Science beyond quantification? integrating objective and subjective views in unpredictable worlds

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***Abstract*—This short paper stresses the importance of extending model-driven research practices to deal more comprehensively with unpredictability in hyper-complex systems (e.g., large socio-cyber-physical systems and planetary eco-systems). This point becomes particularly critical when scientific results inform governance decisions with dire consequences for various stakeholders (e.g. managing pandemics, economic crisis or climate disturbance). Research areas more acquainted with hyper-complexity (e.g. psycho-sociology, biology, business, defence) have proposed specific methods to deal with system unpredictability and management subjectivity. These include strategic prospective, dependability by design, action-research and post-normal science. Research areas more accustomed to stability and objectivity (e.g. natural sciences and engineering) seem to resist such extensions and struggle with the consequences when operating in unstable, multi-faceted contexts. They may issue unreliable predictions and ill preparedness due to over-reliance on models that are unfit, obsolete or one-sided. We emphasise the importance of adopting more suitable methods for studying, describing and managing hyper-complex systems facing unpredictability and subjectivity; and to highlight how integration science (SISSY) may contribute.**

***Index Terms*—unpredictability, hyper-complexity, model-driven research, causal rest, quantophrenia, post-normal, prospective, strategic forecasting, dependability, self-integration**

I. Managing Hyper-complex Systems

Hyper-complex systems [1] are precarious complex systems undergoing constant evolution under the effects of novel and unpredictable phenomena, which emerge, proliferate and cross-pollinate at various scales [2]. Here, novelty sources and ensuing chain-reactions can be such that the system never quite stabilises. Examples include the Earth system and large socio-cyber-physical systems(-of-systems).

Understanding, developing and managing such systems has been an everlasting endeavour in numerous domains. Adaptive actions (reactive and predictive) are often informed via various kinds of system *models*. We employ the term 'model' generally here to mean any formal representation of a system (and its environment) that is used to study the system and issue predictions about its behaviour. Most models rely either on estimates of causal relations among system processes (e.g. expressed via mathematical formulae, formal diagrams or multi-agent simulations) or on data-driven machine learning and stochastic correlations between subsequent system states or behaviours. In general, such predictive models aim to capture the relevant aspects of the targeted system and its environment, for achieving given research objectives.

When employed in relatively stable, sufficiently observable contexts, such formal models represent useful tools for better understanding system dynamics and predicting possible futures to inform complex management decisions. In unpredictable, unstable environments, visionary models may also be employed to simulate imagined situations and inform preparations for conceivable futures. As similar modelling techniques may be adopted in both types of contexts, there is a risky tendency to unadvisedly take for granted the reliable predictive ability of models developed for well-known environments and mistakenly rely on the same ability when applying them within hyper-complex, surprising environments. The model's predictive power is wrongly associated to the model-driven method, while neglecting its limiting applicability assumptions.

Moreover, employing model-driven research to inform key decisions, with significant consequences for diverse human organisations and eco-systems, raises subjective, ethical, value-sensitive issues that exceed the scope of natural sciences and engineering practices. At the same time, scientific model-driven research is increasingly called upon to inform critical administrative decisions [3]; and pushed forward as legitimate, 'objective' determinants to justify official policies– thus shifting responsibility from decision-makers to scientific models [4], [5]. Failing to clarify such misunderstandings is not only risky in terms of unsuitable decisions, but can also backfire and discredit legitimate modelling applications, as well as hinder opportunities for valid future extensions.

As autonomic computing systems may be called-upon to operate within increasingly hyper-complex socio-technical environments, research in this area may also become exposed to the aforementioned issues. We highlight such risks here and start transferring lessons learned from other domains that have set-off to alleviate them. We also emphasise the importance of pursuing research topics relevant to unpredictability management within relevant research communities, including self-* systems in general and self-integrating systems in particular.

Importantly, we do not aim to discredit rigorous scientific investigation applied within its legitimate domain. We merely recall that results reliability does not stem from the method alone, but also from its suitability within the applied context.

