

Interim Report

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Systems Analysis as a System of Methods. How to Study Complex Social-environmental Systems?

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Contents

1	At the end of a big cycle.....	1
2	Starting a new cycle.....	2
3	Historical data, imitation methods and models	2
4	Stages in model-based research.....	3
5	Stage 1. Modeling paradigms and state spaces	4
6	Stage 2. Construction of models.....	5
7	Stage 3. Model assessment.....	8
8	Stage 4. Model-based forecasts	10
9	A multi-model approach.....	11
10	Monitoring and updating	15
	References	16

Foreword from Elena Rovenskaya

This report resulted from the vast experience of its author, Academician of the Russian Academy of Sciences, Arkady Kryazhimskiy, in the field of the methodology of systems analysis.

Academician Kryazhimskiy started working at IIASA in 1993 as the principal investigator in the Dynamic Systems Program and went on to coordinate and lead this program until 2009. In this role Academician Kryazhimskiy used his mathematical expertise in areas ranging from optimization methods to dynamic games in order to advance IIASA's methodological approach. Before retiring from his senior management position at IIASA, Academician Kryazhimskiy oversaw the transition of the Dynamic Systems Program into the Advanced Systems Analysis Program in 2011. Since then and until his unexpected passing away in 2014, Academician Kryazhimskiy was able to devote all his energy at IIASA to his passion of mathematical research.

IIASA's interdisciplinary environment also encouraged Academician Kryazhimskiy to go beyond the traditional boundaries of mathematics aiming to bridging gaps between methodology and applications. This report is his last written piece. It presents Academician Kryazhimskiy's vision of the definition and practice of systems analysis, which, I am sure, will be educational for any systems analyst, and especially for early-career scientists joining IIASA.

Acknowledgments

The author is grateful to Ulf Dieckmann, Arnulf Grübler, Yuri Ermoliev, Tatyana Ermolieva, Matthias Jonas, Pavel Kabat, Simon Levin, Wolfgang Lutz, Marek Makowski, Elena Rovenskaya, Sergei Scherbov and other IIASA colleagues who shared with the author their views on systems analysis in numerous discussions held in the process of preparation to IIASA's 40th Anniversary Conference (October 2012), during the Conference and after it. The author acknowledges DG Research for funding through COMPLEX, Project # 308601, www.complex.ac.uk

Preamble

IIASA's 40th Anniversary Conference (October 2012) triggered numerous scientific discussions in the IIASA community, both before the Conference and after it. Many interesting ideas emerged. One of the ideas was that a group of IIASA's systems analysts would summarize IIASA's understanding of systems analysis in a collective paper. The author of this discussion paper was invited to join the project, which is still in progress. This discussion paper can be a basis for the author's contribution to the project.

There is a strong diversification in 'definitions' of systems analysis. We sharpen our view if we agree, at least temporarily, that systems analysis lies, by definition, in the field of methodology. We sharpen our view even stronger if we say that systems analysis develops and applies methods for exploration of complex social-environmental systems. This is the viewpoint held in this discussion paper.

The paper makes an attempt to position systems analysis as a 'methodological discipline' (somewhat similar to mathematics) by describing a set of 'standard rules' characteristic for that 'discipline'. All those rules have certainly been repeatedly used in research; the paper summarizes them in a 'table form' that may hopefully serve as a zero approximation to a future 'road map for a systems analyst'.

Arkady Kryazhimskiy

Laxenburg, 27 November 2013

Systems Analysis as a System of Methods.

How to Study Complex Social-environmental Systems?

Arkady Kryazhimskiy

1 At the end of a big cycle

In Ancient Greece science was integrative¹. Philosophers desired to understand the universe as a whole. Philosophical speculations led, quite naturally, to specific questions focused on parts of the universe. The desire to answer 'partial' questions triggered the formation of scientific disciplines.

Within each discipline, the number of 'disciplinary' questions and their complexities grew rapidly. The disciplines were losing connections. Knowledge was becoming sharper, deeper and less integrative.

In parallel, generation of truly new disciplinary knowledge was becoming extremely expensive in terms of both money and effort. At the edge of tremendous findings – a controllable nuclear reaction, cheap renewable energy, control on aging, and remedies against fatal diseases – the movement towards these findings has rapidly slowed down. Extreme research efforts have atomized into thousands of paths 'orthogonal' to the main directions.

Disciplinary questions become finer, sharper... Andrew Wiles's proof, in 1995, of the famous Fermat theorem – an exciting avenue, which opened up in 1637 and was gradually becoming thinner – was a full stop in a long and dramatic story of research.

Isn't this example a warning signal? Doesn't it tell us that further refining disciplinary research may lead to similar dramatic endings instead of showing us how to resolve critical problems?

If we take this viewpoint, we easily come to a claim that in parallel to developing well-established disciplinary research, a new, alternative way of progressing in science needs to be tried.

What will be a new way of progressing in science?

We get a simple logical key to answering this question if we state, once again, that the warning signals appeared in a recent phase of the long process of moving away from integrative knowledge towards specialized knowledge. Reversing this statement, we can conjecture that a new way of progressing in science will be reversing the trend – initiating a motion from specialized findings towards integrative knowledge.

