**Martin Kunc: Commentary on Lustick and Tetlock, 2021**

**Introduction**

As a scholar using models to support scenarios, I welcome the article from Lustick and Tetlock. I agree that planning for any event requires well-calibrated conditional forecasts of its impact synthesizing inside- and outside-view analytics. I am surprised the article does not consider a simulation method widely used in simulating large systems, system dynamics (SD) (Forrester, 1961), when SD modellers develop computer simulations that replay historical trends based on social-science models of causation (Kunc, 2017a). The objective of this commentary is to complement Lustick and Tetlock’s article with more information about the SD modelling process and how it is aligned with the principles suggested in their article.

**System Dynamics modelling**

A common used approach to develop SD models consists of **five steps** (Sterman, 2000). **First step** defines the boundary of the system, articulates the purpose of the model and involves selecting key variables with a defined time horizon (past and future). **Second step** comprises the identification of the current theories associated with the causal structure driving the performance of the system. The aim is to explain the dynamics of the system as an endogenous consequence of the feedback structure, which describes processes of circular causality. Feedback processes in social systems have one important characteristic: they are mostly tacit because they are separated in time and space, as well as across multiple stakeholders. Longitudinal observations from stakeholders, who have experienced and observed the system over time, and causal-based theories are the sources of information for designing SD models (Kunc, 2017a). For example, Atkinson and Gary (2016) and Hwang and Kunc (2015) have interviewed multiple stakeholders associated with classes of similar systems and consolidated them in a single model. An example of employing extensive literature is Rocha et al (2020) where they integrated economic and social theories to explain the dynamics of regions. **Third step** consists of formulating the computer simulation. This stage encompasses defining the type of variables: stocks, flows and causal networks, parameters and initial conditions. While numerical data is necessary to run the simulation, SD models are not dependent on numerical data. The most important aspect in the formulation is the logic behind the equations because the model test theory-grounded hypotheses (Kunc, 2017a, b). While SD models are deterministic, modellers are increasingly exploring deep uncertainty in parameters (Kwakkel and Pruyt, 2013). **Fourth step** involves validating the model with respect to the purpose, e.g. correspondence with the system, and its verification, e.g. how the model behave with data uncertainty. Rahmandad and Sterman (2012), Martinez-Moyano (2012) and Monks et al (2018) have proposed rigorous procedures for validation, verification and documentation. **Fifth step** is the experimentation with the model using multiple approaches. One approach is to test the impact of scenarios in a system (Kunc and O’Brien, 2017). In this way, the model can alleviate the issues raised by Lustick and Tetlock in terms of the mental abilities by analysts to compute complexity and achieve consistency. Another approach is to explore uncertainty in terms of future policies and offer a distribution of results rather than specific point forecast (Kunc and Kazakov, 2013). This process can be performed using Monte Carlo or through the elicitation of future values using experts (Willis et al, 2018).

To summarise, SD models are theory-informed computer simulations that can produce scenarios consistently and help to address uncertainty. Applying the “what-world-am-I-in?” matrix (Lustick and Tetlock, 2021), SD models may be suitable for most quadrants. SD models in Q1 will be accurate and suitable to test policy-relevant hypotheses. SD models in Q2 can be used to test the sensitivity of the theories-in-use by stakeholders and analysts to the uncertainty in data, e.g. Kwakkel and Pruyt (2013). SD models in Q3 can test hypotheses about the causation that exist in big data, e.g. Kunc (2019), in order to avoid confusion with spurious correlations. Models addressing Q4 needs to enhance both causation (transfer to quadrant 2 through the identification of rigorous theories) and data availability (move to quadrant 3 by finding comparison-class data). There is a large practice associated with developing SD models with group of stakeholders called group model building (GBM). Research in GBM includes selection of stakeholders, group dynamics, and scripts to facilitate participation (Andersen et al, 2007; Rouwette, 2016). GBM can be used to move up a model from Q4 to Q2.

**Hybrid modelling**

Lustick and Tetlock (2021) suggest there are two more challenges to building simulation tools: the integration or federation of theoretical models and their verifiable operationalization. The use of additional modelling methods, such as Discrete Event Simulation (DES) or Agent Based Modelling (ABM), together with SD can not only increase accuracy and enhance the strengths of each individual simulation method but it is also a growing field (Brailsford et al, 2019).

Brailsford et al (2019) proposed a conceptual framework for hybrid simulation with four categories of hybrid models with different levels of integration. Enriched models have one methodology dominating and minor aspects of the problem addressed by other method. Sequential models have components driven by different methodologies executed in a specific arrangement. Interacting models have the execution order determined dynamically at runtime. Integrated models have undistinguishable components.

Most of the examples of hybrid models published are a combination of SD and DES or SD and ABM (Brailsford et al, 2019). This trend can be associated as the process of enrichment of existing models by using other modelling methods. In any case, “an important feature of this methodology must be an ability to evaluate the benefit of each method for each subsystem and then finally, on a parsimonious principle, determine whether one method would suffice for all (and if so, which). If not, then a hybrid model will be needed.” (Brailsford et al, 2019, p. 729). One of the main benefits of the use of hybrid models is the ability to create ‘digital twins’ to incorporate real time data into the simulation and reflect more realistic behaviours (El Saddik, 2018).

Gu and Kunc (2019) used a hybrid model to rehearse strategies after scenarios. An ABM represented the dynamic of market with heterogeneous customers. DES simulated the operation of stores as customers shopped. SD integrated the financial results and track the intangible assets in the business. Model were grounded in consumer behaviour, operations and financial/strategic theories.

**Conclusion**

Theory-grounded computer simulations are the future of scenarios due to its flexibility to deal with different type of problems in terms of data and knowledge, as well as its ability to complement traditional scenario methods (Kunc and O’Brien, 2017). The quality of the output, and its use in decision making, depend on rigorous modelling processes with extensive participation of stakeholders and social scientists. The use of computer simulations and scenarios should not be restricted to one-off activity. Scenarios, as well as computer simulations, improve over time as lessons are learned. Therefore, scenarios and computer simulations should be long-term investments for companies and governments.

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