II. Modelling Principles and Core Challenges

Generally, modelling requires: selecting an *abstraction level* (or *scale*) for observing and representing the targeted system; and selecting the *relevant aspects to include* in the representation, relative to the modelling objective and the application context [6], [7]. To model large complex systems, multiple scales and their interactions may be included in the model [8], [9]; and, several complementary models can be combined to represent different system viewpoints or concerns [7]. We focus on three kinds of modelling processes in this paper:

- *Model-Based Systems Engineering (MBSE)*: uses models to represent and integrate various cross-domain perspectives and stakeholder interests when developing systems(-of-systems). It enables an iterative refinement and analysis of engineering artefacts– from informal requirements, through coarse-grain design, to fine-grained implementations. It has been applied to a variety of cyber-physical system developments, e.g., defence, space exploration, transport, industry and high-tech systems [6], [10], [11].
- *Models at Runtime (M@R)*: extends the use of models to system execution, to represent and analyse the state of a running system and to adapt it to dynamic changes so as to achieve management goals [12]. Implicit models are also employed in self-adaptation algorithms to predict system reactions to enacted changes.
- *Model-driven research*: employs models to represent, study and predict system developments– either under conditions similar to those observed in the past and present, or in case of future disruptions and interventions.

We focus here on the latter, model-driven predictive research, when employed to inform governing decisions affecting socio-technical ecosystems [3]. This model-driven governance is similar to M@R in technical systems, except for the larger scales, hyper-complexity and subjective implications.

Quite obviously, modelling implies that some (or most) system characteristics and processes are actually left out. Useful models successfully select what to include and what to ignore, depending on the modelling purpose and contextual limitations – hence the well-known quotation (attributed to several authors): 'all models are wrong, some are useful'; which by no means implies that all wrong models are useful.

To predict and manage future developments in a rigorous, objective manner, most model-driven scientific approaches rely heavily on various forms of quantification, and structural or behavioural patterns from previous observations. The following assumptions are inherent in most of these techniques:

A.1 the future will be an extrapolation of the past [13], [14];

A.2 what cannot be unambiguously quantified or approximated (e.g. via stochastic methods) cannot be considered– should be ignored, or excluded, as 'non-scientific' (by the current standards or methods) [1];

A.3 data, numeric estimates and ensuing model-driven results are as objective and just as one can possibly get [15].

Such model-driven approaches become ill-adapted in hyper-complex systems, where disruptive changes lead to futures that no longer resemble the past; hence rendering existing knowledge obsolete (invalidating A.1). Examples of such recent disruptions include unprecedented planetary-scale pandemics, recessions, the advent of DataAI, perturbations of climate, biodiversity and geo-politics. While the consequences of such disruptions unravel, system dynamics during state-transition is difficult (or impossible) to quantify, in any reliable way– e.g. probable infection rates or casualty numbers during a new pandemic; complex psycho-social reactions to crisis; disturbance of undersea biomass and its consequences during climate change.

In some cases, resistance to quantification may be a consequence of the previous concern (i.e. disruptive changes invalidating previous knowledge); as the necessary data for reliable probabilistic predictions is missing. Hence, ignoring phenomena that cannot be quantified may be objective and scientifically sound. Yet, when such phenomena risks impacting key objectives, ignoring them all together may be seriously unwise (challenging A.2)– e.g. the probability of hydrate methane disintegration in seabeds and its impact magnitude on future temperatures [1] (III.2.7., p250-256), [16], [17].

Finally, when disturbances require urgent, high-stakes decisions impacting diverse human organisations and eco-systems, scientific objectivity may become limiting or questionable (challenging A.3). Beyond objective 'truths' (which may also be questionable in hyper-complex contexts), governance-related decisions are expected to consider ethical concerns. These involve subjective, debatable, conflicting viewpoints and values, largely resisting meaningful quantification– e.g. safety and security vs. civic liberties; economic prosperity vs. human dignity and eco-system sustainability.

III. Key Concepts from Literature

We consider three key interrelated concepts from the literature – *causal rest*, *quantophrenia* and *misleading objectivity* – that reflect the current limitations of common modelling practices, as highlighted in the previous section. While many other modelling limitations exist (e.g. data quality, runtime novelty integration), we focus here on issues that are insufficiently addressed, yet are essential for decision processes that rely on model-driven predictions.

