A Bright Future for System Dynamics: From Art to Computational Science and Beyond

Erik Pruyt* (TUDelft) and Jan H. Kwakkel (TUDelft)

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Abstract

This paper presents a bright future for quantitative System Dynamics Modeling. This future relates to all major issues and grand challenges which all happen to be dynamically complex and deeply uncertain. Combining System Dynamics Modeling and Exploratory Modeling and Analysis allows one to generate, explore and deeply analyze tens of thousands of plausible scenarios related to such deeply uncertain dynamically complex issues, and to design and test adaptive policies over all plausible scenarios. By doing so, the art of System Dynamics becomes the computational science of System Dynamics. This innovative approach is explained in this paper starting from the core of System Dynamics modeling, and is illustrated with real world applications (pandemic shocks, resource scarcity, and energy transitions). However, more is needed than the brightest analysts and the best analyses for decision makers to decide and take action when facing uncertain complex issues: that is what experiential System Dynamics gaming is needed for. Only when heart and mind are aligned will knowledge and understanding become effective. The use of experiential System Dynamics gaming for conquering the heart of decision makers is illustrated with real world examples too.

Keywords: Dynamic Complexity, Deep Uncertainty, SD, EMA, ESDMA

1 Introduction – Reinventing System Dynamics Modeling

1.1 SD Modeling: Recognizing the Core and Cherishing the Diversity

The System Dynamics (SD) method and field are firmly established and have a strong common core. That common core of the SD method –according to us– includes: *(i)* a broad, largely endogenous, systems perspective, *(ii)* focus on a particular problem characteristic, ie dynamic complexity, *(iii)* a unifying modeling language to develop models including causal and feedback effects, accumulations, and delays, *(iv)* a set of qualitative and quantitative techniques and tools to derive the system behavior over time, *(v)* a qualitative interpretation of quantitative simulation results, and *(vi)* the goal to better understand dynamically complex issues and design robust policies for dealing with them.

Beyond the common core, the field of SD is endowed with many different practices (Lane 2001a; Lane 2001b), diverse sets of basic underlying assumptions (Pruyt 2006), a plethora of uses, and the use of a variety of techniques and tools. We believe we ought to cherish the common core as well as the diversity: our field needs a way to keep and improve on what is good, but at the same time continuously experiment and innovate. In our perspective on the future of SD, the SD field should be one field unifying a diverse set of mature strands and uses, as well as an experimental sandbox filled with promising strands and uses – the future strands and uses of System Dynamics. We believe that such diversity could only be a handicap if we fail to communicate it well, else it will make the field stronger and richer. Not all System Dynamicists would agree: some seem

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*Corresponding author: dr. Erik Pruyt, Delft University of Technology, Faculty of Technology, Policy and Management, Policy Analysis Section; Delft, The Netherlands – E-mail: `e.pruyt@tudelft.nl`

to have the desire to reserve the SD label for the traditional core and currently accepted uses. Fortunately, many System Dynamicists are open to new System Dynamics practices, SD-based multi-methods, and see SD for what it really is and ought to be, and that goes well beyond narrow definitions of, or perspectives on, SD.

One danger of too broad a view on SD may be to end up using SD for any type of issue, another danger may be to become overly ambitious, for example to want to develop SD into *the* overarching methodology for the social sciences. We believe we need more modesty on the one hand, but much more ambition on the other in order to become one of *the* relevant methods in social science for dealing with issues of great importance as David Lane suggested in his great presidential address. However, in order to realize this ambition we may have to revisit some of the basic characteristics of traditional SD, invest heavily in SD-based multi-methods (ie appropriate combinations of SD with other methods), invent and test new SD uses, and develop new techniques and tools that are crucial for realizing this ambition.

The enormous wisdom and foresight of the founders of the field (Forrester, Meadows, etc) made the SD field uniquely progressive and enlightened for a very long time. The head start was a major blessing, but may have been, at a later stage, a handicap[1] too. Some of the wise choices made then, given the state of computing at the time, may today require appreciation for what they were meant for at the time, not for what they have grown into. We think that some essential SD characteristics of old introduced for practical reasons, may, given the current and near future state of science and computing, be less essential for the current and future practice of SD, whereas other characteristics and ideas may require much more emphasis and development into what they were really intended for. In other words, the SD field of old has evolved somewhat, and could and should continue to evolve a whole lot more.

In order for SD to be truly useful for policymakers for dynamically complex issues that are also characterized –beyond dynamic complexity– by at least one other important characteristic (eg. being fundamentally spatial, multi-actor, networked, multi-dimensional, data-rich, uncertain, et cetera), further investment in SD-based multi-methods, approaches, and tools that allow scientists and practitioners to deal with those characteristics are urgently needed.

Two fruitful innovation strategies are to 'borrow' great ideas from other fields and to bandwagon the winner. Hence, we believe the System Dynamics community should –without betraying the real SD core– adopt a more external orientation (other fields and approaches) in order for it to grow and become better and stronger. A stronger external orientation may help the field to: *(i)* learn from successes and failures of other domains to further develop the SD field, *(ii)* avoid using and marketing SD for uses none of its strands are truly appropriate for, and hence, avoid type III errors, *(iii)* enrich SD with other approaches, techniques and tools, in order to make SD even more useful for real-world policymakers facing dynamically complex issues, and *(iv)* sharpen our understanding of the essence of SD, and hence, reflect on, redefine and strengthen its identity.

1.2   Frustrating Gaps and Promising Solutions

The perspective on the future of SD propagated and the particular SD approach described in this paper, originate from *(i)* traditional SD modeling and policy analysis, *(ii)* the type of issues we are interested in, ie grand challenges and major issues, which are almost all uncertain and complex, *(iii)* our sometimes frustrated attempts to apply traditional SD to such complex uncertain issues, and *(iv)* pioneering work on Exploratory Modeling and Analysis by the RAND Corporation.

Most grand challenges and important issues we address(ed) or believe ought to be addressed by an SD-like approach are not just dynamically complex but also almost always deeply uncertain. Deeply uncertain issues are issues *(i)* for which it is uncertain which of many plausible underlying mechanisms will generate the real-world dynamics, *(ii)* for which it is uncertain which probabilities may be attached to plausible real-world outcomes, and *(iii)* for which different experts may disagree about the acceptability of the outcomes (Lempert et al. 2003). This does not mean that everything

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[1]The dialectics of progress aka the law of the handicap of a head start aka the law of the slowing head start, coined by (Romein 1937), is the theory that an initial head start hinder long-term innovation.

related to deeply uncertain issues is unknown. To the contrary, it means that plausible outcomes could be generated (if combinations of underlying mechanisms are modeled and simulated) or imagined, but that the occurrence of plausible real-world outcomes cannot be captured in terms of one or few scenarios with corresponding probabilities, nor with probability distributions, and mostly neither with a single model.

From our methodological perspective, it follows that if addressing dynamic complexity under deep uncertainty is different from addressing dynamic complexity, then methods for dealing with dynamic complexity under deep uncertainty ought to be used, and if not available, developed. Our applied work for real world policymakers also made us critically aware of the fact that for modeling and simulation to be of any relevance to real world policymakers, key characteristics of an issue need to be taken into account in an intuitively appealing way. And since 9/11, reinforced by the 2008 financial crisis and the 2009 flu pandemic, uncertainty is key to policymakers in our, and many other, application domains. Moreover, modeling is often only relevant and acceptable to policymakers, if they generally understand the modeling approach and model(s) developed, and if the advice provided with the model(s) makes sense and is robust, and if modeling has clear advantages over approaches that are not based on modeling.

Before 2009, we tried to do so using traditional SD techniques and tools, including sensitivity testing and risk analysis[2] with available commercial software packages, which worked to some extent, but proved to be complicated, extremely time consuming, and insufficient for deeply uncertain issues. Using traditional SD techniques and tools does not seem to allow for easy experimentation and exploration beyond parameters and a handful of policies, using different models –for example representing different perspectives on the issue– simultaneously, doing much more than visual inspection with the simulation runs (ie perform advanced time-series clustering), and designing adaptive policies and comparing the effectiveness of alternative policies over the entire multidimensional uncertainty space. Note however, that all this is possible using both commercial SD programs and advanced mathematical programs, although cumbersome, but trying to do so is very time-consuming – which is essential for all pressing issues.