¹ Today's name of the scientific degree, 'Doctor of Philosophy', common for all scientific disciplines, is a trace of the integrative character of ancient science.

2 Starting a new cycle

Global challenges – a critical state of the environment, limits in natural resources, a growing social inequality, world economic crises – create acute demand for systems analysis – a new integrated scientific discipline that would focus on characterizing possible futures of complex large-scale social-environmental systems and actions that may lead to these futures.

The key questions are: WHAT and HOW.

What are the major phenomena the systems analysts should focus on in their studies of the futures of complex social-environmental systems?

How to study the futures of complex social-environmental systems?

In numerous studies of complex social-environmental systems, general features of such systems have been revealed and understood – nonlinearity, multiplicity in scales, heterogeneity, risk and uncertainty among others (Levin *et al*, 2012). These are the key phenomena to be researched, both in general settings and in particular case studies.

Experience shows us that in systems analysis prognostic research and diagnostic research go hand by hand; understanding the future (forecasting) is not separable from understanding the past. Powerful analytic tools – theory of adaptive systems, control theory, optimization theory, game theory, numerous modeling techniques (see Levin *et al*, 2012 for an overview) – have been used to study complex social-environmental systems in both theoretical and applied contexts. This provides us a basis in our thinking of how to answer question HOW.

In this discussion paper we address question HOW. In various combinations, the techniques we discuss here have been used in numerous studies of particular research questions. However, to our knowledge, there has so far not been made an attempt to look at these techniques systematically, put them together, classify them and suggest a prototype ‘toolbox’ for systems analysts. In this paper we make a step in this direction. We hope that further collective efforts in collecting, developing and testing techniques for exploring complex social-environmental systems will gradually lead us to formation of a clearly defined instrumental spectrum of systems analysis.

3 Historical data, imitation methods and models

A historical data set tells us about the real changes, which the complex social-environmental system under investigation survived in the past. The historical data set is highly important from a systems analysis perspective; it reflects all the phenomena (nonlinearities, cross-scale interactions, heterogeneities, etc.) that drive the system.

Theoretically speaking, all sorts of data possess that property. However, in the spectrum of all data that are principally available, some types of data are more informative than the others if we take into account the goal of research. Selection and collection of most informative data is a special important (sometimes very expensive

and time consuming²) task in systems analysis³. Here, for the sake of brevity, we do not discuss this task in any detail (leaving it for further discussions), and focus on techniques for utilizing the data.

Suppose we are given a historical data set (say, a time series) and want to convert it into a meaningful statement about the system's future. To do so, we are bound to use some method for imitation of the system's dynamics; here, we call such methods imitation methods.

Choosing an adequate imitation method is the key technical challenge. The complexity of a large-scale social-environmental system is usually so high and our knowledge about it is (despite the data at hand) so poor that we are principally unable to construct a method that would capture the system's dynamics precisely⁴.

In other words, in systems analysis we are forced to deal with methods that fail to mimic the systems dynamics to a degree, at which we can (like in the case of mechanical systems) claim, in advance, that our method-based forecasts are accurate, or at least not misleading. In this situation, prior to the use of the chosen imitation method one needs to assess the method in order to understand its forecasting ability.

In a traditional view, an imitation method is a model – a set of mathematical formulas representing (to a certain degree of accuracy) the system design. In our discussion, we follow that tradition to a considerable extent; we associate basic types of imitation methods with models. In the end we go further and consider multi-model imitation methods involving several (many) models (section 9).

4 Stages in model-based research

Models representing the systems through mathematical relations are test beds for various analytic tools – from rigorous mathematical analyses to brute force simulations, which help us, indirectly, understand the operation of the systems.

In this section we briefly announce typical stages in model-based research (see Table 1). In sections 5 – 8 we comment on these stages in some detail.

A model-based research starts with choosing a modeling paradigm and a model's state space – two basic 'coordinates' of a model as a research instrument. Next two stages are construction of a model with the chosen basic 'coordinates', and assessment of the model, including a diagnostic analysis. Generation of a model-based forecast finalizes the research effort.

Typically, the first three research stages are not separated in time. Quite often, one updates the model, based on results of model assessment, and one changes the initially chosen modeling paradigm or the initially chosen state space, based on

² For example, Wittemyer (2011) assessed the relations between African elephant mortality and various economic data (livestock and maize prices, change in national and regional GDP, the normalized difference vegetation index, and others) in Kenya to find economic metrics serving as indicators of changes in human use of and resulting effects on natural resources.

³ Here, for brevity, we do not discuss how to cope with data errors, which can be significant and even misleading (we slightly touch upon this issue in section 9; see footnote 12).

⁴ In this context, the complexity of social-environmental systems is of a different type than that of mechanical systems; a mechanical system, no matter how complicated it is, is fully described by the mathematical model coupling the system's design with mechanical laws.

experience in constructing and assessing the model. The updating process may go through several iterations.