A. Causal Rest

Causal rest [1] refers to any phenomena that affects a managed system, yet is excluded from its model (Fig. 1).

On the one hand, it may arise from common factors such as: ill-considered modelling abstractions (i.e. mistakenly excluding phenomena that is actually causally relevant); or predicted uncertainties (i.e. inaccurate information due to stochastic or chaotic processes; noise; observation or execution errors). These cases already receive significant attention from several areas – e.g. the art of modelling [6], control theory [18] and uncertainty management in self-* systems [19].

On the other hand, omitting relevant causal phenomena may also occur for phenomena that are known, yet that elude meaningful quantification– in terms of their occurrence probability, amplitude, consequences, or utility. This mostly affect sciences dealing with hyper-complexity, e.g. psycho-sociology or anthropology– unadvisedly labelled as ‘soft’. As American Anthropologist Gregory Bateson indicated in reference to such sciences, “There are the hard sciences, and then there are the really difficult ones.” Moreover, beyond the difficulty in assessing the likelihood of occurrence of various causes, there is the struggle of selecting the relevant causal-chain to include into the model from a complex space of potentially conflicting, subjective options (cf. misleading ‘objectivity’, III-C)– e.g. conflicting opinions about what might have happened [20]. Finally, causal rest may be due to limited knowledge and imagination about the studied system (i.e. blind spots, or “unknown unknowns” [21]). We focus here on these three latter cases, as less studied and increasingly critical (e.g. technical infrastructure embedded in modern societies; climate and biodiversity studies, interrelated with socio-technical systems).

B. Quantophrenia

We consider the definition of quantophrenia in [1], as a tendency to: a) limit the representation of phenomena to quantitative representations; b) only employ these quantitative representations to inform political decision processes; and, c) largely employ quantitative criteria as tools for implementing and evaluating ensuing policies [22], [23], [24], [25].

The notion of quantophrenia (i.e. or “the cult of numerology”) was initially employed by sociologist Pitirim Sorokin, in 1959 [26]. He deplored the misuse of mathematical and numeric representations in psycho-social theories, which hoped to enhance their legitimacy and solidity (previously reserved to ‘hard’ sciences). While acknowledging the appropriate use of mathematics to study psycho-social phenomena that lend themselves to analytical investigation, he denounced its application “when the true quantitative method is replaced by pseudo-mathematical imitations; when the method is misused and abused in various ways; when it is applied to phenomena which, so far, do not lend themselves to quantification; and when it consists in the manipulation of mathematical symbols in a vacuum or in the mere transcription of mathematical formulae on paper without tying them to the relevant psycho-social units. In such cases, the mathematical approach “misfires” and “becomes a mere quantophrenic preoccupation having nothing in common with mathematics and giving no cognition of the psycho-social world.”

C. Misleading Objectivity

Misleading ‘objectivity’ may occur when applying formal modelling to analyse subjective, human-related phenomena, which may be perceivable via different points of view, related to different values, potentially in dispute. Establishing an objective, absolute validity of such overlapping views and values goes beyond the applicability domain of natural sciences and associated scientific methods [14], [20].

Beyond the potentially biased selection of relevant aspects to model (cf. causal rest, III-A), model sensitivity to parameter configurations may raise additional objectivity issues. Whether intentional or unconscious, modellers may tune model configurations in ways that provide divergent predictions, prompting to opposite decisions. This is especially the case with overly complex models, e.g. including too many free variables that can be tuned to fit any phenomena (cf. ‘mind the hubris’ [3]). We recall Enrico Fermi’s famous critique in response to Freeman Dyson’s claim that their model fitted the data, using four parameters: “With four parameters I can fit an elephant, and with five I can make him wiggle his trunk.” [27].