But if SD in isolation may not be appropriate for doing so, SD-based multi-methods may be. Lempert et al. (2003) showed us one way forward by 'borrowing' a SD model –a slightly adapted version of the Wonderland model as published in (Sanderson 1995), explored in (Milik et al. 1996)– and using it to illustrate their Exploratory Modeling and Analysis (EMA) methodology. EMA is a computational methodology for systematically exploring deeply uncertain issues and testing the robustness of policies under deep uncertainty. A group of scientists at RAND Corporation developed the initial ideas of EMA and the first computer software to perform it. Since EMA requires easily manageable computational models, for example SD models, and SD requires a methodology for dealing more appropriately with deeply uncertain issue, they perfectly match: EMA and SD modeling are indeed fully complementary. Hence, we further developed the EMA methodology for dynamically complex issues, combined it with SD, called the resulting multi-method ESDMA, developed our own EMA software, developed new or adapted existing data visualization and analysis algorithms, and applied this multi-method to many complex and deeply uncertain issues in order

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[2] In this paper, we use the following phrases short definitions for different types of analyses: **Sensitivity analysis** refers to the analysis of the effect of a small change to or the slightly different value (plus or minus 20%) of parameters and lookups from a base case on the mode of behavior (behavioral sensitivity) or choice of policy (policy sensitivity). **Uncertainty analysis** refers to the exploration of the influence of the entire uncertainty range; so if the uncertainty range of a parameter ranges from 0% to 100%, then 0% and 100% need to be tested (as well as all values in between). **Extreme value testing** refers to checking whether the model structure is acceptable given extreme (even totally unrealistic) values. **Risk analysis** refers here to the use of sampling over probabilistic inputs in order to generate probabilistic outputs which are interpreted as such. **Robustness testing** or **robust decision methods** refer to methods that seek decisions that perform satisfactorily for the widest range of assumptions (Bankes 2012). **Robustness** refers here to the general acceptability of outcomes over the entire uncertainty space. Robust policies are therefore policies that perform acceptably across the entire uncertainty space.
So we may set the size of the Dutch population of about 16670000 (in 2011) to 0 citizens for an extreme value test; it may have an uncertainty range between 14 million and 24 million 50 years from now; and we may want to test the sensitivity of some model outputs to a 10% difference in size of the population or an increase with 10% from 16670000 to 18337000.

to further develop it, and to generate awareness and enthusiasm in several application domains[3].

But even if this multi-method –or any other multi-method for that matter– leads to more profound analyses and better policy advice, then that does not mean that the advice is per definition acted on – quite the contrary. Some policymakers may understand but not trust model-based analyses related to complex uncertain issues. Other policymakers may trust their own experience and intuition better than 'difficult' model-based advice. Just involving policymakers in the first phases of the research, for example through GMB (Vennix 1996), may not be enough in case of uncertain complex issues: that is why we started to complement ESDMA with Exploratory Group Model Specification and Simulation (EGMSS) workshops, and Experiential SD-based Gaming (ESDG) workshops too.

1.3 Aims and Organization of this paper

In this paper, we will discuss, refer to, and illustrate one multi-method innovation in the field of SD, more specifically the combination of SD modeling and EMA for issues that are not only dynamically complex but also deeply uncertain. The aim of this paper is not to discuss and illustrate the future of the whole field of SD, just our SD future, as we happen to see it now. It should be clear that this is just one possible route, one plausible strand of future SD, but we think a very promising one, which may be one day one of the pillars of the future field of SD. The main question addressed in this paper is thus: How to develop and use SD models for deeply uncertain dynamically complex issues such that uncertainty and complexity are truly dealt with and design appropriate policies that policymakers will implement?

Some definitions and explanations are first of all provided in section 2. Then SD, EMA, and ESDMA are briefly introduced in section 3. Section 4 is dedicated to a detailed discussion of ESDMA. Examples of needs beyond ESDMA are discussed in section 5. Section 6 illustrates two different uses of ESDMA. Section 7 will position ESDMA into the broader SD context. And concluding remarks are formulated in section 8.

2 Dynamic Complexity & Uncertainty, and SD & Uncertainty

2.1 Levels of Dynamic Complexity and Deep Uncertainty

2.1.1 Dynamic Complexity

Dynamic complexity relates to the dynamic behavior of systems over time. It arises in systems because they are dynamic, tightly coupled, governed by feedback, nonlinear, history dependent, self-organizing, adaptive, counterintuitive, policy resistant and characterized by trade-offs (Sterman 2000). Although the concept is clear to all System Dynamicists and does not need further explanation here, it is very hard to properly define levels or degrees of dynamic complexity. Since properly defining levels or degrees of dynamic complexity is not the goal of this paper, we simply distinguish between situations and models that show no or little dynamic complexity and situations and models that show some to extreme dynamic complexity, the latter being interesting cases for SD.

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[3]In health (Pruyt and Hamarat 2010b; Hamarat et al. 2012a; Pruyt and Coumou 2012; Hamarat et al. 2012a), energy (Pruyt et al. 2011; Pruyt 2011a; Kwakkel and Yucel 2011; Eker and van Daalen 2012; Hamarat, Kwakkel, and Pruyt 2012; Hamarat et al. 2012b), water (Kwakkel and Slinger 2012; Kwakkel and Timmermans 2012), resource scarcity (Kwakkel and Pruyt 2011; Auping 2011; Auping et al. 2012; Kwakkel et al. 2012), safety and security (Pruyt and Kwakkel 2011; Kovari and Pruyt 2012; Pruyt and Kwakkel view), societal issues (Logtens 2011; Pruyt, Logtens, and Gijsbers 2011; Logtens et al. 2012), and economic-financial issues (Pruyt and Hamarat 2010a).

LOCATION	LEVEL					NATURE		
	recognized uncertainty	shallow uncert.	medium uncert.	**deep uncert.**	recognized ignorance	ambiguity	epistemology	ontology
fundamental surprises					✓			
system boundary				✓	✓			
conceptual model				✓	✓			
computer/formal model				✓	✓			
- model structure		✓	✓	✓	✓			
- parameters in model	✓	✓	✓	✓	✓			
- input param. to model	✓	✓	✓	✓	✓			
input data	✓	✓	✓	✓	✓			
model implementation	✓	✓	✓	✓	✓			
processed output data	✓	✓	✓	✓	✓			

Table 1: Uncertainty matrix for classifying & communicating uncertainties in model-based policy analysis. Source: (Kwakkel and Pruyt 2012)

Level of Uncertainty	Description	Approaches for dealing with the levels
Level 1: recognized uncertainty	Recognizing that one is not absolutely certain, and that uncertainty is a marginal issue.	Performing sensitivity analyses on model parameters by changing default values with some small fraction.
Level 2: shallow uncertainty	Being able to enumerate multiple alternatives and provide probabilities (subjective or objective)	Being able to enumerate multiple possible futures or alternative model structures, and specify their probability of occurrence
Level 3: medium uncertainty	Being able to enumerate multiple possibilities and rank possibilities in terms of perceived likelihood. However, how much more likely or unlikely one alternative is compared to another cannot be specified	Being able to enumerate multiple possible futures or alternative model structures, and being able to judge them in terms of perceived likelihood, not in terms of probabilities
Level 4: **deep uncertainty**	**Being able to enumerate multiple possibilities wo being able to rank order the possibilities in terms of how likely or plausible they are**	**Being able to enumerate multiple possible futures or specify multiple alternative model structures, without being able to specify their likelihood**
Level 5: recognized ignorance	Being unable to enumerate multiple possibilities, because one does not or cannot know the generative mechanisms at play nor the possibilities that will be generated	Keeping open the possibility of being wrong or being surprised because existing mental and formal models are known to be inadequate

Table 2: Five levels of uncertainty. Source (Kwakkel and Pruyt 2012)

2.1.2 Uncertainty

Uncertainty is defined here as any departure from the unachievable ideal of complete determinism (Walker et al. 2003). Uncertainty is not simply a lack of knowledge, since an increase in knowledge might lead to an increase of knowledge about things we do not know and thus increase uncertainty (van Asselt 2000).

Table 1 shows a slightly adapted version of an uncertainty matrix to support policy analysts in identifying uncertainties and communicating these uncertainties to decision makers as proposed by (Walker et al. 2003) and updated by (Kwakkel et al. 2010b), called the W&H framework, which synthesized various taxonomies, frameworks and typologies related to uncertainties from different decision support fields. Three of these taxonomies were used in (Pruyt 2007) to assess how SD deals with different uncertainties. Given the summarizing character of the updated W&H framework, it makes sense to continue here following the later framework. Issues and systems are characterized in it by one of five levels of uncertainty as proposed by Kwakkel and Pruyt (2012) and listed in Table 2.

