of the people involved. For instance he recommends to consider the steps for handling and manufacturing goods, the reaction times of group and mass populations, and the characteristics of our communications and cognitive processes, for example:

> We must depart from the current practice of assuming that current decisions in the economy depend on only the current values of gross economic variables (or some of these lagged by a year). The extended past history of many of the economic variables condition people to certain reactions, also the yearly changes in a variable (liquid asset *increases* or *decreases*, wage *changes*, price *changes*, *new* products) can be more important than the total magnitudes of these quantities (p. 341).

Symbolism and correspondence with real counterparts**:** the possibility of having a pictorial representation—a flow diagram—of the relationships within the system, how information, money, goods, and people, are moved, i.e. simulated, time-step-by-time-step from place to place.

I take the three previous elements as necessary to have a model in operational terms, that is, to have a model of "the physics" of how something "really works". This operational approach means that the performance of a social system is understood as driven through the continuous inter-action of actors ("agents who act"), the way in which such actors, and their decisions, are arranged, the different use of information and resources that they make, and the impact that those decisions have in the rest of the system. Indeed, a system dynamics model is essentially a model of decisions rules employed by actors, according to the modeler, in a specific situation.[1] A large part of the craft of building this type of model requires, then, the ability to study decision-making processes and to model and represent the decision rules so as to "produce" the decisions that such rules generate (Sterman, 2000). In his magnum opus, "Industrial Dynamics", Forrester (1961) discussed in detail how to model decision processes, which are particularly defined by general policies, i.e. rules that state how operation decisions are made converting information into action; he called this conversion process "decision making".

Decision making processes reveal, in turn, feedback structures. Already in 1960 Forrester demarcated: "an information-feedback system exists whenever the environment leads to a decision that results in action which affects the environment" (Forrester, 1975a, p. 54). The "decision" point is pivotal for this type of model:

> The word "decision" is used here to mean the control of an action stream. Such an action stream may be the time devoted to sleeping in response to one's physical state, the effort to improve products in response to market information about product acceptance, the change in interest rates in response to money supply, the change of prices in response to a worldwide commodity shortage, or the rate of consumption of rabbits as a response to the size of the coyote population. As in these and all other decision streams, the action resulting from the decision stream affects the state of the system to which the decision stream itself is responding (Forrester, 1968, p. 402).

Indeed, the system dynamicist who knows his Forrester and his Sterman, understands that the foundation on decision-making brings a feedback (dynamic) worldview which in turn drives

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[1] An actor is not necessarily a human being. Indeed, the main actors in the quote of Richmond that opens this article are the milk producing cows. I take this clarification from Sterman (2000):

> The decision processes of the agents refer to the decision rules that determine the behavior of the actors in the system…The agents in models need not be human decision makers. They might be other types of organisms (such as wolves and moose in a predator-prey model) or physical objects (such as the sun and planets in a model of the solar system). In these cases, the decision rules of the agents represent the ways in which the moose, wolves, and planets respond to the state of the systems in which they operate (p. 514).

knowledge in function of understanding how those feedback structures explain the behavior of the system (Figure 1). These models help to generate such statements of relations between structure and behavior, called "dynamic hypotheses", which are mechanisms with distinctive explanatory power (Olaya, 2004, 2005). Forrester (1968) underlined this *theory of structure*: "industrial dynamics is a philosophy of structure in systems. It is also gradually becoming a body of principles that relate structure to behavior… every decision is responsive to the existing condition of the system and influences that condition" (pp. 406, 408). Certainly, this kind of models generates structure-based and not content-based explanations (Lane, 2001), i.e. they are not defined from properties of objects or entities but from the consequences of the way in which actors, processes and activities, are arranged and organized. The main goal of these models is to help to organize knowledge in order to enhance learning processes and systems design.

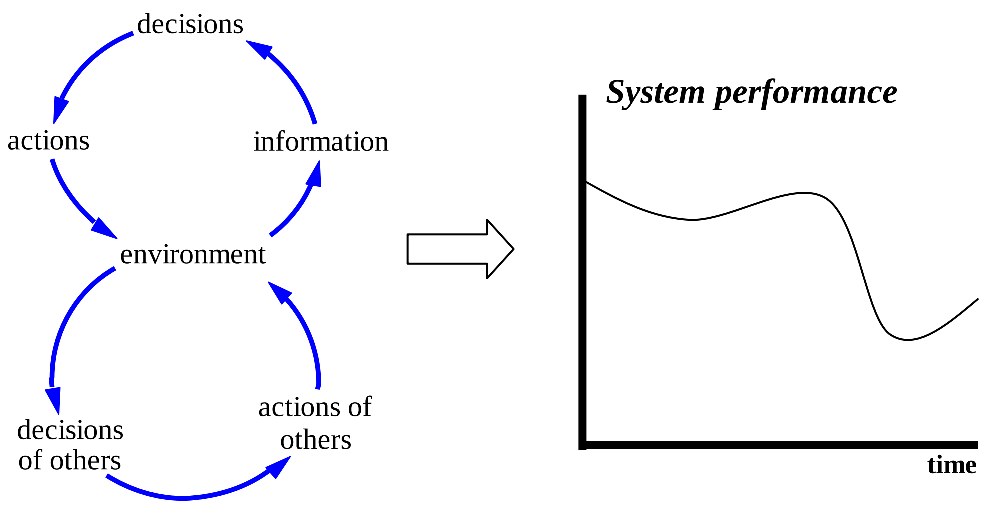

Figure 1. *System dynamics builds the explanation of the performance of a system as a result of the feedback structures generated by decision processes*

Forrester, an engineer, used as a driving force a strong criticism to economic models from an engineering point of view. Economists, as social scientists, intend to build *theories* of socio-economic systems, usually by means of gathering and analyzing *data*. Engineers, on the other hand, intend to produce designs and solve problems, frequently by means of *models* that are built in *operational* terms. This difference means a very different way of thinking, two different epistemologies. In the rest of the paper I will explore this difference.

2. Data vs. Operations, or the Milk Production Affair

Richmond (1993) ended his example of milk production in this way:

> Thinking operationally about milk production, one would focus first on cows, then on the rhythms associated with farmers' decisions to increase and decrease herd size, the relations governing milk productivity per cow, and so on (p. 128).

I will advance the suggestion of Richmond with a simple *operational* model of milk production that includes cows, farmers, and their decisions.

With Cows

Let us consider a small model of a dairy farm. Figure 2 shows a possible stock-and-flow model.