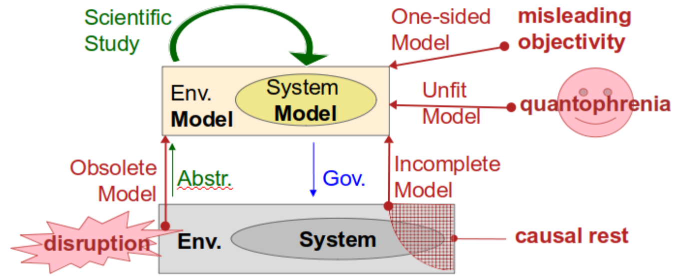

Fig. 1. Key factors affecting modelling fitness for reliable predictions: the *causal rest* means that important aspects are excluded from the model; *quantophrenia* includes unsuitable abstractions into the model (excluding important details); *misplaced objectivity* ignores other valid perspectives; *disruptive changes* invalidate existing models.

IV. Ways Forward

A. Contributions from Existing Methodological Extensions

Promising directions for alleviating the aforementioned methodological issues have been developed over the last decades in areas more directly facing hyper-complexity and its limiting implications for predictive science (e.g. psycho-sociology, space systems, defence, business innovation, philosophy of science). We introduce some of these below.

Prospective: promotes envisioning potential future scenarios and exploring their implications, as a way to inform and guide critical strategic decisions. Here, reflection preceding strategic processes relies not only on past experiences, but also on imagined futures [28]. These latter can be expressed via simulation tools or plain language argumentation. Such strategic foresight allows “organisations to guide the reflection that precedes strategic processes, calling for a better understanding of the potential for profound changes and their consequences, over the shorter or longer term.” ([29], p.35).

Within the prospective approach, “a scenario is a tool for describing a possible or desirable future. (...). A prospective approach generally develops several scenarios (...).” ([29], p. 87). According to the Organisation for Economic Co-operation and Development (OECD), such scenarios are an “explicit and structured exploration of possible futures to inform present decisions” [30]. Model-Based Systems Engineering (MBSE) practices also promote Scenario-based Engineering Processes (SEP) to ensure “manageable user-centered process for gathering, analyzing, and evaluating requirements that can vastly improve the success rate in the development of medium-to-large size systems and applications” [31]. This approach is in-line with the prospective initiative, while in principle having to deal with less subjectivity and fewer conflicts among various user perspectives (cf. post-normal science, below).

Dependability by design: promotes inherent dependability qualities – e.g. robustness, resilience, availability, safety, security, anti-fragility [32] – as first-class system requirements; pushing optimal performance to the second plane. This is a fundamental inversion of priorities relative to many traditional systems, which capitalise on relatively stable environments and the reliability of models they confer, to focus on efficiency optimisation at the cost of other system qualities [33].

In a future where unpredictable events of increasing magnitude become more frequent, dependability-promoting adaptability will make the difference between systems(-of-systems) that survive and those that do not [34]. In such cases, it becomes critical to prepare systems for unknown challenges by endowing them, at the minimum, with the capacity to recognise novel, surprising situations and to establish whether they can deal with them or not. Handling novelty implies further abilities such as open adaptability and creativity (e.g. highly reusable adaptation strategies combined with self-integration and self-evaluation for generating new viable system versions at runtime; online machine learning; human-in-the-loop). Drawing inspiration from biological species that have adapted over significant epochs to a wide range of environments and cataclysms may be essential here [35].

Post-normal science: promotes a new type of "issue-driven" science [14] to address situations featuring: acute uncertainty levels (about facts and consequences); conflicting stakeholder values; and urgent, high-stake decisions. It concerns cases where science is employed to manage public affairs (e.g. pandemics, socio-economic crisis, climate disturbance, biodiversity decline). It opposes the 'post-modern' stance, which focuses on the unrestrained criticism of contemporary cultural phenomena, conveying towards nihilism and despair.

The post-normal initiative emerged more than three decades ago [14], in reference to Thomas Kuhn's view of 'normal science' (i.e. routine puzzle-solving advancements within a given theoretical framework); which then evolves via sudden conceptual revolutions (i.e. 'paradigm shifts') to deal with phenomena that current theories cannot address. The problematic issues here are science-informed governance decisions, in a context of acute unpredictability, high stakes and subjective values. In such contexts, traditional sciences loose their effectiveness. While common scientific methods do guarantee a high-degree of objectiveness when acquiring knowledge from observed phenomena; the choice of what is relevant (included) and what isn't (excluded) in the scientific process is often subjective and relative to individual points-of-view, preferences or purpose.