Table 1: Stages in model-based research

Stage 1	Choosing a modeling paradigm and a state space
Stage 2	Constructing a model
Stage 3	Assessing the model
Stage 4	Generating a model-based forecast

5 Stage 1. Modeling paradigms and state spaces

A modeling paradigm is a disciplinary niche for a model, understood in a mathematical sense. The modeling paradigm pre-defines the style of the model-based research. A model can follow approaches in modeling of dynamical systems (see, e.g., Ljung and Glad, 1994) and pretend to imitate the system's dynamics by imitating relations between the system's components; it can follow theory of optimal central planner control (Pontryagin, 1962; see also Aseev and Kryazhimskiy, 2007, presenting a control-theoretic technique applicable to problems of economic growth) and represent global optimization principles; it can follow theory of differential games (Isaacs, 1965; Krasovskii and Subbotin, 1988; Basar and Olsder, 1982) and implement global equilibrium principles; it can follow theory of evolutionary games (see, e.g., Weibull, 1995) and demonstrate learning/adaptation schemes. The list can certainly be extended. Complex models can lie under several modeling paradigms (occupy several disciplinary niches) simultaneously.

A model's state space is a set, within which the model's states are allowed to vary. The model's state space characterizes the model's ability to capture details, its resolution scale. The more complex is the model's state space, the more details are captured by the model and the finer is the model's resolution scale.

Finite-dimensional vector spaces (whose points are finite-dimensional vectors of given dimensions) are the state spaces for widely used deterministic models described by finite-dimensional ordinary differential equations and their discrete-time analogues. Deterministic models described by partial differential equations and infinite-dimensional ordinary differential equations operate in infinite-dimensional functional spaces whose points are functions defined on solid sets⁵. By choosing a deterministic model, one 'declares', implicitly, that one has a good understanding of the mechanism driving the system.

Stochastic models deal with probability distributions of points. Their state spaces are structured as probability spaces, in which points act as elementary events. Usually, one chooses a stochastic model if the mechanism that drives the system is uncertain though one has an understanding of a statistics related to its operation.

⁵ Here, by a solid set we mean a set whose cardinality (a mathematical generalization for the number of elements) is not less than that of the set of all real numbers (the cardinality of the continuum).

The points serving as states for the deterministic models (as elementary events for the stochastic models) are as usual regarded as direct prototypes of real, 'physical' values characterizing (not necessarily entirely) the real systems; the models and systems 'speak the same language'.

In a less straightforward model design a model's states are images of the 'physical' values; the transformation converting the 'physical' values into their images is not necessarily one-to-one. The transformation 'compresses' the 'physical' space by not distinguishing between the 'physical' points having the same image. The use of such image states can be efficient in forecasting radical structural changes (catastrophes)⁶. Indeed, on the one hand, the image variables representing clusters of 'physical' points are by construction less sensitive to weak perturbations in the dynamics than the 'physical' points themselves. On the other hand, transitions between the clusters reveal remarkable irregularities in the model's behavior and can signal on upcoming critical changes (catastrophes).

Table 2 summarizes our preliminary classification of modeling paradigms and state spaces as 'basic coordinates' for models.

Table 2: Modeling paradigms and state spaces

Modeling paradigms				
Disciplinary niches	Models' functions			
Modeling of dynamical systems	Imitation of the systems' dynamics			
Optimal control	Implementation of global optimization principles			
Differential games	Implementation of global equilibrium principles			
Evolutionary games	Implementation of learning/adaptation schemes			
		Vector spaces	Probability spaces	Image spaces
				State spaces

6 Stage 2. Construction of models

As mentioned in section 4, construction of a model is not separated from the choice of

⁶ For example, Kryazhimskiy and Beck (2002) use binary, 'minus' and 'plus', images of short-term transitions to assess tendencies towards catastrophes; the transitions regarded as dangerous have 'minus' images and those regarded as safe have 'plus' images. Keilis-Borok *et al* (2003) use binary images (codes) for crime trends to forecast homicide surges.

a modeling paradigm and a state space, and from the choice of a model assessment method (see Table 1, stages 2 and 3). Accordingly, in this subsection we partially overlap with the previous one (discussing modeling paradigms and state spaces) and the next one (discussing model assessment methods).

We dare to say here that choosing a modeling paradigm is, conceptually, not a too difficult task. Principally, one can have in mind the following simplified pattern.

If the mechanism that drives the system does not include non-specified time-varying inputs or actions (the system is 'closed'), or if we, for some reason, decide to ignore such actions, approaches in modeling dynamical systems will be an appropriate disciplinary niche and our model's mission will be to imitate the system's dynamics.

On the contrary, if we view the system as an 'open' system driven by time-varying actions not given in advance, we construct an 'open' model and equip it with an action selection principle, based on which we study the model's behavior by generating selected (extreme, most likely, etc.) paths within the infinite pool of the model's potentially allowable action-driven trajectories.

Action selection principles base on several methodological approaches.

The scenario-based approach is widely used. Scenarios represent exceptional 'typical' actions (as given functions of time) and 'encircle', in some sense, the set of all the system's allowable paths into the future. Usually, the design of a set of scenarios results from an informal analysis, and the number of scenarios, especially for complex models, is small. Each scenario generates a 'closed' model with 'frozen' actions. Each 'closed' model represents a variant of the system's behavior and fits with the modeling dynamical systems approach as a disciplinary niche.

The agent-based modeling approach (see, e.g., Bonabeau, 2002) aims at exploring repeated interactions of multiple agents that from their actions based on 'typical' individual feedbacks. Combinations of the agents' 'typical' feedbacks result in a global action selection principle and transform the original 'open' model representing the agents' society with 'free' actions into a 'closed' one.