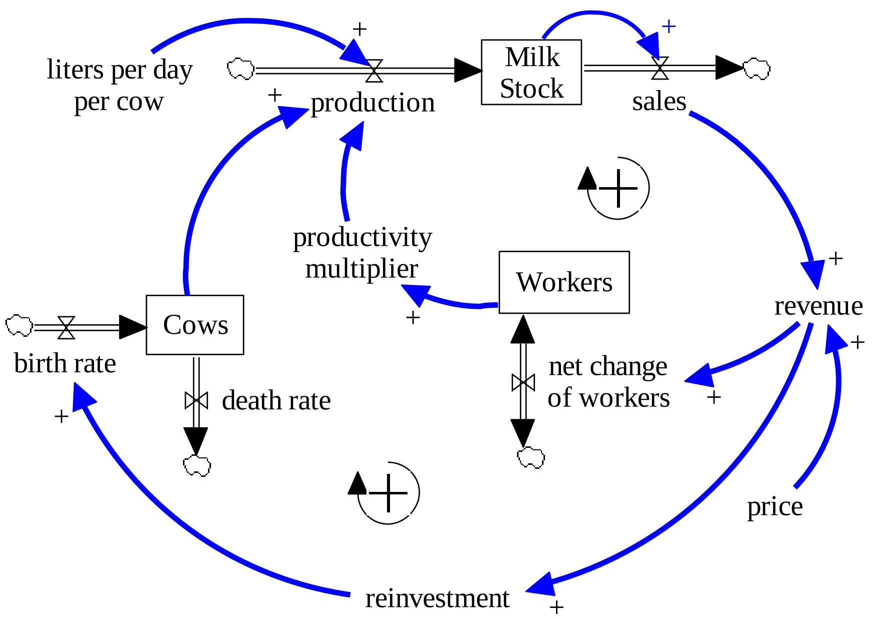

Figure 2. *Operational model for milk production*

Let:

M = Milk Stock
p = production
s = sales
l = liters per day per cow
C = Cows
br = birth rate
dr = death rate
W = Workers
ncw = net change of workers
pm = productivity multiplier
rv = revenue
pr = price
rt = reinvestment

This operational model shows *dynamic structure*, that is, the sequences of actions that occur in the system (e.g. sales → revenue → reinvestment → cow breeding → production) and the forces that trigger (or temper) such actions (e.g. price). It also shows *information flows* and a possible *symbolic correspondence* with the system that the model intends to capture. The operations in the model are defined by the equations.

Differential equations bring the first clue for recognizing operational thinking. The system of equations that define the stocks of the model in Figure 2 are:

$$dM/dt = p(t) - s(t) \qquad \text{(Eq. 1)}$$

$$dC/dt = br(t) - dr(t) \qquad \text{(Eq. 2)}$$

$$dW/dt = ncw(t) \qquad \text{(Eq. 3)}$$

For instance take Equation 1, the question "how does the milk stock *really work*?" is answered "take the milk you have, add what you produced today, and do not forget to subtract what you sold".

In addition to these *operations* on accumulations, the model of Figure 2 shows diverse decision processes, for example the reinvestment in the milk business (breeding more cows) and the change in workers (e.g. hiring, firing), both decisions according to revenue. Let us focus on the production of milk. This decision point is in function of the number of cows, the liters of milk that each cow can deliver, and a productivity multiplier according to the amount of workers. That is:

$$production(t) = f\,(C, l, pm)$$

A possible function for milk *production*, a very simple one, is:

$$production(t) = C * l * pm \qquad \text{(Eq. 4)}$$

Equation 4 establishes that the production of milk per time (for example production per day) equals the number of cows (at that point of time) times the amount of milk that each cow produces per day (in liters/day/cow); this amount is also affected by a productivity multiplier which in turn depends on the amount of workers (available each day). This is not a *law* of milk production. It is not even a *theory* of milk production. It does not uncover any law-like statement, either. This equation for *production* is a decision rule for this particular case, that is, the definition of how the actors in this system act and decide *in order to actually produce milk*, according to the modeler.

Moreover, all of the values of the variables in Figure 2, the equations that define them, and the configuration and arrangement of the system, as displayed in the model, are specific to this particular farm. For example, *l* (*liters per day per cow*) refers to the type of cows that this farm uses, and the *productivity multiplier* is specific for the workers that this farm employs and the way in which these workers (and no others) affect the production of milk on this farm according to their particular skills, available technology in the farm, mode of working, historical accumulated knowledge, etc. It does not necessarily work for other farms; not even for the very next neighboring farm, the impact of the amount of workers on productivity for other farms is most likely different (affected by, e.g., lazy workers, better or worse milking techniques, etc.). This task-specific reasoning is a trademark of engineering thinking in which a model stands for a concrete case and for a particular purpose, instead of the typical bias to general theoretic statements pursued by natural science (Olaya, 2012), know-*how* over know-*that*. Equation 4 is an example of an equation that captures *how* decisions and operations (milk production in this case) are actually produced in this particular system as a function of actions of actors, resources, use of material and information.

Without Cows

The previous model makes a sharp contrast against models of data, models that work under a very popular premise: induction. Mkhabela (2004) develops a typical data-based approach for a dairy farm in South Africa in order to forecast subsequent milk production with a model that "could estimate seasonal effects and time trends…These forecasts could then be compared with actual production levels to estimate increases in production" (p. 484). The technique that Mkhabela uses is a modification of generalized least squares regression fitting with a multiple regression to develop a time series model that seeks to predict future values based on observed values. This time the equation for milk production looks very different:

$$\gamma_t = \beta_0 + \beta_i t + \beta_s A + \varepsilon_t \qquad \text{(Eq. 5)}$$

γ_t: milk production (liters) for time period t.
s = 1 (autumn), 2 (winter), 3 (spring), 4 (summer).
A = 1 if s = 2, 3 or 4, and 0 if s = 1.
β_i: Regression coefficients.
ε_t: random error.

This time-series equation (Eq. 5) uses historical milk data from 33 observations for the period 1990 to 1998 in order to forecast milk production, and it is a good example of non-operational thinking. Such a formulation does not include cows, workers, decision rules, sequences of actions (dynamic structure), utilization of information by decision-makers, flows of material, use and flow of money, and so on. Rather, the equation is an abstract generalization from past observations (data). Agency, as the capacity of actors to act in the world, is conceptually left out from this mode of representation. Instead, the equation defines milk production as the result of some sort of natural force. Indeed, after delivering the data-based forecast, Mkhabela concludes that "time series forecasting is useful in evaluating time trends on farms because it follows the natural progression of change" (Mkhabela, 2004, p. 488). But such an assertion on a "natural progression", that just happens, adds mystery and gives no understanding at all about *why* the system behaves in a certain manner, even less allows to understand the behavior of such a system as driven by the direct results of the actions of decision-making agents.

Stock, Flows, and still no Cows

The ability to relate different observations has many uses. A potential system dynamicist could think that to build a stock-and-flow model is a sufficient warranty for developing operational thinking. Well, it is not. Figure 3 shows a possible stock-and-flow, data-driven model (or what Richmond would call a "correlational model") that lacks operational thinking. Instead it is constructed from data analysis.