Instead, the post-normal approach acknowledges the plurality of legitimate perspectives within hyper-complex systems where ethical issues occur. It proposes involving in the scientific process multiple investigators with complementary expertise– scientific experts and domain specialists; but also non-experts who possess actual experience with the studied phenomena and who will be affected by the ensuing decisions.

As a complex phenomena may appear quite different when observed or utilised from different view-points, with different purposes (e.g. across animal species [36] or different stakeholders [14]), integrating multiple view-points may increase the objectivity and relevance of the overall result. This is also in line with related studies on collective knowledge management in ancient democratic societies [37] and its potential applications to socio-technical systems [38]. It is also compatible with Elinor Ostrom's 3rd design principle (i.e. participatory decision-making), facilitating decision acceptance and contributing to sustainable resource management [39].

Action-research: promotes an interactive inquiry process that seeks to achieve transformative change via a cyclic process between concrete action and reflective science about action. Action provisions the reflective understanding of action, which in turn promotes better-informed action. The process develops through an iterative spiral, cycling from planning to action and fact-finding about the action consequences. It may also involve co-research, or cooperative inquiry with the people performing the actions. It is a philosophy and research methodology employed in social sciences, initially proposed by Kurt Lewin as part of his pioneering work on social, organisational and applied psychology [40]; and later refined via further variants and for concrete application domains (e.g. space systems [41]).

Precautionary Principle: promotes a cautionary approach, in cases where scientific knowledge or evidence are missing, to prevent the adoption of innovations that may lead to disastrous, irreversible harm [42]. For instance, in Medicine, it requires extensive tests of new drugs before releasing them for public use. In engineering, it requires thorough formal validation and empirical safety tests before planes, trains or automobiles can be mass-produced. At the same time, for innovations where the causality-chain between action and its effects is more complex, and may include indeterminate social factors [21], this principle becomes less straightforward to apply with similar rigour, for providing similar guarantees. In such cases, reliable scientific knowledge becomes difficult to obtain – e.g. the effects may depend on how the innovation is used later-on, within which context, and involving interactions with future innovations. Such aspects make it quasi-impossible to predict potential effects in the classic scientific sense. This raises concerns about the extent to which trying to prevent any unfortunate events, however rare or improbable, would also deter most profitable innovation and 'progress'.

The answers to such complex questions about the indeterminate consequences of present actions stretch beyond the rigorous, objective domain of natural sciences. One difference with predictive models discussed earlier is that precaution shifts the responsibility more upstream [21]. Another difference is that the scope of potential impacts may become much larger, making it difficult to even identify all relevant stakeholders, as was the case in e.g. post-normal science and action-recherche proposals. Precautionary questions may have to consider broader social, moral and cultural perspectives and involve more extensive debates within the entire populations to be affected by the ensuing decisions. Surely, there is no silver bullet – viable solutions to complex problems are rarely simple or binary, and pushing any one-sided paradigm to its extreme only generates absurd results.

B. Contributions from Integration Science and Engineering

With the ever-increasing complexity of engineered systems and their operation environments, several development and management methods were devised to deal with increasing uncertainty and user subjectivity. Going beyond the rather rigid, linear cascade methodology, such methods introduced increasing flexibility, adaptability and plurality in the engineering processes: e.g., iterative flows, scenario-driven engineering, co-operative requirement specification, agile and extreme programming. While these approaches provide valuable enhancements for engineered systems, they mostly operate before the product is delivered; and require punctual updates for upgrading operational systems.

Moreover, current engineering methods rarely deal with ethical issues, viewed from diverse or conflicting user perspectives. This remains the case even when the use of engineered products raise increasing ethical questions (e.g. privacy, long-term psycho-social effects, inequality, sustainability). Value Based Engineering (VBE) (cf. ISO/IEC/IEEE 24748-7000 standard) is one exception. It integrates into system development specific steps for identifying stakeholders and their values; and for deriving a set of Ethical Value Requirements (EVR) to be incorporated into system design. Extending such approaches to dependably deal with hyper-complex environments and become accountable for ethical concerns becomes increasingly desirable in modern societies. Drawing inspiration from the above methods (cf. IV-A) may be valuable here.