Table 1 also acknowledges that there are many locations for uncertainties in model-based decision support: uncertainties may relate to initial values, parameters inside the model, input parameters to the model (possibly time-series inputs), functions, generative model structures, feedback loops, model boundaries, modeling methods and paradigms, different perspectives and preferences related to different world-views, and multiple policies and the mediating effects of policies. Being serious about dealing with uncertainties therefore means exploring and taking into account the influence of uncertainties related to initial values, parameters inside the model, input parameters to the model (possibly time-series inputs), functions, (generative) model structures, feedback loops, model boundaries, different models, modeling methods and paradigms, different

	None to little dynamic complexity	**Some to extreme dynamic complexity**
Recognized uncertainty	Well-known case or static model possibly with sensitivity analyses	Known case or dynamic model possibly with sensitivity analyses
Shallow Uncertainty	Static model with risk analysis and probabilistic interpretation	Dynamic model with risk analysis with probabilistic interpretation
Medium Uncertainty	Most likely cases or models, wo probabilistic interpretation	dynamic model with mode of behavior interpretation
Deep Uncertainty	static models or morph. box with deep uncertainty & robustness analyses (in other words EMA)	**Dynamic models with deep uncertainty & robustness analyses (eg ESDMA)**
Recognized Ignorance	(((EMA and/or creative process to whiten some of the black swans)))	(((Extreme ESDMA to whiten some of the black swans, or generate very implausible scenarios)))

Table 3: Combining different levels of uncertainty and different degrees of dynamic complexity, and suggested approaches

perspectives and preferences related different world-views, and mediating effects of policies.

2.1.3 Dynamic Complexity and Uncertainty

Combining the five levels of uncertainty with two levels of dynamic complexity (*none to little* and *some to extreme*) gives the ten combinations in Table 3. The combinations in the top two row cells only require base case model runs with some sensitivity analysis or risk analyses or appropriate case descriptions. Issues of medium uncertainty require at least alternative scenarios with associated perceived likelihoods or the use of (either static or dynamic) models for generating modes of behaviors or scenarios with associated perceived likelihoods. However, most important issues are at least deeply uncertain – likelihoods cannot truly be assigned nor can outcomes be interpreted probabilistically. Deeply uncertain issues require method(ologie)s to enumerate/generate all –or at least a whole lot of– plausible scenarios (before selecting a set of scenarios that are representative or of particular interest), such as EMA or morphological box-like approaches. Either the method(ologie)s used for deeply uncertain issues pushed to their limits or processes focussed on stimulating creativity could be used to some extent for dealing with recognized ignorance by identifying grey swans, trying to turn black swans into grey swans, by generating the broadest possible set of scenarios (ie from least surprising to wildest possible), or by developing a set of scenarios spanning the outcome space, all the while keeping open the possibility of being wrong or surprised.

The right-hand side column requires methods for dealing with some to extreme dynamic complexity, eg SD. The two bottom rows require methods for dealing with deep uncertainty and recognized ignorance, eg EMA. This paper is thus really only about the two bottom-most cells in the right hand side column of Table 3.

2.2 SD and Uncertainty

System Dynamicists deal with uncertainties in several ways, as was analyzed in (Pruyt 2007) using the typologies of uncertainty of (van Asselt 2000). The engrained mainstream way for dealing with uncertainties in SD can be found in the stance that uncertainties are omnipresent and that qualitative 'mode of behaviour' interpretations are therefore the highest attainable. Referring to human unpredictability, Meadows and Robinson (1985, p78) formulate it –when reviewing the use of econometrics– as the 'believe that human unpredictability is too dominant a factor in social systems to allow anything more than qualitative behavioral forecasts, even for aggregate systems where much unpredictability can be averaged out.'

That position was –and is still rather– unique in science, and was –and often still is– misunderstood by outsiders of the field. Except for some univariate and multivariate sensitivity

analyses –which are very often, without proper evaluation, too poor an exploration of at most shallow uncertainty– it looks to outsiders as though uncertainties are not really explored or explicitly taken into account in SD, which may be a reason for the SD approach to be perceived as too deterministic and therefore inappropriate for dealing with issues characterized by ever more important and abundant uncertainties.

Apart from the specific stance on uncertainty and the use of some techniques and tools for dealing with uncertainty and risk, we sincerely think that given today's computing power there is not enough attention paid to the issue of uncertainty in today's SD practice. One of the reasons might be that uncertainty adds another dimension, on top of the dimension of dynamic complexity addressed first and foremost by SD – and even without considering deep uncertainty, is SD considered a difficult art. The differences in level, nature and location of uncertainty makes the dealing with uncertainty even more difficult. Another reason might be that there is only a limited set of tools for dealing with uncertainty and risk available in most of the SD software packages (e.g. sensitivity or risk analysis), but not more advanced tools to perform comprehensive sensitivity analyses, to deal with deep uncertainty or to assist the design of robust adaptive policies. The thorough exploration of deep uncertainty is therefore in SD in isolation a daunting, almost impossible, task. Finally, computing power was until recently insufficient to support extensive exploration of uncertainties while at the same time keeping analyses and conclusions transparent. Today however, even desktop computing power is sufficient, and the methods, techniques and tools are available.

3 From SD to ESDMA

3.1 System Dynamics

As the participants of this conference know very well, System Dynamics (SD) is a modeling and simulation method for learning about and dealing with dynamically complex issues (Sterman 2000). Traditionally, SD is used for modeling and simulating dynamically complex issues and analyzing their resulting non-linear behaviors over time in order to develop and test the effectiveness of structural policies.

Mainstream System Dynamicists have assumed for decades that uncertainties are omnipresent, and hence, that trajectories generated with SD simulation models should not be interpreted quantitatively as point or trajectory predictions, but that they should be interpreted qualitatively as general 'modes of behavior'. And although univariate and multivariate sensitivity analyses are often performed, they are mainly aimed at validation starting from a base case – not at exploring over the entire uncertainty space. It seems therefore that in traditional SD the omnipresence of uncertainties is accepted but that they are not really explored or explicitly taken into account.

However, SD models may also be built specifically for the purpose of exploring the potential influence of uncertainties on dynamically complex issues. Such exploratory System Dynamics models are preferably fast-to-build and easily-manageable models, and consequently, rather simple and highly aggregated, and slightly less closed/endogenous than traditional SD models (Pruyt 2010b). Using such models is an interesting approach for exploring uncertainties, and testing the effectiveness of policies in the face of these uncertainties. However, in isolation it may still be insufficiently broad and systematic to firmly base policymaking under deep uncertainty on.

3.2 Exploratory Modeling and Analysis

Exploratory Modeling and Analysis (EMA) is a computational approach to systematically explore the influence of uncertainties on deeply uncertain issues and test policy robustness under deep uncertainty (Bankes 1993; Agusdinata 2008; Lempert et al. 2003)[4]. It consists of using exploratory

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[4]See also (Lempert and Schlesinger 2000; Lempert et al. 2006; Van der Pas et al. 2007; Van der Pas et al. 2008; Agusdinata et al. 2009; Bryant and Lempert 2009; Kwakkel et al. 2010a; Kwakkel et al. 2010c; Kwakkel and Slinger 2011; Bankes, Walker, and Kwakkel 2012; Kwakkel and Haasnoot 2012).

models to generate tens of thousands of scenarios –an 'ensemble of plausible futures'– in order to explore and analyze this ensemble of plausible futures, and test the robustness of policy options across the ensemble – in other words, to test whether the outcomes are acceptable for all scenarios generated by sweeping the entire multi-dimensional uncertainty space.

EMA could be used for *(i)* generating a very large ensemble of all sorts of plausible futures (artificial time-series data), *(ii)* advanced exploration and analysis of the influence of a plethora of uncertainties (ie the artificial time-series data and their origins), *(iii)* directed searches into (particularly problematic) areas of the uncertainty and scenario spaces, *(iv)* model and expert testing and triangulation, and 'deep validation' (Bankes 2012) (ie. testing and updating models as they are used), *(v)* adaptive policy design informed by the whole ensemble, and *(vi)* deep policy robustness testing (testing policy effectiveness over the entire multi-dimensional uncertainty space).