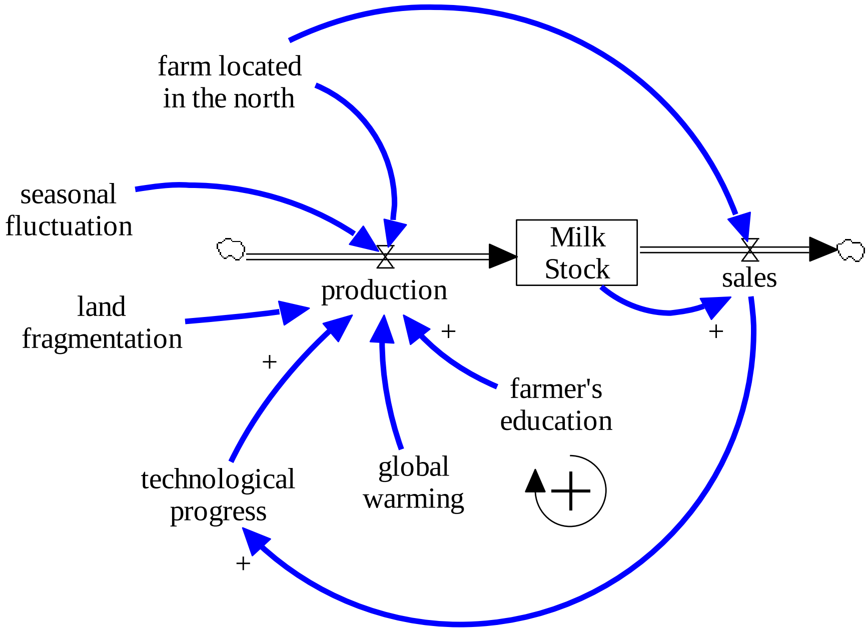

Figure 3. *Correlational (non-operational) model for milk production*

Let us focus again on the function that defines the inflow (milk) *production* (Fig. 3) which is constructed based on *apparent* (observed) effects of diverse factors on milk production. Indeed such factors have been proposed by diverse data-driven research: farm location (El-Osta & Morehart, 2000), the mentioned seasonal fluctuation study of Mkhabela (2004), land fragmentation (del Corral, Perez, & Roibas, 2011), technological progress (Ahmad & Bravo-Ureta, 1995), farmer's education (Mariam & Coffin, 1993), and global warming (Topp & Doyle, 1996). The list could grow as large as the researchers enthusiasm allows to. But none of these factors are easy to associate with the actual operation of milk production. If someone asks "how is milk produced?" the chance that "global warming" appears on the answer is very low. The same reasoning applies for other factors in Figure 3.

What sort of equations could then be used for the model in Figure 3? No doubt that those would have to be non-operational formulations. Let us examine, for example, the relationship between *production* and *technological progress*. An option is developed by Ahmad and Bravo-Ureta (1995) who use 1072 observations of ninety-six Vermont dairy farms for the 1971-1984 period to estimate that technological progress contributed 1.01% to the annual increase in milk output. Perhaps the most sophisticated thing to do would be to formulate normalized, nonlinear, data-based relationships between each pair of variables, for example, *technological progress* = f_1 *(sales)*, *production* = f_2 *(technological progress)*, *sales* = f_3 *(Milk Stock, farm location), etc.* In turn the complete equation for *production* could be a multiplicative or additive normalized formulation of nonlinear effects on *Production*. Such a model would have several elements that are system dynamics trademarks: accumulation, non-linearity, and notice that there is also a positive feedback loop. And yet, the model lacks the elements of operational thinking: there is no dynamic structure, in terms of sequences of actions that occur in the system, the feedback loop is deceiving since it does not reflect processes of decision-action-reaction (Figure 1), it lacks information flows and decision criteria used by decision makers, and there is no correspondence with actual operational counterparts, starting with the absence of cows.

Is the Absence of Cows a Problem?

Some approaches to milk production may include cows (Equation 4), and others may not (Equation 5 and the model in Figure 3). A first question to ask is if the lack of cows is in itself problematic. Is this just a question of boundary selection or of data availability?

One of the first answers to the question of inclusion of this or that variable is data availability. In fact, the author of the mentioned time-series study of milk production underlines: "In most empirical studies of efficiency in dairy farming, the output and input variables included have been determined largely by data availability. Often the only output is milk, and less important outputs like farm-grown feed, culled cows and male calves that are sold have been ignored". (Mkhabela et al., 2010, pp. 117-118). In such cases, data availability drives the definition of boundary, which on the first place should not be such a thoughtless matter. Forrester questioned such criterion:

> Many persons discount the potential utility of models…on the assumption that we lack adequate data on which to base a model. They believe that the first step must be extensive collecting of statistical data. Exactly the reverse is true… There seems to be a general misunderstanding to the effect that a mathematical model cannot be undertaken until every constant and functional relationship is known… This often leads to the omission of admittedly highly significant factors…because these are unmeasured or unmeasurable. To omit such variables is equivalent to saying they have zero effect—probably the only value that is known to be wrong! (Forrester, 1961, p. 57).

Indeed even authors of no-cow models of milk production show some concern about the exclusion of the main protagonists: "there is something unsatisfactory about not including the size or value of the dairy herd as an input in the production of milk" (Mkhabela et al., 2010, p. 110), though it seems only a matter of "dissatisfaction" and they dismiss the issue in the same way that many scientists do it, as a mere technical matter:

> Perhaps the most interesting issue is the inclusion of the dairy herd as an input, which is done in some studies but not others, with the decision again based mostly on data availability. ..Thus, cows do not appear as an input, as although it is not possible to produce milk without them, they are both produced and consumed on the farm and so can be subtracted from both sides of the farm accounts (Mkhabela et al., 2010, p. 118).

We learn such an assertion in high school: "If equal terms [let us say, cows] appear on both sides of an equation, then we may cancel them".

If it were only a problem of algebraic cancellation…

Both the time-series Equation (5) of Mkhabela and the stock-and-flow model of Figure 3 illustrate the popular "science by observation" in which the world dictates the source of knowledge that imprints the data-analyzer researcher that concludes based on what s/he observes. Those approaches do not build milk production as an *operation* carried out by decision makers. Instead, milk production is built on non-operational relationships between variables arranged on very abstract formulas that work on data. Is this problematic? I think it is, at least for addressing human systems. But the reason is not an apparent dogma about a certain way to build certain type of models ("because the technique says so"), the usual and unfortunate answer nevertheless. Apart from having different ways to define a particular equation for milk production, there are different modes of thought behind each approach. The fact is that behind any model there are conscious and unconscious assumptions regarding what the model is for, what the model represents, how the model can be used, for what purposes, etc. For example, all of the data-based cited studies aim to identify policy and action levers. Such actions allegedly work if we push the correct buttons (so-called policy levers, causes, factors, and similar names) so that we can obtain the *production* that we want, even regardless of cows, farmers, milking and reinvestment. The world is thus taken (perhaps unsuspectingly) as a type of machine ruled by a sort of causal law-like principles, instead of driven by decisions taken by agents. I will develop this idea in the following section.