A central planner action selection principle aimed at finding the globally optimal scenario for the system's performance brings us to optimal control theory as a disciplinary niche. A well-known example of the use of the global optimization principle is Nordhaus's Dynamic Integrated Climate Economy (DICE) model (Nordhaus, 1994), which optimizes the global social welfare utility index under a feedback from the global climate system. Of special interest are cases where the optimal scenario agrees with historical data (checking this is part of the model assessment task – see Table 1 and section 7 below). In such cases the optimal scenario turns into a business-as-usual one, which gives us a strong reason for conjecturing that optimization (with respect to the given long-term performance index) is an underlying law in the system's performance (see Figure 2 in section 7 for an example). As usual, the process of construction of a model realizing the central planner's optimal action scenario includes a serious control-theoretic analysis, through which the original 'open' model is converted into the final 'closed' one.

If the system is driven by several agents pursuing individual interests, theory of differential games or theory of evolutionary games will be an appropriate disciplinary niche.

Theory of differential games (as well as the related theory of multi-stage games) suggests methods for selecting the equilibrium (mutually acceptable and therefore most likely from a theoretical perspective) action strategies for 'forward looking' agents

that measure their benefits based on the system's overall performance. A well-developed branch of theory of differential games, the theory of zero-sum differential games, covers in particular a typical situation, in which the single agent steers the system affected by non-predictable and non-observable dynamical disturbances (treated as actions of the agent's opponent whose interest is opposite to that of the agent). The theory suggests techniques for constructing the agent's optimal feedback action strategy that maximizes the agent's global benefit under the worst action strategy of the opponent.

Theory of evolutionary games departs from an assumption that interacting and interdependent agents act 'myopically', 'boundedly rational', trying to adapt and, if possible, win in the changing environment. The theory is close in spirit to the agent-based modeling paradigm and refers primarily to models of biological evolution and models of social behavior.

Action selection principles help us explore futures of 'open' systems by modeling exceptional ('boundary', 'most likely', 'most typical') behaviors. A technical motivation for the use of this 'selective' approach is evident: it is hardly possible to model all possible futures. However, in some situations, advanced control-theoretic and computational techniques allow one to construct, for any given future 'target' point in time, the attainability domain of an 'open' model – the set of all the model's states reachable at the 'target' point under all possible action scenarios (see Figure 1).

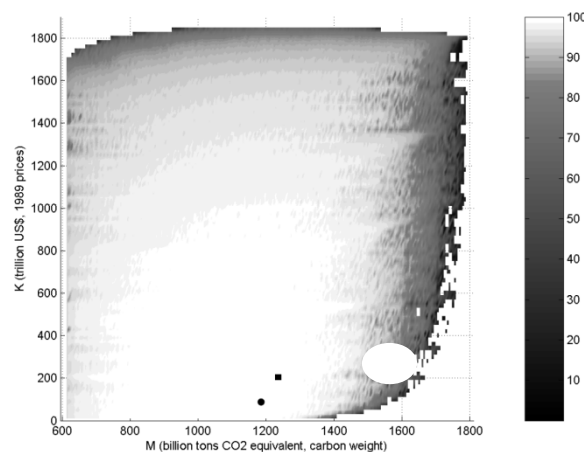


Figure 1: The attainability domain for Nordhaus's simplified DICE model (Nordhaus, 1994) for year 2100, with 1965 as the starting year, and the landscape of the values of the global social welfare utility index; the small black circle is Nordhaus's optimal point (Smirnov, 2005).

As opposed to the choice of a modeling paradigm, the choice of a model's state space and the model's complexity is the most difficult and most sensitive task in the process of model construction. Traditionally, researchers aim to achieve the highest possible degree of precision in imitation of the systems' dynamics. A common tendency is to use complex models operating in high-dimensional state spaces and incorporating numerous relations between their compartments⁷. Such models are usually

⁷ This tendency is represented by, for example, complex agent-based models.

mathematically intractable in the sense that they leave no room for rigorous mathematical analyses, appealing, primarily, for brute force simulations. Moreover, for such models (which are inevitably inaccurate), there is always a danger that small failures distributed across the models' compartments and links will multiply and result in fatal modeling and forecasting failures. Model assessment exercises with the use of historical data (see section 7) can help estimate a probability of fatal failures; however, the cost of such assessment exercises – in terms of time, effort and reliability of the result – grows dramatically with the increase of the model's complexity. Simplifying the situation, we can say that reliability of a model-based forecast is inverse proportional to the model's complexity and to the dimension of the model's state space.

In this context, aggregated, low-dimensional, mathematically tractable (and well assessed against data – see section 7 below) models produce the most reliable forecasts; a drawback of such forecasts is that they are highly aggregated and miss many important details. Models operating in simple image spaces (whose elements represent clusters of 'physical' points – see section 5) and having extremely rough resolution scales have also a potential for being highly reliable from a prognostic point of view; on the other hand, such models are targeted to forecasting strong events (catastrophes) only and unable to capture any smooth trends.

Finding the optimal compromise in the tradeoff between a model's complexity and its ability to produce reliable forecasts is the key challenge at the stage of model construction.