EMA consists more precisely of (i) developing 'exploratory' –fast and relatively simple– models of the issue of interest, (ii) generating an ensemble of futures (thousands to millions of scenarios) by sweeping uncertainty ranges and varying uncertain structures and boundaries, (iii) analyzing and clustering the dynamic behaviors, to discover particular types of behaviors, et cetera, (iv) and/or specifying a variety of policy options (preferably adaptive ones), and simulating, calculating, and comparing the performance of the various options across the ensemble of futures.

In step (iii), advanced data analysis techniques could be used to investigate the effect of underlying mechanisms/(inter)actions/conditions, to search for areas in the multi-dimensional uncertainty space with high concentrations of highly undesirable behaviors, to cluster the ensemble into different modes of behavior, to determine the conditions that lead to these different modes of behavior, to find bifurcation points and critical variables, et cetera. The results of these analyses may be useful in their own respect or may provide key information for step (iv). These analyses may be extremely insightful to analysts and for policymaking, filling the analytical gap in traditional SD. However, policymakers may not be all that interested in these analyses –at most in the key findings– or may simply not understand the analytic tools and their outcomes.

However, step (iv) actually makes life of policymakers much easier, since it allows defining different (adaptive) policies and immediately testing their (relative and absolute) effectiveness given all these uncertainties, in other words, their robustness. The effectiveness of policies could indeed be evaluated over the entire multi-dimensional uncertainty space without the need to understand millions of outcomes and assessing their likelihoods or probabilities. In other words, the robustness of policies could be evaluated and compared without reducing uncertainties related to the system of interest and without getting overwhelmed by combinatorial complexity. Advanced analyses may also be necessary for designing robust adaptive policies.

3.3   Exploratory System Dynamics Modeling and Analysis

Since EMA is appropriate for systematically exploring deep uncertainty and testing the robustness of policies, and exploratory SD models are particularly appropriate for generating plausible dynamics over time, it follows that their combination –which we call Exploratory System Dynamics Modeling and Analysis (ESDMA)– is particularly appropriate for *systematically* generating, exploring and analyzing tens of thousands of plausible dynamic behaviors over time, and for testing the robustness of policies over all these scenarios. As opposed to EMA, ESDMA goes beyond the calculation of end states or static values, but focuses on artificial time-series data, which makes ESDMA much more challenging than EMA. ESDMA is dealt with at length in the following section.

4 ESDMA in Depth

4.1 Using Models as Experimental Lab Equipment

Bankes (2009) suggests viewing models used for EMA as laboratory equipment, rather than as veridical artifacts representing their target system. He concludes that the design of tools (ie models) should fit the task at hand which is determined not only by the system being studied, but also by the question being asked.

In light of the EMA uses listed above, SD models used for EMA and ESDMA could be viewed as possible experimental set-ups for generating large and broad ensembles of futures, and/or performing directed searches, and/or testing ensemble of models and/or experts, and/or iteratively designing adaptive policies, and/or testing policy robustness over large uncertainty spaces.

4.2 ESDMA – Different Uses

Hence, ESDMA could be used for: (*i*) ensemble generation, (*ii*) ensemble exploration, (*iii*) direct searches, (*iv*) scenario discovery and selection, (*v*) advanced analysis, (*vi*) adaptive policy design, (*vii*) policy robustness testing, and (*viii*) deep validation (model verification and validation) and triangulation between experts/models.

Many of these uses have not been explored and developed to their full potential. Although the first EMA related paper goes back to 1993, progress was rather slow given the limited number of scientists working on it. ESDMA is of even more recent date: as far as we know, Lempert et al. (2003) provided the first illustration of ESDMA on a single SD model, the modified wonderland model, immediately illustrating a set of ESDMA uses (ensemble generation, ensemble exploration, policy robustness testing). Picking up from there, our first attempts included ensemble generation and policy testing on an oversimplified bank crisis model (Pruyt and Hamarat 2010a), and a H1N1 flu model (Pruyt and Hamarat 2010b). The flu model developed into a test case for our software tool[5]. Our first multi-model ESDMA was performed on simplistic radicalization models, presented in (Pruyt and Kwakkel 2011). The first Exploratory Group Model Specification and Simulation workshop (see subsection 5.1) was organized for our work related to societal aging, reported on in (Pruyt, Logtens, and Gijsbers 2011; Logtens 2011; Logtens et al. 2012). Special ESDMA model structures were developed for and described in (Pruyt et al. 2011; de Groen 2011; Auping 2011). The first EMA on an Agent-Based Model was performed using an ABM of the transition of the Dutch electricity system by Kwakkel and Yucel (2011). Scenario discovery and selection was applied almost simultaneously in (Kwakkel et al. 2012; Pruyt and Coumou 2012; Pruyt et al. 2012). Using ESDMA with robust optimization for designing adaptive policies was first implemented in (Hamarat, Kwakkel, and Pruyt 2012; Hamarat et al. 2012b; Hamarat et al. 2012a). All of the above was applied simultaneously across many risks in (Pruyt and Kwakkel view; Pruyt et al. 2012). Kwakkel and Timmermans (2012) performed, in the ESDMA context, the first direct search with Active Non-linear Testing (Miller 1998). And a first attempt at using Formal Model Analysis in ESDMA is reported on in (Keijser et al. 2012).

4.3 ESDMA – The Process

ESDMA in general consists of following five main steps starting what is certain and uncertain:

1. conceptualization of the issue and its associated uncertainties,

2. developing 'exploratory' –fast and relatively simple– SD models of the issue of interest,

3. generating an ensemble of futures (thousands to millions of scenarios) by sweeping uncertainty ranges and varying uncertain structures and boundaries,

4. analyzing the dynamic behaviors, bifurcations, et cetera, and exploring the ensembles in search of undesirable behaviors and outcomes,

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[5]See `http://simulation.tbm.tudelft.nl/ema-workbench/contents.html`.

5. and/or designing policies (preferably adaptive ones), and simulating, calculating, and comparing the performance of the various options across the ensemble of scenarios.

Steps (3) and (4) require a systematic and structured exploratory research approach and proper documentation. Especially the succession of analyses and deeper-and-deeper explorations if warranted in step (3) require proper documentation in some sort of lab report (see for example (Logtens et al. 2012)). The order in which to apply different techniques is rather logical, from general/broad to specific/detailed, and conditional upon the findings in previous steps. Only if results are obtained with a more general exploration technique that shows the need for further exploration, is the application of a more specific technique justified. In (Logtens et al. 2012), a preliminary visualization stage with successive but conditional deepening with envelope plots, lines plots, interactive plots, 3D KDE plots, and cluster plots, is followed only for those key performance indicators with problematic outcomes by a further analysis stage focused on *(i)* identifying undesirable outcomes based on the preliminary (visual) inspection and clustering, or specific directed searches *(ii)* classifying the data set into different levels of (un)desirability, *(iii)* identification of uncertainties that contribute most to generating this classification by means of the Feature Selection and Random Forest algorithms, and *(iv)* identification of sets of uncertainty values that generate areas in the multidimensional uncertainty space with high concentrations of (un)desirable behaviors by means of PRIM. See 6 for a concrete example.

The same is true for the iterative process of designing adaptive policies that are robust over the entire uncertainty space. See for example (Hamarat et al. 2012a). The process of designing one particular adaptive policy would –starting from an existing ensemble– consist for example of *(i)* identifying unacceptable outcomes, *(ii)* using PRIM to identify areas in the multi-dimensional uncertainty space with high concentrations of such cases, *(iii)* identifying uncertainties (parameters, time-series, functions, mechanisms, loops) and the instances that to a large extent cause those undesirable dynamics, *(iv)* identifying possible policies to influence those uncertainties to keep them from causing the undesirable dynamics from happening, and finally, *(v)* optimizing the trigger values of the adaptive policy. After simulating the ensemble with the policy, the process starts all over from *(i)* until all outcomes are acceptable or improvements become too marginal or costly. Pairwise comparison of different competing (adaptive) policies with regret-based robustness analysis as in (Lempert et al. 2003) then allows policymakers to select the most robust policy. See 6 for a concrete example.