3. Uniform Nature or Agency?

Beyond the significant problem of boundary adequacy indicated above by Forrester, I find two additional problems with non-operational modes of reasoning. On the one hand, milk production itself is not explained beyond some obscure force or mechanism (since Galileo, scientists like the term "law") that the researcher, passively instructed by data, attempts to uncover. This attitude reduces the issues of explanation and understanding to the employment of law-like accounts discoverable through data analysis (instead of understanding *why* things happen this or that way). On the other hand, this obscurity entails a larger issue: induction is perhaps the most contradictory way to source knowledge in a non-uniform world. This section addresses these problems and shows the scope of operational thinking which is able to meet a world that, I want to believe, is continuously changing since it is constantly re-created by free human beings through their decisions and actions that do not obey laws.

The Problem of Induction

Human beings believe that if conditions are similar, then what has been observed will happen again. This process of generalization in space and time, i.e. induction, is commonly taken as the method of science, that is, to use data as a source of knowledge in order to establish general statements that go beyond data.[3] Such statements run under different names such as theories, hypotheses, predictions, laws, among others.

There is a problem with such a belief. Figure 4 shows a timeline in which the "Past" section displays the historical (observed) data for milk production presented in the mentioned paper of Mkhabela (2004); the vertical dotted line represents the present. A forecast (for example using Equation 5) is generated based on those repeated instances of (observed) phenomena. Now let us suppose that there will be a first-ever mad cow outbreak—a *novelty*. This sort of thing happens—the technical expression that forecasters use is "structural break". Evidently, the forecast is unable to capture such a type of contingency. Inductive knowledge cannot capture, by definition, unobserved events. When observations are used to "understand" the world in order to hypothesize what can, may (e.g. probability estimations), or will happen, then such a world has to be uniform; otherwise, all innovations, including outbreaks, become "black swans", unexpected rarities. It easy to appreciate the unreliable way to meet a changing world through analysis of data. The real mystery is why today very popular and fashionable epistemologies rely on such a belief.

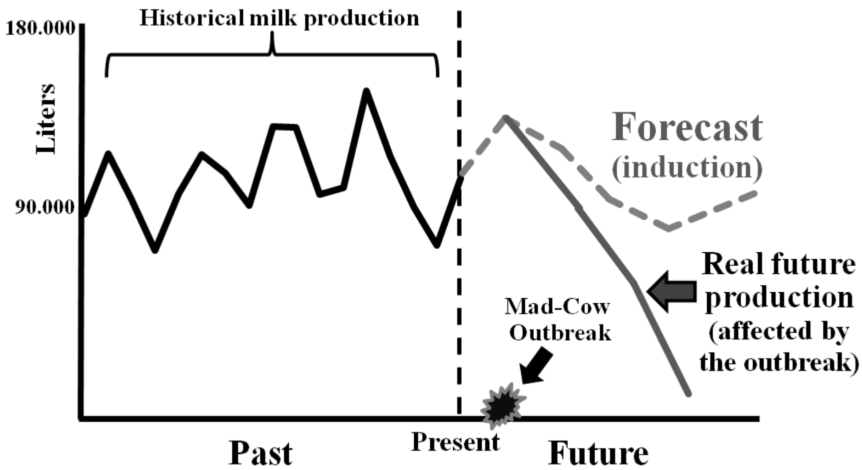

Figure 4. *Knowledge based on data misses unexpected events*

[3] Researchers often claim to work under alternative ways such as "abduction", "deduction", or combinations of these. However, abductive reasoning, typically "inference to the best explanation", is a type of inductive reasoning (Fumerton, 1992), regardless even of the redefinitions of induction and deduction made by Peirce who claimed that along with abduction would conform a method of discovery (Frankfurt, 1958). Moreover, deduction belongs to a distinct category since it concerns consistency, not inference (Harman, 1992).

The assumption that underlies the principle of induction is that "the future will resemble the past, or, somewhat better, that unobserved cases will resemble observed cases" (Bonjour, 1992, p. 391), a supposition that aims for a preconception of a given uniformity and that draws attentions to the old Humean *problem of induction*.[4] Perhaps the best and simplest way to picture it is with the traditional example: a strong and long-lasting prevalent "theory", until the 18th century, was that "all swans are white*", inferred from uncountable repeated observations (for centuries)* of white swans in Europe. Indeed, until that century, it was not a theory but a truth. Then, the black swans of Australia were "discovered" in 1698. The theory happened to be very "wrong", and for a very long time, regardless of the perfection of past data. The expression "black swan" has become the name for unexpected, high-impact novelties. In fact, a forecaster of the dairy industry states: "Forecasting the dairy markets has almost become a fool's errand, because of the frequency with which 'black swan events' turn our outlooks upside down. There is no 'normal' anymore." (Levitt, 2011, p. 34).

David Hume (1740) questioned our belief in the uniformity of nature (i.e. the future will be like the past) and rejected, at least in principle, inductive arguments: "there can be no demonstrative arguments to prove, that those instances, of which we have had no experience, resemble those, of which we have had experience" (p. 62). He summarized his argument in this way:

> Here then are two things to be considered, viz. the *reasons* which determine us to make the past a standard for the future, and the *manner* how we extract a single judgment from a contrariety of past events… We may observe, that the supposition, *that the future resembles the past*, is not founded on arguments of any kind, but is derived entirely from habit, by which we are determined to expect for the future the same train of objects, to which we have been accustomed. This habit or determination to transfer the past to the future is full and perfect; and consequently the first impulse of the imagination in this species of reasoning is endowed with the same qualities… Though perhaps very little are necessary to perceive the imperfection of every vulgar hypothesis on this subject, and the little light, which philosophy can yet afford us in such sublime and such curious speculations. Let men be once fully perswaded of these two principles, *that there, is nothing in any object, considered in itself, which can afford us a reason for drawing a conclusion beyond it;* and, *that even after the observation of the frequent or constant conjunction of objects, we have no reason to draw any inference concerning any object beyond those of which we have had experience* (pp. 92, 95).