7 Stage 3. Model assessment

Three 'universal' model assessment techniques are calibration, retrospective forecasting and sensitivity analysis.

Calibration is a procedure, through which one adjusts a model to data. Calibration is usually understood as identification of the model's parameter values, which give the best fit with the historical data. For deterministic models the best-fit parameter values minimize the distances between the models' trajectories and the historical ones. For stochastic models producing bundles of trajectories with different probabilities, the best-fit parameter values are usually defined to be the ones that provide the maximum likelihoods for the historical trajectories.

Retrospective forecasting is a diagnostic stage of analysis. A goal is to qualify the model's ability to mimic the system's dynamics in the past. If we find that the model is satisfactory in this respect, we arrive at an important diagnostic conclusion that the system operated (in the past) in agreement with the chosen modeling paradigm and the chosen model design. This gives us a basis for stating that the model will most likely produce a satisfactory forecast ('most likely' implies here that we assume that the system's dynamics will not survive a serious change in a subsequent period).

Retrospective forecasting is organized as a test for checking the ability of the calibrated model to produce forecasts in retrospect. To perform the test we split the historical time series in two periods – a virtual past and a virtual future, the latter following the former. Then we 'travel to the past' – virtually, we bring ourselves to the end of the virtual past. We use our model to process the data in the virtual past and to produce a forecast for the virtual future. Finally, we 'travel back to the present' and compare our model-based forecast for the virtual future with the data series for the virtual future. Assessing the fit between the model-based forecast and data in the virtual future, we make our decision on the model's ability to forecast. To get better knowledge on the model's ability to forecast, one carries out retrospective forecasting tests several (many) times, each

time choosing new virtual past and virtual future periods. Based on the resulting set of forecast-data fits, one assesses the model's ability to forecast statistically (see Figure 2 for an illustration)⁸.

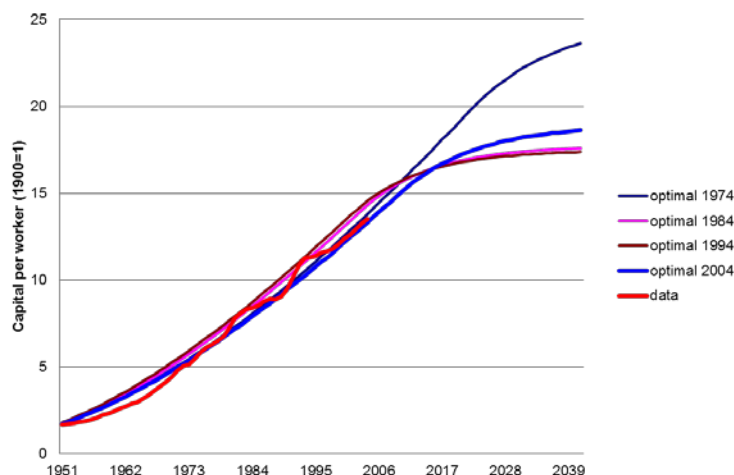


Figure 2: A retrospective forecasting test (Krasovskii and Tarasyev, 2010). The red curve is the capital-per-worker time series for the UK (in ratios to the level of 1950) in period 1950-2006 (Groningen Total Economy Data Base, <http://www.ggdc.net/>). The four other curves are the simulated optimal capital-per-worker growth trajectories for the UK for the same period (each simulated trajectory is optimal in the sense that it maximizes the integrated consumption index – a standard growth criterion used in theory of endogenous economic growth). The optimal trajectories are simulated using an aggregated optimal economic growth model. The model was calibrated four times, with four virtual past data series – 1950-1974 (dark blue); 1950-1984 (pink); 1950-1994 (lavender); and 1950-2004 (blue). In the three former cases, the retrospective forecasts for virtual futures cover, respectively, 1975-2006, 1984-2006 and 1995-2006, and show good fits with data, telling us that the model produces reliable forecasts. Based on success in retrospective forecasting, the researchers extended the simulated trajectories beyond 2006 to provide forecasts for the real (not virtual) future. These forecasts show a trend change in a not far-distant future – linear growth (seen in the time series) switches to saturation.

Sensitivity analysis is an instrument for testing robustness of model- and data-based forecasts to errors in data and in the model's design. The underlying phenomenon is bifurcation. Bifurcation occurs if a small change in a model's parameter values makes the model switch to a radically different behavior. Such behavior switches happen if the changed parameter values cross the so-called bifurcation curve

For a simple model, one can find the bifurcation curve analytically and see if the vector of the reference parameter values identified through calibration lies far enough from the bifurcation curve, or close to it. In the former case, the reference model configured by the reference parameter values is robust in the sense that if one assumes that the calibration result is (slightly) inaccurate, one can still believe that the model- and data-based forecast given by the reference model is essentially correct; let us call this situation regular. If the reference parameter values lie close to the bifurcation curve (the irregular situation), the reference model is sensitive – the model configurations corresponding to different behaviors provide alternative forecasts. In both situations, the model-based forecasts (supported by a successful retrospective forecasting

⁸ To make the statistics fitter to standard definitions of probability theory, one can carry out 'statistically identical' retrospective forecasting tests with fix lengths of the virtual past and virtual future periods.

exercise) can be considered as reliable (here we come back to our earlier statement on reliability of simplified models – see section 6).