Self-* systems in general, and several research topics in self-integrating systems (SISSY) in particular, aim to bring some of these techniques into the runtime, enabling systems to self-manage while allowing strategic human intervention. Research in these areas promises to provide valuable knowledge for extending current research and development practices in hyper-complex socio-technical eco-systems [43].

SISSY's research emphasis on system self-integration is highly relevant here. Firstly, it implies integrating several knowledge representations, from different systems, into a functional whole. On the one hand, this may facilitate interrelations between objective scientific models, representing partial expertise on specific aspects of hyper-complex problems. On the other hand, it is also essential for the ability to adopt several subjective viewpoints for developing multi-perspective models. Heterogeneous model integration in this context requires dealing with diverse, perspective-specific concepts, which may be novel, incompatible or conflicting; and may represent various system parts at different scales.

Importantly, models representing different viewpoints do not necessarily need to be forced into compatible representations of an objective 'truth' (as is the case in natural system studies), or into a coherent set of requirements (as is the case in product engineering). Such coherence is only required when deciding about concrete policies or courses of action, where contradiction cannot be implemented. Such conflict-free model integration can be achieved dynamically, case-by-case, upon taking each decision; rather than only once for the entire integrated model. Inspiration can be taken here from context-specific behaviour merging in living systems [44], [45], to similarly merge conflicting models based on their relevance and priority in each context.

Secondly, SISSY strives to create new behaviours via self-integration and self-improvement. This may enable system adaptation to surprising situations, hence contributing to its dependability (as discussed above). Over time, it becomes clear that matters of uncertainty and unpredictability must be integrated as first-class considerations into system development and management processes [19]. These latter must be conceived so as to be able to deal with continuous change [43], not only by selecting among preexisting solutions, but most importantly by being able to innovate on-the-fly. This requires creative, self-critical process that can, on the one hand, produce novel system versions (able to address a new challenge); and, on the other hand, evaluate new versions relative to goals or survival criteria. Most SISSY topics are relevant to such innovative self-adaptation: self-evaluation, self-modelling, automatic meta-model extensions, reflection, goal-orientation, online learning, self-explanation; and integrating the above processes at various, interrelated scales.

Beyond automated self-* processes, human-in-the-loop options may help to deal with new situations. Here again, knowledge integration methodologies and platforms promoted by SISSY may facilitate interactions among human actors with various backgrounds, in case of surprising situations or crisis.

V. Conclusions and Future Perspectives

This short paper emphasised the key role that formal models and simulations play in developing and managing hyper-complex systems– e.g. socio-technical systems and planetary ecosystems. Considering their critical role in key decision-making processes, we highlighted some of the main limitations inherent in traditional model-driven prediction techniques and the dangers behind overlooking them. These included *causal rest*, *quantophrenia* and m*isleading objectivity*; leading to models that are incomplete, one-sided and unfit for reliable predictions, while maintaining decisional overconfidence in the modelling method. We identified several promising approaches from relevant fields that propose interrelated and complementary extensions to modelling methods – e.g. strategic prospective, dependability-by-design, post-normal science, action-research and precautionary principle – to be applied when model-driven predictions may have serious ramifications in unpredictable contexts. Finally, we brought to the fore several SISSY research topics that appear most relevant to supporting such extensions, notably including the (self-)integration of heterogenous knowledge and behaviours.

In future work we will interact with researchers and practitioners dealing with hyper-complex systems across various domains– via dedicated interviews, relevant conferences and seminars. This will enable us to acquire and disseminate better insights into how unpredictability and subjectivity concerns are dealt with within various disciplines and how such concerns may subsequently affect important decisions informed by these disciplines. Better understanding such matters and the recurring methodological shortcomings for addressing them will help provide concrete recommendations for improving mainstream processes that transfer scientific insights, through expert consulting, to governing policies.

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