4.4   ESDMA – Tools

We currently build our ESD simulation models in Vensim DSS, use a shell written in Python to generate experimental designs, and use Python to force Vensim DSS to execute tens of thousands of experiments (i.e. combinations of uncertainties and models) to generate tens of thousands of transient scenarios (simulation runs). Python stores the data when generated. We then use a library of algorithms coded in Python, C, and C++ to analyze the ensemble of scenarios, and (interactively) visualize the most interesting findings. Reasons for this particular choice of tooling, are (i) the ease with which different types of uncertainties can be handled and ensembles can be generated, (iii) the ease with which existing algorithms (in python libraries) can be adapted and used, (ii) the ease with which new algorithms can be developed, tested, used, and compared to existing algorithms, (iv) the ease with which large data sets can be handled and explored, and (v) the possibility of sampling and using algorithms across multiple models, even multiple modeling methods, and policies. This choice of tooling also has drawbacks: currently the software is not particularly user-friendly for people unfamiliar to python. Hence, we will need to invest in a user-friendly interface to allow modelers without Python scripting skills to perform ESDMA with our software. Note however that ESDMA is also possible without our software by using commercial SD software together with advanced mathematical programs.

Uncertainties we are currently able to deal with include: uncertainties related to initial values and parameters (floats, integers and categorical), functions, lookups, generative structures, model formulations, model boundaries, different models, different modeling methods and paradigms,

different preferences and perspectives related to different world-views, and policies[6].

4.5 ESDMA – Techniques

We currently use many different techniques, some of which were already used in SD. We use for example many different plotting techniques such as Lines plotting (behavior over time graphs and phase diagrams), Envelope plotting, Kernel Density Estimate (KDE) plotting, 3D Kernel Density Estimate (KDE) plotting, and pairs plotting or multiplotting of existing correlations between output indicators in order to select a useful set of output indicators and verify whether particular relationships that are known to exist work out fine in complex models.

To get an idea of the most important uncertainties for a non-binary classification function, we use both the Random Forest (Breiman 2001) and Feature Selection algorithms (R. Kohavi 1997).

Uncertainty space boxes (with the fraction of positive matches and the mass of the box relative to the total scenario space) that perform below/above a particular threshold are generated with a new version of the Patient Rule Induction Method (PRIM) (Friedman and Fisher 1999) –one that can deal with categorical and continuous uncertainties– with a binary classification function and PRIM box plotting. PRIM is particularly valuable for discovering catastrophic subspaces of uncertainty space, and hence, for developing specific adaptive actions for adaptive policies (see for example (Hamarat, Kwakkel, and Pruyt 2012)).

In order to cluster time series data based on attributes and select the similarity level at which to classify/plot clusters, we use a time-series clusterer algorithm –a more advanced version of the one proposed in (Yucel and Barlas 2011)– with dendrogram and cluster plots. Using this clusterer and visualizing exemplars for each of the selected clusters is a very powerful scenario discovery and selection approach.

Robust optimization and ANT are currently performed using Genetic Algorithms. And specific scripts are used for many other uses, such as data set splitting and data set handling.

Techniques that will be worked on and added in the near future include: Automatic function perturbation techniques based on (Eker, Slinger, and Yucel 2011), Loop knock-out analysis (to detect critical feedback loops and much much more – see (Keijser et al. 2012)), Eigen-value elasticity analysis (to detect dominance and dominance shifts in feedback loop systems), Key Mechanism Structure-Behavior testing (to detect critical mechanisms), and a multi-method MCDA suite including Multidimensional partial ordering methods.

5 Beyond SD as Computational Science

But even if ESDMA leads to more profound analyses and better policy advice, then that does not mean that the advice is per definition acted upon – quite the contrary. Some policymakers may understand but not appropriate and buy into the solutions because they were not involved in the specification of the models and the simulation of the results. Other policymakers may trust their own experience and intuition –their certainties– better than model-based advice under deep uncertainty. Just involving policymakers in the first phases of the research, for example through GMB (Vennix 1996), may not be enough in case of uncertain complex issues: that is why we started to complement ESDMA with Exploratory Group Model Specification and Simulation workshops, and Experiential SD-based Gaming workshops.

5.1 Exploratory Group Model Specification & Simulation Workshop

The first Exploratory Group Model Specification and Simulation (EGMSS) workshop was organized as part of the societal aging research (Logtens 2011; Pruyt, Logtens, and Gijsbers 2011; Logtens et al. 2012) in order to elicit and include 10 key uncertainties from different experts in a prefab model (developed before the workshop based on expert interviews and the literature).

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[6]See `http://simulation.tbm.tudelft.nl/ema-workbench/contents.html`.

The experts were asked to provide inputs for 9 time-series (lookups over time) and 1 relationship (lookup).

First the model and the (re)main(ing) uncertainties were presented (see Figure 1(a)), the experts were asked to develop plausible evolutions and relations for the remaining uncertainties (see Figure 1(b)). These expert opinions were immediately added to the model and python shell, and the ensemble of scenarios was calculated during the break, after which the preliminary 'ensemble of scenarios' was presented and discussed (see Figure 1(c)) and possible policies were suggested for problematic futures. The workshop ended with a methodological discussion on improvements related to this type of modeling and the workshop (see Figure 1(d)).

(Pruyt 2009) (Pruyt 2008)

(a) Introduction to pre-modeled structures and remaining uncertainties

(b) Harvesting and adding expert opinions to the SD model and python code

(c) Front: adding different expert opinions – Back: methodological discussion

(d) Post-analytic discussion based on ESDMA ensembles (pop. w/o function uncertainty (lkps))

Figure 1: Pictures of the EGMSS workshop

5.2 Experiential SD Gaming

However, more is needed than the brightest analysts and the best (ESDMA) analyses and involvement of policymakers for them to decide and take action when facing uncertain complex issues: that is what Experiential SD Gaming may be needed for. Experiential SD Games are designed specially to allow participants to experience, in our case, the importance of uncertainty on possible futures and of taking uncertainty seriously into account in decisionmaking. The use of experiential SD gaming for conquering the heart of decision makers is illustrated in (Pruyt 2011a; Pruyt 2011b)

Experiential games require at least the development of: (i) a plan for reaching a particular workshop goal, (ii) a small and manageable SD model related to a system participants are familiar with, (iii) a relatively simple interface – sufficient for reaching the goal – including a dashboard with sliders for the most important decision variables and interactive plots displaying information that would be available to them in the real world too, and (iv) plausible but very dissimilar scenarios (eg generated with ESDMA and selected with scenario discovery). The whole development phase –modeling excluded– takes about two days. And the modeling should not take much more time, since even simple models are good enough for participants to really experience deep uncertainty by being immersed in context they are familiar with. The set of scenarios used may well be more important than the model for the experiential session itself. However, the model may have been used as scenarios generator for ESDMA scenario discovery in which case, the model needs to be good enough for ESDMA.

6 Three Illustrations

6.1 Scenario discovery for mineral and metal scarcity

The first case explores uncertainties related to the availability of minerals/metals that are crucial for the sustainable development of all developed and developing societies. Potential mineral/metal scarcity poses a serious challenge for civil protection in at least three ways (Pruyt 2010a). First,

any crucial minerals and even some base metals –such as copper (Alonso, Gregory, et al. 2007; Valero and Valero 2010) and lead (Ayres 2007)– may in a few decades become more difficult and expensive to mine and process, possibly posing threats to satisfy increasing overall demands for those metals in order to sustain a higher standard of living of an increasing world population. Second, The disparity between the expected exponential growth of metal demand and the expected limited growth of metal supply (especially of crucial low-volume metals such as rare earth metals that are required in ever bigger quantities for many innovative technologies and electronics) may result in temporary and/or chronic scarcity. Third, strategic or speculative behavior of countries that have a quasi-monopoly on the extraction of (rare earth) metals may seriously hinder the transition of modern societies towards more sustainable ones.

The asynchronous dynamics of supply and demand, aggravated by reinforcing behaviors and knock-on effects, is a breeding ground for acute and/or chronic crises (Pruyt 2010b): how and when these dynamics and crises may materialize remains highly uncertain. EMA is used in this case to create insight into plausible dynamics that can occur and which combinations of assumptions produce which kind of dynamic. This is also known as scenario discovery, which is a model driven approach to scenario development that builds on the intuitive logic school (Bryant and Lempert 2009).

6.1.1 Models

Minerals and metal scarcity is characterized by long time horizons, diverging believes and ideas about system functioning, and complex interactions between supply, demand, substitution, and recycling, necessitating a more exploratory approach. Figure 2 displays the main feedback loops of a generic simulation model developed to create insight into the types of dynamics that can occur. The two recycling loops displayed in red are reinforcing loops. The linked extraction sector feedback loops are controlling loops. This suggests that if recycling takes off, it is intrinsically limited by the extraction sector loops. These extraction sector loops in turn are limited by the steeply increasing costs of extraction. The stock-flow diagram of this small generic simulation model is displayed in Figure 3. More details on the model can be found in (Pruyt 2010a).