For a complex model, we have, typically, no way to find the bifurcation curve (manifold) analytically and, consequently, no way to understand in advance if the situation is regular or irregular. We approach some understanding if we carry out a numerical sensitivity analysis – run the model several (many) times, with different parameter values concentrated around the reference ones. In the regular situation the simulated trajectories lie close to each other, in the irregular one we see divergent trajectories. The cost for sensitivity analysis – in terms of time, effort and reliability of the result – grows with a model's dimension and complexity. For super-complex models having thousands of parameters (including those that are not measurable in principle), various combinations of which can, potentially, configure bifurcation manifolds, it is hardly possible to carry out meaningful sensitivity analyses. As mentioned in section 6, forecasts based on very complex models cannot be regarded as reliable ones.

8 Stage 4. Model-based forecasts

A model-based forecast results from extension of the model's trajectory into the future. If the model is satisfactorily assessed against historical data, we are quite confident that the forecast is reliable⁹. However (in contrast to the case of mechanical systems), we can never guarantee that our model-based forecast is correct. A model assessment exercise (see section 7), no matter how accurate and successful it is, is coupled with the system's history (past data). The latter may not capture some 'hidden' phenomena in the system's dynamics. A model agreeing with the system's history may fail to adequately represent the system's dynamics in a subsequent period if a 'hidden' phenomenon becomes active.

If we do expect a new 'hidden' phenomenon to become active in the future and if we understand (to some extent) the way it acts, we can, accordingly, modify our model design prior to forecasting. Having no data on the operation of the new phenomenon, we are bound to modify the model based only on our theoretical understanding of the expected change. To compensate for the fact that the model's parameters responsible for the new phenomenon are not calibrated against data, we can vary these parameters in some reasonable range and produce a corresponding set of the model's future trajectories. The latter set serves then as a 'fuzzy' forecast showing us a range of the system's possible paths into the future under the action of the new phenomenon that is not understood in all detail and has never operated in the past.

The model assessment techniques discussed in section 7 – calibration, retrospective forecasting and sensitivity analysis – aim at raising reliability of model-based 'quantitative' forecasts expressed in terms of values of 'real' variables characterizing behavior of particular real systems under investigation. There are forecasts of a different type – 'qualitative' ones. A qualitative forecast characterizes trends and relations expected to occur in the system's future, without specifying these in terms of numbers¹⁰. A qualitative forecast results straightforwardly from a theoretical or numerical assessment of a model in no strong connection to real data.

⁹ Based on the results of model assessment (see section 6), we can complement the forecast with estimates for the forecasting errors.

¹⁰ The statement 'species X will extinct', with no indication of any time horizon, is an example of a qualitative forecast. See Figure 6 for an example of a qualitative forecast.

9 A multi-model approach

Here we come back to the statement (see section 3) that the laws that drive a complex social-environmental system are never perfectly understood. A rephrased formulation is that any model captures the system's operation only partially. Consequently, the use of a single model can be misleading¹¹. This leads us to a conjecture that analysis of complex social-environmental systems should tend to employ a multi-model approach. Following the multi-model approach, we use a family of models showing the system from different angles and complementing each other (see Figure 3 for a metaphoric illustration).

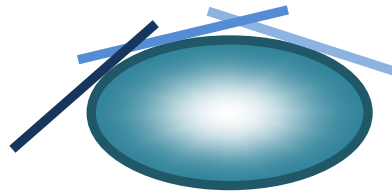


Figure 3: Earth maps as a metaphor for the multi-model approach. A detailed map is an image of a part of the Earth surface. Due to the curvature of the Earth surface, the image, which is quite precise at the center, loses its precision at the periphery. If we want to get a better precision in some small area in the periphery, we look at another map centered in that area. Thus, two, or more maps serve as complementary models of a part of the Earth surface. (This approach is used in differential geometry in studies of complex manifolds using families of local Euclidean maps.)

Once we decide to use a family of models, we abandon the area of (single-)model-based research (discussed in sections 4 – 8) and enter a broader area of research based on multi-model imitation methods (we use the terminology introduced in section 3).

A multi-model imitation method employs alternative models that may differ structurally. The core of multi-model imitation is integration of models – methods for generation of integrated knowledge about the systems, based on pieces of knowledge provided by the 'partial' models employed (see Figure 4 for an illustration).

¹¹ For example, any model from a given family of models can fail to be satisfactory in retrospective forecasting (see section 7).

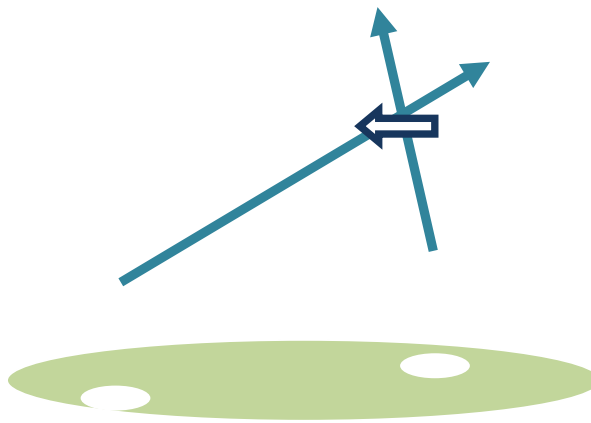


Figure 4: An illustration to integration of models. A plane is observed from two observation stations. Each station provides limited information on the location of the plane – the straight line connecting the station and the plane. The two lines are two alternative models for the plane's location. The plane is located at the point, at which the lines intersect. Intersecting the lines is a method to integrate the models.