That is another way of saying: "data analysis, understood as a *source* of knowledge for constructing more general statements, is futile". Hume showed that induction is an untenable position for generating knowledge. The problem is the contradictory aspiration to go beyond empirical observations in order to affirm a more general statement of any kind based on such evidence. Within a strict empiricist tradition, "we must work with what we are given, and what we are given (the observational and experimental data) are facts of the form: this F is G, that F is G, all examined F's have been G, and so on" (Dretske, 1977, p. 249). And yet, for instance, we say that "all men are mortal", though such a generality cannot be inferred from observation. For example, if one were a radical empiricist, what would be one's source of knowledge in asserting that all humans are mortal? It would be the observation of all humans, from the first born to the last to die. Considering that there have been around 106.5 billion people on the planet since the beginning of human history (Haub, 2002), and that now there are about 7.0 billion alive, then there are still approximately 6.5% of cases not supporting the hypothesis, a non-negligible amount. Naturally, it would be worse to affirm that "the probability of dying is close to 0.94" or that "men are normally mortal".[5] But then, why can we affirm that "all men are

[4] The identification of Hume with the problem of induction is inevitable. Weintraub (1995) exposes the historical antecedents, before Hume, of the critique of induction. A similar discussion is developed by Milton (1987).

[5] It might sound as a joke but that is how the argument goes. For instance, such an inductive reasoning was used in the famous von Foerster's "Doomsday Equation" published in *Science* in 1960 (von Foerster, Mora, & Amiot, 1960) that predicts that the world will end next November 13th, 2026, since "at this date human population will approach infinity if it grows as it has grown in the last two millennia" (p. 1291). An operational alternative that includes human action was delivered in 1972 in the seminal work "Limits to Growth" (Meadows et al., 1972).

mortal”? The source of knowledge is different, it is not past experience of mortality. Perhaps it is operational thinking about “how the human body works”.

Uniform Nature

Thus, how can induction be justified? The justification of induction is induction itself, that is, “induction works because it has worked so far”.[6] Since such a reasoning borders insanity then a theoretical devise had to be invented: the *principle of the uniformity of nature*, for instance:

> Only a few of a large number of known or possible cases are selected for analysis, and the result obtained is known to be strictly true only of these few selected particulars. Yet the outcome of this induction is expressed in a generalization claiming to be true not only of the analyzed but of all cases. How is this justified? The answer has been: there is uniformity between the analyzed and the unanalyzed cases, and this uniformity justifies the extension to all cases of what has been found to be true in the few. Once true, always true, thanks to uniformity (Gotshalk, 1932, p. 149).

To rely on induction implies that one assumes some type of uniformity and lack of variance in the universe. Such assumption was explicitly stated by Mill: "What happens once, will, under a sufficient degree of similarity of circumstances, happen again, and not only again, but as often as the same circumstances recur" (as cited by Gotshalk, 1932, p. 141). This principle implies that the observed regularities are invariable with respect to location in space and time (Schlesinger, 1990). Furthermore, if there is a “strange” observation (unrelated to previous observations), then it can be explained because of the different space or the different time in which the observation is made and not because of changes in the nature of the things that are observed. This is a common assumption that has become popular in science, e.g. Keynes in *A Treatise on Probability* (1921) justifies induction based on the Principle of the Uniformity of Nature, and thus: "A generalisation which is true of one instance must be true of another which *only* differs from the former by reason of its position in time or space" (p. 295). Indeed, this is a core principle of current science, since "if difference in date or position alone could make particulars unalike, then inductive reasoning, based on the belief that like things behave alike, would have no application" (Schlesinger, 1990, p. 529).

On the other hand, if the observer considers that a truly different observation appears, then it can be stated that it is “genuinely different” since it is not a confirmatory piece of evidence; in this way, the particular inferred theory is protected, and the method remains safe. The difference can also be explained as an observational imperfection: "In fact, examining any of the seeming counter-examples to the principle of uniformity of nature, will lead to the conclusion that in the past no violation of that principle had ever taken place and the appearance of violation can *always* be shown to have been the result of the wrong application of the inductive method" (Schlesinger, 1990, pp. 531-532, emphasis added). Indeed, if the principle of induction is to be guarded, then whenever and wherever observations are not as expected, it can always be argued either that the new case is truly novel (and thus that it does not belong to the class of regularities to be observed and expected), or that it is a problem of *observation*—with familiar labels such as “sampling problem”, “inadequacy of the selected cases”, “survey design defect”, “measurement problem”, “acceptable error”, “bias”, and so on.

Popper (1974) took seriously this problem, e.g. “We never argue from fact to theories” (p. 97). For him induction is a fashionable myth: “as for induction… I assert, with Hume, that there is no such a thing…there is no rule of inductive inference—inference leading to theories or universal laws—ever proposed which can be taken seriously for even a minute” (p. 168, 169). Nevertheless, currently many scientists seem to be obsessed with observational problems and

[6] The account of Bertrand Russell pictures it: “The inductive principle, however, is equally incapable of being *proved* by an appeal to experience. Experience might conceivable confirm the inductive principle as regards the cases that have been examined; but as regards unexamined cases, it is the inductive principle alone that can justify any inference from what has been examined to what has not been examined. All arguments which, on the basis of experience, argue as to the future or the unexperienced parts of the past or present, assume the inductive principle; hence we can never use experience to prove the inductive principle without begging the question” (Russell, 1912, p. 38).

data analysis, and keep on embracing an uniform world so as to favor *regularities* instead of recognizing *change*. This is inherently attached to the empiricist tradition and its methods, and such a view is even taken by many as the very definition of science.[7] This position shows the still powerful and influential ideas of the Vienna Circle (Ray, 2000) and its influential positivist thinkers of the 20th century, i.e. Wittgenstein, Ayer, Carnap, etc., who propelled the Machian epistemology that became the dominant philosophy of physics that we know today (in spite of the opposition of Planck, Einstein, and others). This position, in turn, became largely the dominant philosophy of science,[8] up to now. The fact that the most influential scientists of modern times (Newton, Darwin, Einstein) did not inferred their theories from data seems to change nothing. That is, Newtonian mechanics, the evolutionary theory of Darwin, and the special theory of relativity, were not induced from particular cases or "data".

Scientism: The Quest for a "Natural Social Science"

The principle of uniformity sustains, in turn, the search for natural *laws*. In words of Russell (1948): "The uniformity of nature…has no definite meaning except in connection with natural laws… the laws must be the same in one part of space-time as in another… This principle…presupposes the existence of laws" (p. 335). Such a *deterministic* conception of the world represents a problem for human systems, to name a few: moral responsibility and freedom.

In 1926 the neurologist Charles Judson Herrick, aware of the increasing tendency and pressure to use inductive methods of natural science in the human domain, summarized the question in his appropriately entitled paper "Biological Determinism and Human Freedom":

> There is, however, a growing demand for an attack upon problems of human behavior by the methods of natural science—observation, experiment, and the formulation of empirically determined rules of uniform, orderly, and verifiable natural process… Human nature can be studied by the methods of natural science in so far as the data employed are natural events inhering in a unitary system of orderly cause-and-effect sequences. The disruption of such a unitary system by the admission of uncaused action, of mystical factors, or of metaphysical absolutes or sanctions violates the scientific method as commonly defined by experts in this field. It is of interest, accordingly, to ask how far it is profitable to push the inquiry into problems of human behavior with the ordinary methods of natural science. The natural order is regarded by most scientific investigators as deterministic. Human conduct is commonly regarded as in some respects free. The natural history of man is therefore confronted at the outset with a hoary problem which must be clarified before we can fix the limits of the inquiry. *Is it possible so to define determinism and freedom as to conform with current scientific and popular usage and at the same time clarify the most acute problems of human conduct-self-control, self-determination, self-culture, social control, social culture, personal and social morality?* (Herrick, 1926, pp. 36-37).