This small and simplistic System Dynamics model was developed in about one day in close collaboration with a mineral/metal expert, based on his mental model of the underlying structure of the mineral/metal system. For the expert, the objective of the joint modeling endeavor was twofold: (i) to help the expert explore plausible dynamics of mineral/metal abundance/scarcity, and (ii) to identify, describe and visualize interesting scarcity scenarios for his client. Both objectives were at first achieved by means of System Dynamics modeling and manual exploration of the influence of key assumptions, changing one assumption at a time (see (Pruyt 2010a)). At a later stage, the model was used for the simultaneous exploration of many uncertainties and assumptions. This ESDMA use of the model is reported below.

6.1.2 Uncertainties

The future evolution of the extraction and recycling is intrinsically uncertain. The presented model allows us to explore alternative evolutions across the various uncertainties. Table 4 gives a high level overview of the key uncertainties that are taken into consideration. Note that we explore across both parametric variations and what typically would be considered more structural variations. We generated 1000 computational experiments using Latin Hypercube sampling.

6.1.3 Analysis of Results

The aim of this case is to provide insight into the types of dynamics that can occur. Thus, the results from the series of computational experiments have to be clustered based on the type of dynamics. This requires a form of time series clustering. The goal of clustering is to organize an unlabeled data set into homogenous groups where the similarity within the group is minimized and the dissimilarity between groups is maximized (Theodoridis 2003; Liao 2005). Typically,
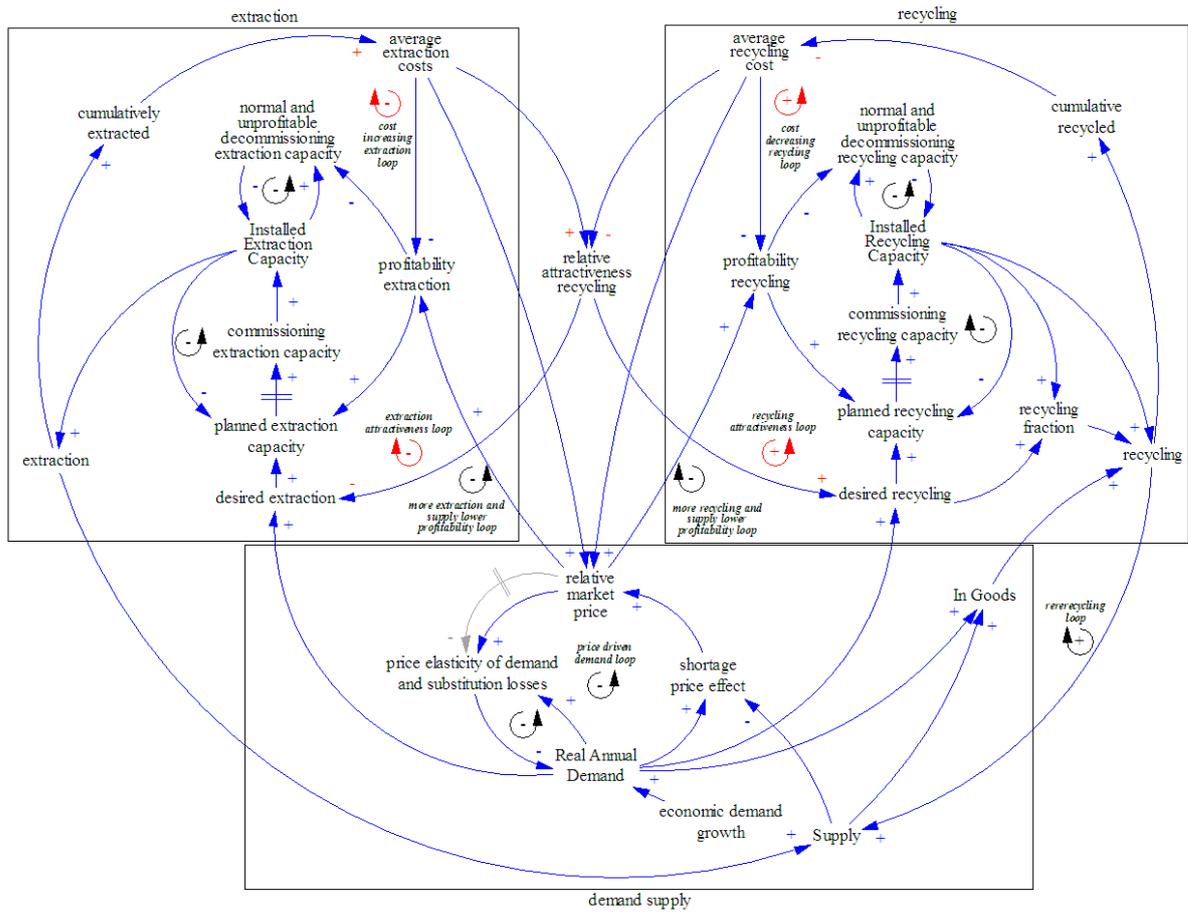
Figure 2: Main views and feedback loops of the SD simulation model

clustering approaches are applied to static data (Liao 2005). In general, time series clustering approaches try to modify existing clustering approaches for static data so that they can cope with time series data. Either the algorithm is modified to deal with the raw time series data, or the time series are processed in such a way that static clustering methods can be used directly (Keogh and Kasetty 2003). A relatively recent review of the state of the art in time-series clustering can be found in (Liao 2005). In this paper, we adopt an agglomerative hierarchical clustering approach. That is, we start by positioning each time series in its own cluster, and then hierarchically merge each cluster into larger and larger clusters (Liao 2005). Similarity of dynamics is determined based on an extension of the behavior pattern features discussed in (Yucel and Barlas 2011), see (Yucel 2012) for details.

Figure 4 shows two graphs. The graph on the left shows the dynamics for the thousand runs for the relative market price. The figure on the right shows the results after applying time series clustering. Each cluster is represented here by just a single exemplar. From the right hand picture, we can deduce that the model can exhibit oscillation with a fast or slow growing amplitude, slow but steady growth, or more or less stable oscillations. The steady growth and minor oscillation dynamics do not constitute acute crises, the oscillation with growing amplitude, be it fast or slow, however does. For in this case material scarcity results in very high prices, which can in turn affect other parts of the economy. Moreover, it is plausible that these high prices result in substitution behavior, that in turn reduces the demand for a particular material. So, also from the perspective of the industry itself, very high prices and high price volatility is undesirable. As a next step, the
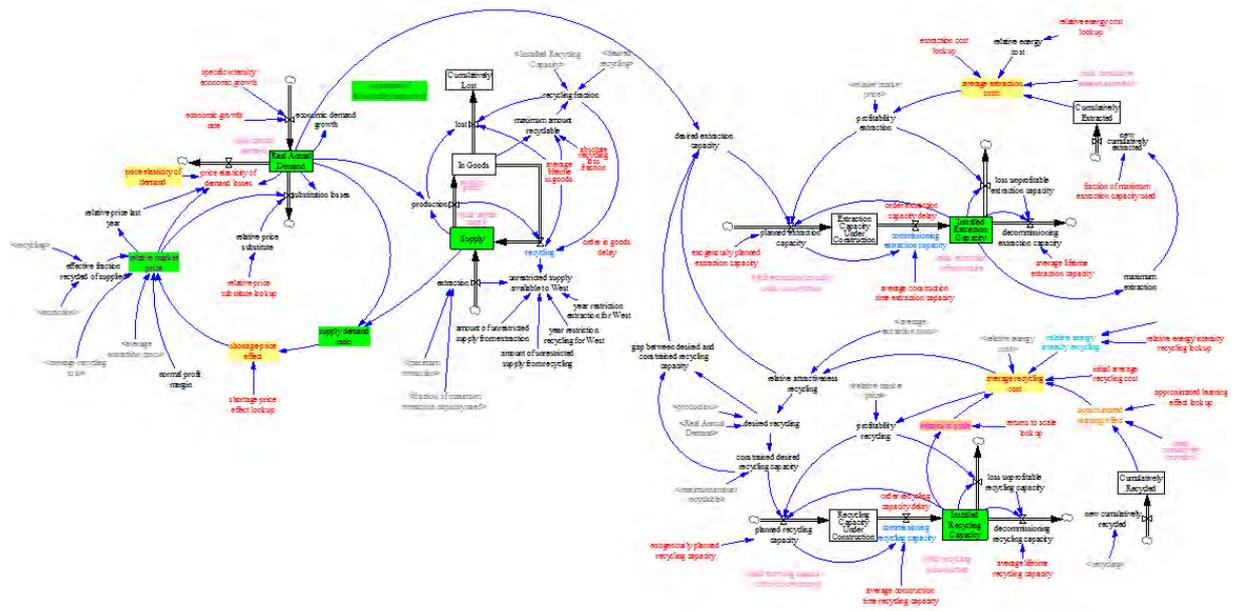
Figure 3: Stock-flow diagram of the scarcity model (Pruyt 2010)