Model integration has already been used in studies of complex social-environmental systems (see Figure 5 and Figure 6 for examples); in particular, the idea of model integration lies behind participatory methods (see, e.g., Pahl-Wostl, 2002), which synthesize knowledge from experts' opinions serving as individual models.

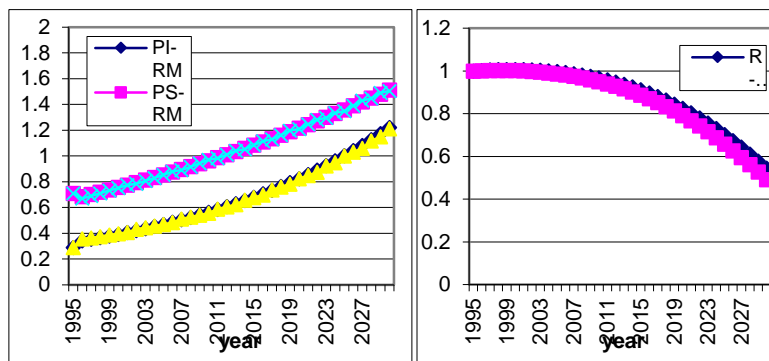


Figure 5: Simulated time series of the food-secure (PS) and food-insecure (PI) rural populations (left) and the resource stock (right) for the detailed (EM) and simplified (RM) PEDDA (population, environment, development, agriculture) models for Mali in 1995-2027 (Lutz *et al*, 2002). The simplified model disregards the urban population, aggregates over education, age and sex, and reduces the number of population states from 1600 to two (food-secure and food-insecure rural population). A good fit in the simulation results (which is also seen in other simulations corresponding to different parameter values) shows that the composition of the population states and the resource degradation process are insensitive to the education, age and sex structures. The latter observation is an integrated knowledge obtained from the use of two alternative models.

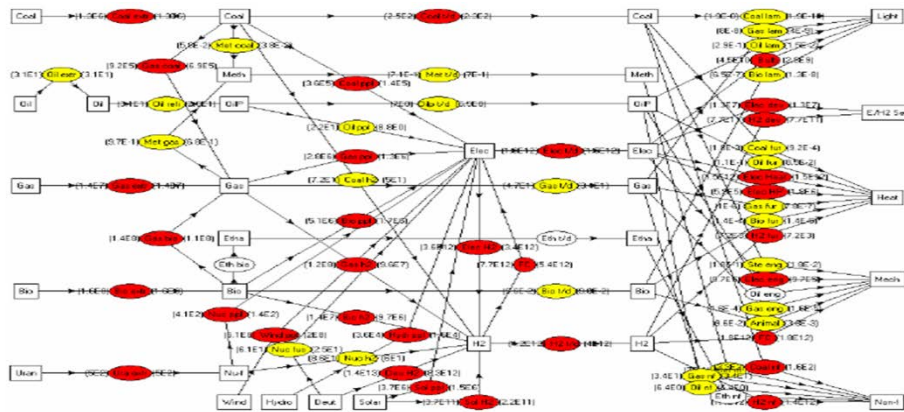


Figure 6: A snapshot from a typical model run of a model conceptualizing the emergence of new technologies and their combinations as a random process (reflecting the unpredictability of technological innovation) subject to resource constraints and economic incentives (Ma *et al*, 2008). Ellipses represent primary energy technologies, which combine into alternative technology chains. The technology color codes indicate the level of development of various technologies ranging from large (red), very small (either emerging embryonic technologies or technologies being phased out, yellow) to technologies not used at all (white). Arrows indicate the directions of linkages, whereas the extent of linkages is given as numerical values of the corresponding energy flows. The individual trajectories obtained in 200 runs can be viewed as alternative models for historical development of the global energy system. The researchers analyzed the alternative histories and revealed their common features. For example, they found that the simulated evolution of the global energy system is characterized by increase in complexity (in terms of the number of energy chains), a ‘complexity peak’, and decline in complexity; another finding is that in all simulations there is a powerful tendency towards “decarbonization” – decrease in the carbon intensity of energy systems. These and other general conclusions (qualitative forecasts – see section 8) resulting from analysis of multiple simulations integrate pieces of knowledge provided by the individual; models.

Although model integration does not seem to be commonly recognized as a promising research avenue today, it may have a strong potential to develop into a powerful instrumental framework for systems analysis. One can think of a ‘model calculus’ – a structured family of partially formalized model integration techniques. Below we suggest a sketch on possible model integration methods.

In the model integration toolbox, cross-verification of models will be an important instrument. Models viewing a complex uncertain system from different perspectives cross-verify each other by registering identical phenomena in the system’s behavior; in this situation we get a strong evidence for regarding the registered phenomenon to be a true feature of the system¹².