Although the debate on determinism is a very old one, I want to stress that the question of Herrick is about *the relevance of the methods of natural science for approaching the human world*, even if some researchers restrict those methods to positivism in which data is the source of knowledge that imprints the researcher that pretends to confirm those observations with future observations. For Herrick, the method is not negotiable since for him human nature can be studied if *data corresponds to natural events of a unitary system of orderly cause-and-effect sequences*. That is, for him the method rules over the domain of study. By the middle of the 20th century, Hayek (1942) called to this type of uncritical posture *scientism*: "an attitude which is

[7] Schlesinger (1990), for example, states: "We would only give up our assumption about uniformity if it always turned out to be false, in which *of course* we would have to abandon the entire scientific enterprise" (p. 533, emphasis added).

[8] Bartley (1987) makes a short explanation of this process: "The logical positivists, including Carnap, who formed their famous group around Moritz Schlick in Vienna—the "Vienna Circle"—named themselves the "Ernst Mach Society", even though not all were presentationalists. And with the mass exodus of philosophers of science from Austria and from Hitler's Germany immediately before the Second World War, phenomenalist, presentationalist philosophy or science—under various names: operationalism, positivism, instrumentalism, and so on—spread around the world, firmly establishing itself in the universities of the English-speaking countries, where it remains dominant today" (pp. 16-17).

decidedly unscientific in the true sense of the word, since it involves a mechanical and uncritical application of habits of thought to fields different from those in which they have been formed. The scientistic as distinguished from the scientific view is not an unprejudiced but a very prejudiced approach which, before it has considered its subject, claims to know what is the most appropriate way of investigating it" (p. 269).

It is easy to appreciate that particles, contrary to human beings, are not decisions makers. It is also easy to appreciate that hydrogen atoms, contrary to human beings, are all equal to each other. Such characteristics of the material world help to explain why induction seems to work *in natural science*. However, the fact that a social system is driven by decision makers that in turn are different to each other and that change through time, suggests the question if such characteristics are relevant to be considered in the methods that we use to investigate such systems and if such methods, that require *uniformity of nature*, are adequate for human systems. Seemingly such a truism needs to be stated. It is possible to have alternatives to the quest for trying to uncover the mysteries hidden in data allegedly to know some regularity behind. Operational thinking offers a possible alternative: to understand a human system in terms of its *operations* (human decisions, human actions). This is why operational thinking is not just a technicality to build some type of models. It is not only a desirable skill in learning processes, either. Operational thinking is a way to meet a changing world constructed by free agents, a statement that implies to conceive the transformation of a social system in terms of transformations in the decision-processes, actions, arrangements and use of information that human agents carry out. The next section outlines this idea.

4. Design of Social Systems

Science cannot be only contemplation. Science brings also the promise of improving the state of affairs. However, data-analysis, as the way to unveil the forces that drive social systems, seems to be a very indirect way to try to change the human world since agency is excluded. Yet, a large part of scientific practice follows this path.

Homo Molecules Sapiens

It seems to be widely believed that the task of social science is to find forces or mechanisms that drive and "explain" the social world, for instance: "there are social phenomena independent of cognition to be explained in terms of underlying mechanisms (which may not be directly observable)… The task of social science is to understand the way in which mechanisms work in conjunction with contextual factors to generate social outcomes" (Sanderson, 2002, p. 8). This type of enterprise is carried out through the analysis of observations that rely on protected assumptions; the final result is a law (or a law-like statement, i.e. theory, hypothesis, etc.) that explains the observed regularities and that would allow to transform the world.

A good example is the rather recent "evidence-based" boom,[9] which may serve as an illustration of the risk of assuming data as the supreme authority to create knowledge that apparently would allow us to act and to change the state of affairs. Consider "evidence-based economics". Reiss (2004) defines what he calls its "fundamental" questions, which concern *measurement*: "do the associated measurement procedures measure the quantities of interest correctly and accurately?" (p. 347), and *induction*: "do past observations of a relationship of interest justify projections onto unobserved situations?" (p. 347). The motivation of Reiss is to have valuable recommendations for action: "suppose you are a member of a central bank committee deciding on whether or not to change the interest rate. It is central bank policy to target the country's inflation rate, and the measured rate is above the set target. What do you recommend?" (p. 346).

[9] It started in Medicine (Timmermans & Kolker, 2004) and, regardless of early warnings about the flaws of extremist data-based methods (e.g. Diamond, 1989), this type of research practice has been growing and spreading to other areas, e.g. psychology (Melnik, Oliveira, & Atallah, 2011), Education (Davies, 1999), Criminology (Welsh & Farrington, 2001), Public Policy (Sanderson, 2002), Management (Pfeffer & Sutton, 2006).

He concludes his paper in this way: “to urge that before any valuable recommendation can be given at all, one should have a sizeable amount of evidence at one’s disposal” (p. 362). In this case is evidence, instead of operational understanding, what is required. The economic system seems to be explained as the consequence of natural-like forces discoverable with evidence, method that is guarded by its own assumptions, e.g. changes are taken as the product of exogenous forces instead of endogenous operations. The world becomes a determined machine that follows laws. If we know the laws, we can push the right buttons. Examples of this physicalism in social systems are plentiful—e.g. *entropy* is a favorite law-like device among some physicalists. For instance, a way of thinking —beyond metaphor—for explaining wealth exchange among economic agents runs this way:

> The interaction among agents consists of a exchange of a fixed or random amount of their wealth. The process of exchange is similar to the collision of molecules in a gas and the amount of exchanged wealth when two agents interact corresponds to some economic “energy” that may be transferred for one agent to another. If this exchanged amount corresponds to a fixed or random fraction of one of the interacting agents wealth, the resulting wealth distribution is – unsurprisingly – a Gibbs exponential distribution” (Iglesias & De Almeida, 2012, p. 2).

Hayek’s scientism in plain sight. Nevertheless, instead of “molecules” and “gas” we can acknowledge *agents* and *social systems*. The recognition of decision making and freedom should bring *unpredictability* and, with this, changes in questions and expectations. Instead of asking “what will (or may) happen?” and expecting a law or theory, we can ask “how does it work, and why?” and expect operational intervention through redesign.

How does it work? Why?

I think that in order to redesign (transform) a system we first need to understand how the system “works”, why the system delivers the performance that it shows, in terms of its own *operations*. This requisite can be met with the help of an engineering trademark practice: modeling, that is, *operational* modeling.