Name	Description	Ranges
Parametric uncertainties	A wide variety of parametric uncertainties are explored, including the lifetime of mines and recycling facilities, the initial values, and behavioral parameters such as price elasticity and desired profit margins	Typically plus and minus 50% of the default value
Orders of time delays	There are various time delays, such as the building of new recycling capacity and mines	First order, third order and tenth and 1000th order
Non-linear lookups	There are various non-linear relations, modelled with lookups. Examples include learning effects, the impact of shortage on price, and substitutions in case of shortages. These non-linear relations are varied by changing start, end and slope	Start, end, slope

Table 4: High level uncertainties of the mineral/metal scarcity case

causes for the undesirable dynamics could be identified and a discussion and testing of alternative policies to address the undesirable dynamics could be carried out.

6.2 Worst Case Discovery

In the first days, weeks and months after the first reports about the outbreak of a new flu variant in Mexico and the USA, much remained unknown about the possible dynamics and consequences of the at the time plausible/imminent epidemic/pandemic of the new flu variant, first known as Swine or Mexican flu and known today as Influenza A(H1N1)v. Many nations were at first particularly concerned about the potential loss of human life, and later -after it became clear that the case fatality ratio was moderately low- about the potentially disruptive effects both on health care systems and societies/economies at large in case large fractions of the (active) population would be immobilized simultaneously by the flu. Therefore, the aim of this case is to investigate what the worst cases could be for the total loss of life and for the worst social disruption. We are thus interested in the deceased population and the highest peak of the fraction of the population that is infected at a given point in time.
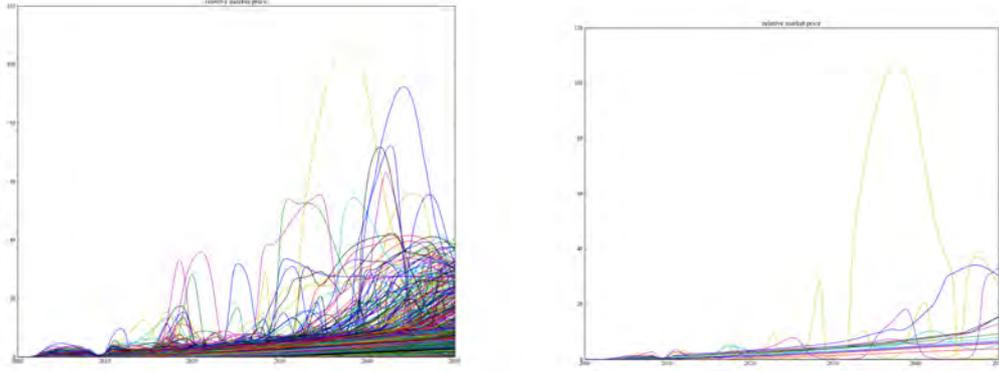
Figure 4: Clustering applied to 1000 experiments in order to reveal the types of dynamics

Uncertainty	Description	Range
additional seasonal immune population fraction per region	Seasonal immunity effect	0-0.5
fatality ratio per region	Fatality rate of the flu	0.0001-0.1
initial immune fraction of the population per region	Initial fraction of population that is immune for this flu	0-0.5
normal interregional contact rate	Contact between regions	0-0.9
permanent immune population fraction per region	Fraction of population that remains permanently immune	0-0.5
recovery time per region	Time to recover from illness	0.2-0.8
root contact rate per region	Lowest possible contact rate p.r.	1-10
infection ratio per region	Ratio for infectivity	0-0.1
normal contact rate per region	Normal contact rate per region	10-200

Table 5: Uncertainties of the flu case

6.2.1 Models

The Exploratory SD model displayed in Figure 5 was developed shortly after the first signs of a potential outbreak were reported in order to foster understanding about the plausible dynamics of the flu outbreak (Pruyt and Hamarat 2010b). The exploratory model presented here is small, simple, high-level, data-poor (no complex/special structures nor detailed data beyond crude guestimates), and history-poor. The model was used in an ex-ante exploratory way: developments were not waited for and uncertainties were amplified and explored instead of reduced or ignored. From a non-exploratory point of view, such simple/aggregated/high-level exploratory models are of course always wrong -especially with hindsight. We believe nevertheless that the model and method presented here has value in case of imminent outbreaks that are deeply uncertain.

The modeled world is divided in three regions: the Western World, the densely populated Developing World, and the scarcely populated Developing World. Only the two first regions are included in the model because it is assumed that the scarcely populated regions are causally less important for dynamics of flu pandemics. Below, the figure shows the basic stock-and-flow structure. For a more elaborate description of the model, see (Pruyt and Hamarat 2010b).

6.2.2 Uncertainties

Table 5 list the uncertainties of the flu case. These uncertainties are inspired by the various unknowns and guestimates as reported by the European Center for Disease Control over the period of early April 2009 up to late August 2009 (Pruyt and Hamarat 2010b). The ranges have been chosen quite widely, given our interest in finding the worst possible cases.
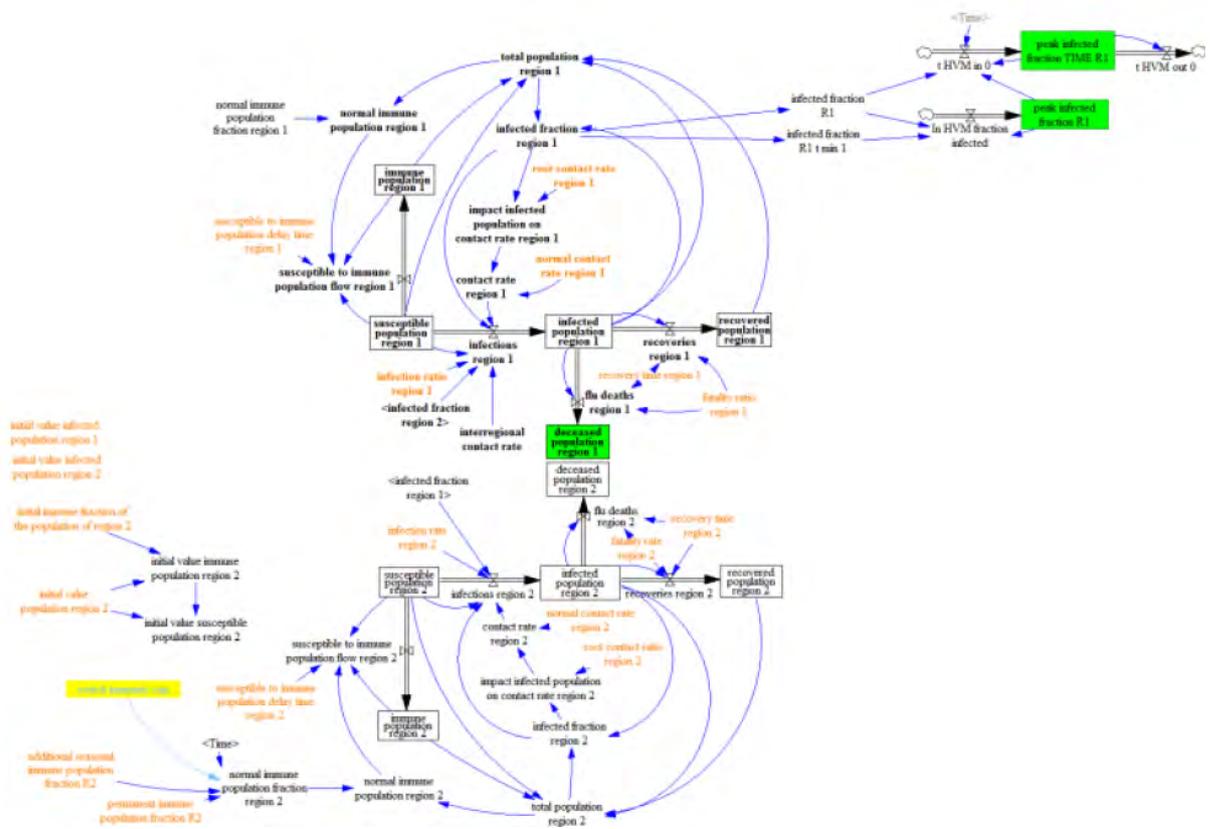
Figure 5: Stock-flow structure of the flu model
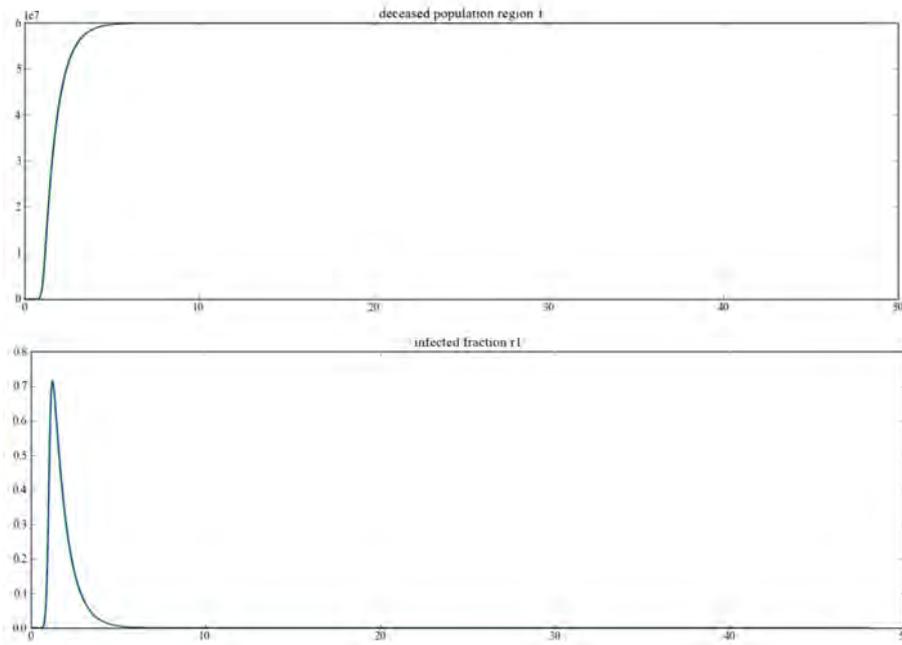
Figure 6: Two most extreme flu cases