Quite often, due to modeling and observation errors, the outcomes from different models disagree with each other (even observation data resulting from different

¹² A good fit in the simulation results for the full and simplified PEDAs models in the Mali case study (see Figure 5), and the common features of the simulated alternative trajectories of the global energy system (see a comment to Figure 6) are illustrations for the model cross-verification phenomenon.

observation methods can differ essentially¹³); the models seem to be inconsistent. Situations of a similar type are addressed by theory of ill-posed problems (Tikhonov and Arsenin, 1974), which deals with solutions in poorly defined cases including those where the constraints for the sought solution are incompatible. The theory suggests regularization techniques allowing one to 'reconcile' the constraints and find appropriate 'surrogate' solutions. We expect that this theoretical background can be used in the context of systems analysis.

In analysis of complex social-environmental systems, in situations where models' outcomes disagree with each other, one is usually inclined to look for the 'most accurate' model, implying that the models are ordered in accuracy (though the order is unknown). In this context, a challenging question would be if there is a test for identifying the 'most accurate' model.

One can expect that, typically, the models whose outcomes disagree with each other are not ordered in accuracy ('model A' can in some aspects be more accurate and in some aspects less accurate than 'model B'). In this situation, the models can be assumed to be 'equally inaccurate'. We come to a need to develop a methodology for synthesizing an 'integrated outcome' (an analogue of a 'surrogate' solution in theory of ill-posed problems) that would incorporate the features of the models' alternative outcomes. A thorough analysis of extreme (possibly, very rare) cases where the models' outcomes 'come to agreement' could be the key.

Often, in analysis of a complex social-environmental system, one departs from 'disciplinary' models representing different compartments of the system (for example, an economic model and an ecological one) and capturing the impacts of other compartments through exogenous parameters¹⁴. Traditionally, one follows the integrated assessment modeling approach (see, e.g., Argent, 2004) and establishes links between the 'disciplinary' models (by letting, for example, part of the output variables of the economic model enter the ecological model as exogenous inputs and vice versa).

This approach has a very clear motivation. Its drawbacks are not so obvious but can be critical. The complexity of the resulting integrated model (in terms of the dimension of the state space and the number of links between the model's compartments) is higher than the 'sum' of the complexities of the original 'disciplinary' models. Adding more 'disciplinary' modules, we find that the complexity of the integrated model grows much faster than the number of the 'disciplinary' modules. A highly complex integrated model can turn out to be not reliable enough (in section 6 we argued that 'reliability of a model-based forecast is inverse proportional to the model's complexity and to the dimension of the model's state space'). Moreover, due to nonlinear integration of the system's parts in the entire complex system, simple mechanical interlinking the 'disciplinary' models can result in an inadequate representation of the entire system

¹³ See, e.g., Nilsson, *et al* (2007) for analysis of uncertainties in estimates for regional terrestrial biota full carbon accounts.

¹⁴ In analyses of spatially distributed systems one can use 'regional' models instead of 'disciplinary' ones, or both types of models.

even if all ‘disciplinary’ models represent the corresponding parts of the system satisfactorily.

To compensate for possible errors in the outcomes from the complex integrated model, one can apply the cross-verification instrument (see above) involving the original ‘disciplinary’ models and/or partially integrated models.

A promising line in model integration research will be developing ‘dialogues’ between complex agent-based models and conceptual aggregated models. The agent-based models operate at microscopic scales. They flexibly implement detailed assumptions about the agents’ behaviors but do not serve as instruments for generating general conclusions. Conceptual aggregated models operate at macroscopic scales. They capture general trends but are unable to interpret them at the micro-level. A challenging task will be to interlink agent-based and aggregated models so that the aggregated models will convert the microscopic trajectories generated by the agent-based models into macroscopic trends, and, conversely, the agent-based models will interpret the macroscopic trends suggested by the aggregated models in terms of microscopic behaviors.

We conclude with a presumption that research employing the multi-model approach will go, typically, through the same stages as research employing a single model (see Table 1 in section 4). One starts with choosing modeling paradigms and state space for the models to be employed. Next, one constructs and assesses models and model integration techniques. Generation of a forecast is the final stage in research.

10 Monitoring and updating

We expect systems analysis to be a process of constant generation of new knowledge about complex social-environmental systems. Generation of new knowledge includes refining knowledge through learning from experience. Forecasts produced earlier provide solid bases for learning. In the course of time, a forecast produced earlier overlaps with a recent history and turns into a retrospective one (see section 7); one can see if it fits with recent historical data¹⁵. As time moves on, a basis for retrospective model assessment (in both single- and multi-model settings – see section 9) is automatically extended, which appeals for carrying out retrospective model assessment repeatedly, on-line. Periodically, the changes in the current assessment results will make the researchers update their instrumental research components – the modeling paradigms, state spaces, models and estimates of the models’ forecasting abilities (as mentioned in section 4, the research stages are not separated from each other). On-line monitoring/updating will be a promising approach to constantly enhancing our knowledge about complex social-environmental systems and their futures.

¹⁵ Simulated time series for 1995-2027 (Lutz *et al*, 2002), shown in Figure 5 were generated as forecasts. Now they appeal for comparison with data for the last decade.

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