In the second section I used the inflow equation of *production* (Eq. 4 for the operational model in Figure 2) as an example of operational thinking. Such an equation, though very simple, has several virtues. For instance, it allows us to capture hypothetical events that may have never been observed on the real farm. Such fictitious events can be simulated with a computer, we usually call them “scenarios”. Since the human mind is very limited in its capacity for examining the consequences of our assumptions (Norman, 1983), we can use a computer to represent and simulate models to enhance and promote conceptual change. Computer models can be used to create task environments in which experiments can be made to examine the scope of such modeled assumptions. Simulated data are generated using the actual functioning, arrangements, and operations of a system. The computer allows for the exploration of scenarios, however improbable, and of different policies to understand how and why this specific arrangement of variables, values and equations (that is, decision processes) for this particular system, explains its performance.

What are the expected results of the simulation? Did the results turn out as expected? Why did the results turn out the way they did? The model allows for addressing “what if…?” questions that can be answered according to the decision rules of involved agents. The “if” captures contingency, i.e., “what happens if decision-makers choose this or that…?” This contingency recognizes a changing, uncertain world in which free decision-makers can take diverse decisions according with local and temporal (contingent) conditions. Such agents create and re-create a social system through incessant decision processes and under unknown futures. These explorations permit us to conjecture how and why the system “produces” its own behavior and what the system is able to “produce” under different unknown circumstances (Figure 5). As experimentation continues, new questions surface and further trials are tested with the simulator, fruitless trials are discarded and successful ones are retained. New knowledge can be generated through this process. This knowledge is specific, temporal, contextual, and pragmatic.

This model-based approach, driven by operational thinking, develops a contingent, task-oriented form of Popperian science (Olaya, 2012).

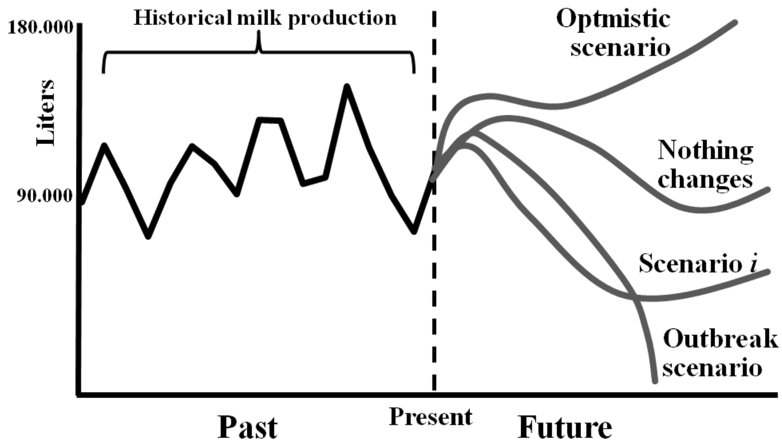

Figure 5. *Exploration of scenarios. Operational knowledge delivers how a system works (according to the operations of the system, not according to the data) under diverse, unknown future conditions*

The simulated "data" for (milk) *production* that the model generates (Fig. 5) is not based on past production but rather on the simulation of the actual operation of production, i.e., "how production works" according to the system to which it belongs. In this case, the values through time of the variable *production* are not induced from its past values but rather generated as the result of the operation of the whole model that simulates, iteratively, *every contingent decision*. The behavior of *production* is therefore understood as the outcome of the combination of decision rules, feedback loops, delays, nonlinearities, and so on. Milk *production* is "produced by the system". This reasoning applies to all of the other variables; each one is formulated accordingly for this specific organization. For instance, a scenario of a mortal epidemic in which cows start to disappear—because of, for example, a mad cow outbreak—can be simulated by progressively decreasing the cow's *birth rate*. Eventually the stock of cows can decrease (when the outflow rate surpasses the inflow rate) and cows can go to zero. In this latter case then the equation of *production* guarantees that production will be zero, no cows, no milk. Simple, and yet, powerful. This operational approach allows us to understand how and why an scenario of a possible outbreak impacts the behavior of the whole system as a result of its own configuration.

The "future" behaviors of milk production in Figure 5 are the result of the continuous operations of the arrangements, physical structure, relationships and decision processes represented in the modeled farm system, in this case all of the scenarios are a result of continuous operations of production, sales, revenue, reinvestment, breeding, etc. The challenge of a modeler is to propose reliable functions for such operations, including operations in ranges of variables that may have never been observed, and thus, "the model should predict modes of behavior which could occur but which have perhaps never been encountered in the past" (Forrester, 1975b, p. 156). Naturally, the formulation of such decision rules requires the collection of a special type of "data", e.g. from interviews with the respective decision-makers in order to capture the way in which such agents "produce" a decision in function of the use of information, resources, etc.

Intelligibility

This type of knowledge of how and why the system behaves as it does, as a function of its own structure, its own decision rules employed by involved actors, its particular configuration and feedback loops, its specific material and information delays, its nonlinearities, etc., is captured in higher-level statements: *dynamic hypotheses*, i.e., explanatory *mechanisms* (Olaya, 2004) of the behavior of the system in terms of its own structure. Such descriptions render *intelligible* explanations, as opposed to obscure forces that are allegedly unearthed by data analysis, since such explanatory mechanisms seek to explain

> how a phenomenon comes about or how some significant process works…i.e., to explain how it was produced… The explanation renders a phenomenon intelligible. Mechanism descriptions show *how possibly, how plausibly, or how actually* things work. Intelligibility arises not from an explanation's correctness, but rather from an elucidative relation between the explanans (the set-up conditions and intermediate entities and activities) and the explanandum (the termination condition or the phenomenon to be explained)… [It] provides intelligibility by showing how the phenomena might possibly be produced. We should not be tempted to follow Hume and later logical empiricists into thinking that the intelligibility of activities (or mechanisms) is reducible to their regularity. Descriptions of mechanisms render the end stage intelligible by showing how it is produced by bottom out entities and activities. *To explain is not merely to redescribe one regularity as a series of several. Rather, explanation involves revealing the productive relation*. It is the unwinding, bonding, and breaking that explain protein synthesis; it is the binding, bending, and opening that explain the activity of Na+ channels. *It is not the regularities that explain but the activities that sustain the regularities* (Machamer, Darden, & Craver, 2000, pp. 2, 21-22, emphases added).

Apart from such intelligibility, operational thinking helps to identify our own ontic commitments regarding the models that we build and the systems that we deal with. The scenarios in Figure 5 are not "possible forecasts". They are not prospective speculations either. We change the question, so instead of asking "what will (or may) happen?," we can ask "how does it work?" in order to intervene and transform a system with robust policies that incorporate our operational understanding of the way in which the particular system is organized and how its specific actors act. This statement implies, in turn, that beyond a question of level of aggregation, if the goal is the transformation of social systems through the recognition that such systems are recreated and sustained by decision makers, then we should make such operational variables and processes explicit in our models in order to devise the intervention and redesign of decision processes, which reveals how we think that the system changes, if it changes at all. That is, particular levels of aggregation can be misleading as long as we exclude from our explanations the decision processes that transform a system.[10]

In spite that Jay Forrester explicitly underlined these elements in the very beginnings of system dynamics,[11] it seems that a statement on the significance and the scope of this posture is much needed nowadays. If what the systems does is driven by the decisions that the corresponding actors make and the way in which such decisions occur (e.g., the arrangement of actors, delays, the use of resources and information, specific decision rules, etc.), then the redesign of these systems means transformations for new arrangements, new configurations, the promotion of new decision-making processes, and the generation of processes of growth of knowledge within the system.

5. Outlook

I teach an undergraduate system dynamics course. One of my student's activities is to develop through the academic term an application project on a real problematic situation that they choose. One of the most difficult beliefs to fight against (and that my students embrace), is the anxiety and the dependence that they show on "data" (understood as observed values of variables). For them, the success of the project depends on the availability and quality of such

[10] I want to thank to Martin Schaffernicht and to an anonymous reviewer for pointing at this direction.

[11] For instance Jay Forrester in 1960 refers to the first of three parts that for him would conform the basis of methodology on which to build the new field: "The goal is to design better systems, not merely explain what is now done. Models are not primarily for predicting specific future events, but are for displaying the general performance characteristics of a system. Models must be based on our vast body of descriptive knowledge and not merely on that for which numerical data exists… We know what would happen under many limiting conditions even though data has never been collected. *Functional relationships* which meet all of the known boundary conditions are constrained so that they cannot be far wrong in the normal operating regions " (Forrester, 1975a, p. 56, emphases added). Forrester remarked that this is "the same *philosophy* that has succeeded in complex engineering" (p. 56, emphasis added) .

data. I deliver from the start of the course the ideas expressed in this paper, i.e. “a system dynamics model is not a model of data, is a model of decision rules”. Perhaps I am a very ineffective teacher because I have found that this is one of the most difficult ideas to deliver. But it is easy to see the same persistent obsession with data as both the criterion for defining boundary of models and as the source of knowledge, everywhere when a consultant or scientific project is being developed. Perhaps, we, human beings, suffer from a combination of two cognitive disabilities (among other several ones): a very strong propensity to explain the world in terms of the past in order to believe that the future will be like the past, and a very weak capacity to reflect on and to challenge our own beliefs (for instance, the belief that the future will resemble the past).

It is hard to overestimate the necessity of basic reflection for any scientific inquiry. Unfortunately there seems to be nowadays a persistent division between philosophy (that is, reflection) and science. The Platonic dogma, as built in history books, has traditionally endorsed the dichotomy between *episteme* and *techne* and has grounded human knowledge on a passive and mimetic reception of information that seems to live up to the present day (Floridi, 2011). In this respect I endorse the eloquence of Blackmore (1979):

> Few things are more ironic than for a self-styled 'empiricist' openly to repudiate philosophy, when he himself has unconsciously adopted the philosophical views of Comte, Mill, Mach, or Carnap and unconsciously repudiated the scientific *practice* of anti-positivists such as Lavoisier and Dalton in chemistry, Lyell and Darwin in biology, and Galileo, Newton, Planck, and Einstein in physics who *all* assumed the reality of a physical world *beyond* sensory appearances and who thought that the primary task of science was to understand that trans-empirical world (i.e. 'elements' and 'atoms' were not observable, geological and biological history are not observable, the real motion of the planets is not observable, and the absolute speed of light in a vacuum is a constant whether observable or not). In other words, 'anti-philosophical' empiricists are commonly the victims of the most *anti-scientific* of all philosophies, namely the phenomenalism and subjective idealism of Berkeley and Hume, *who aimed above all else to restrict the scope and importance of science as had earlier phenomenalists even as far back as Pyrrho the sceptic* (pp. 130-131).

The common-sense attitude of “learning from data” seems to persist. It is easy to see that analysis of data is usually assumed as the way to source knowledge, and the correct application of technical tools is taken as the warranty of rigor and academic authority. I share with John Allen, professor of Biochemistry at the University of London, his concern with the strong resurgence of the view that there is a direct route from observation to understanding—“the data speak for themselves” (Allen, 2001), in which the intellectual challenge seems to be the technical collection and the analysis of data. Several researchers seem to ignore Hume’s arguments against induction and read (unknowingly perhaps) Bacon’s *Novum Organum* too literally. Operational thinking presents an opportunity to question common preconceptions about “what science should be.” One of the strengths of system dynamics is that it promotes the reflection upon our own assumptions. This attitude can be extended to general inquiries we make about the world, the tools that we use for making such inquiries, and the strength of the epistemic arguments in our modes of reasoning—which always surpass the particular tool in hand. To understand a social system as the product of its operations, instead of approaching it through mysterious repetitions of data furnished by law-like principles waiting to be discovered, or in other words, to understand a social system as the result of the actions of free agents that make decisions, instead of a sort of determined machine, is perhaps one of the most important epistemic shifts that any academic and any practitioner can make.

Barry Richmond, as a concerned educator, proposed two decades ago a series of easy-to-grasp concepts in order to transfer the framework, the process, and the technologies of system thinking to the rest of the world. One of such concepts was “thinking in terms of how things really work” (Richmond, 1993, p. 127), he coined it as *operational thinking* and identify it with getting “at the core stock-and-flow infrastructure that lies at the heart of a system or issue” (Richmond, 1994, p. 141). Richmond highlighted the value of this thinking skill in educational settings because it is a learning virtue that "grounds students in reality" (Richmond, 1993, p. 128). In this paper I extended the scope and the significance of "operational thinking" to identify it with a particular underlying mode of reasoning behind a certain type of models. Thus, it is not only a thinking skill, it is much more, it is a characteristic mode of reasoning, a special epistemological posture. It is a mode of reasoning that deals with non-uniform nature. It delivers a special type of understanding in function of the operations of the system (not in function of laws), which in social systems means in function of free decision makers. Thus, in summary, the significance of operational thinking is this: it rejects induction as a way to *know*, on the contrary, it recognizes a non-deterministic (social) world, that is, a non-uniform world, it assumes that agents do not follow some kind of laws or any other mysterious force that data would permit us to uncover (and that yet, leaves the phenomenon unexplained). Instead, it gives the attribute of *freedom* to decision-makers and thus, a social system is assumed to be the dynamic product of those decision makers. No less.

As a final point, first-hand information has always been a good starting heuristic to learn about something. Operational thinking comes with a *method*. Instead of measuring data, the researcher should go and ask the cows, I mean human beings, how they do what they do.

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