6.2.3 Results

Using a directed search approach we found the two distinct worst case scenarios displayed in Figure 6. The first worst case is the maximum number of casualties. The second worst case is the highest social disruption, which we operationalize to mean the highest fraction of the population that is ill at some point in time. A suitable optimization algorithm for directed search in the context of System Dynamics should be able to cope with the non-linearity of the model, a non-linear objective function, discontinuities in the search space, a search space that is rife with local optima, and noise (Miller 1998). In the context of ESDMA, two additional complications are added, namely a potentially very large search space, and a discontinuous search space arising out of the inclusion of variations in e.g. structural equations. On top of this, a suitable optimization algorithm should be economical. That is, it should be able to find the optimum relatively quickly, without requiring a very large number of computational runs. As argued by Miller (1998), Genetic Algorithms (GA) are a perfect candidate that is able to meet the outlined requirements. Figure 6 shows the results for the two cases that have been found. They are almost identical, thus the socially most disruptive case is almost identical to the case with the highest number of casualties. In both cases, the flu spreads very quickly. Thus leaving very little time for policymakers to react, let alone leaving time for the development of vaccines. The only type of actions available to decision makers is social distancing related measures that reduce the speed with which the pandemic spreads.

6.3 Adaptive Policy Design

Energy systems are also a crucial domain where a fundamental transition towards cleaner energy production is necessary. The challenge is to find an effective policy that can steer the system to a more desirable functioning, despite the presence of a wide variety of uncertainties. There is an emerging planning paradigm for planning under deep uncertainty. This paradigm holds that, in light of the deep uncertainties, one needs to plan dynamically and build in flexibility (Albrechts 2004; Kwakkel et al. 2010d; Walker, Marchau, et al. 2010). According to the new
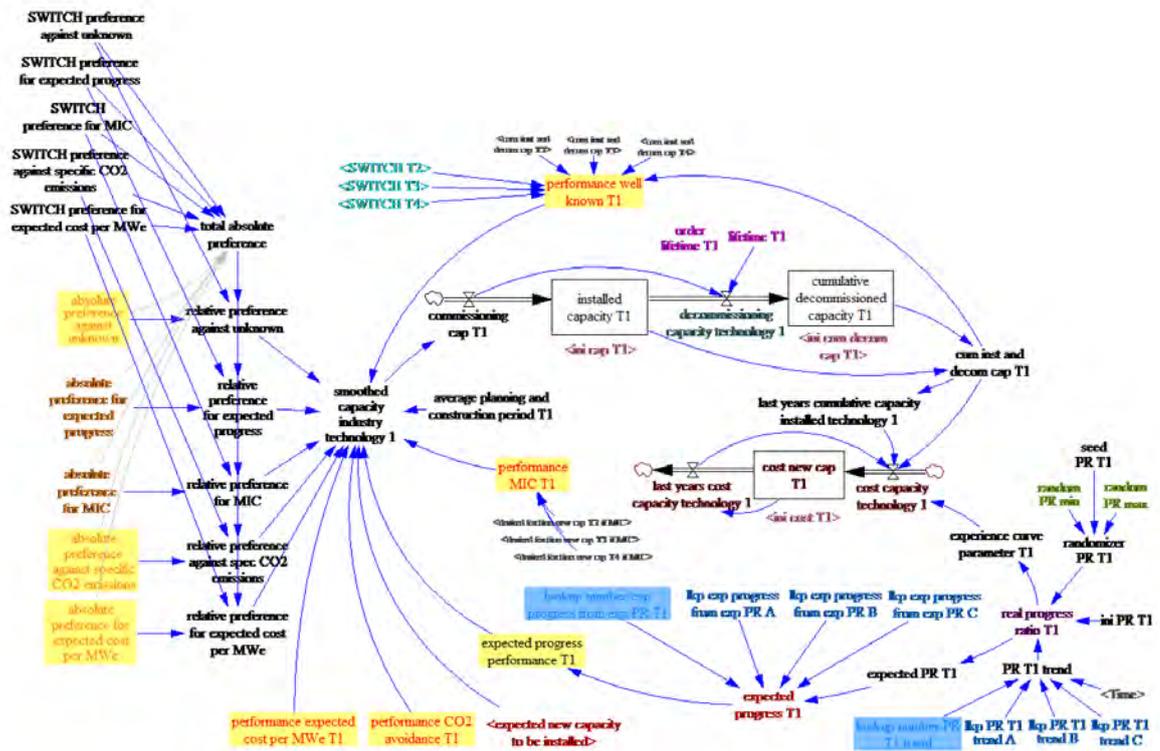
Figure 7: Basic stock-flow diagram for Technology 1, for the other technologies a similar structure is used

planning paradigm, a plan should consist of a set of actions to be taken now and be combined with a framework for guiding future actions. In this case, we show how such a plan can iteratively be developed. We start with an open exploration to identify plausible futures, next we identify undesirable futures and their causes. In light of this, we design actions tailored to addressing these futures. We test and refine these actions iteratively using open exploration.

6.3.1 Models

In order to explore the transition problem and the uncertainties, a System Dynamics model developed for exploring the transition dynamics of energy systems (Pruyt et al. 2011) is used in this study. The SD model incorporates, on a high aggregated level, the main structures of the energy system. The model represents the competition between four energy technologies, where Technology 1 is the old dominant technology that is non-renewable and mainly fossil fuel based, and the other three technologies are renewable and sustainable technologies. Since fast and relatively simple models are employed in EMA, the more sustainable technologies 2, 3 and 4 are considered to be generic for the sake of simplicity. The four technologies compete with each other in order to increase their share of energy generation driven by mechanism such as total energy demand, cost of commissioning capacity of a technology or effect of learning curves on costs. Figure 7 shows part of the stock and flow diagram. A more detailed explanation of the model can be found in (Pruyt et al. 2011) and for this case see (Hamarat, Kwakkel, and Pruyt 2012)Hamarat et al (accepted).

Name	Description	Range
Initial Capacity	Starting value of capacity of a technology	1 − 16000 MW for different technologies
Lifetime	Expected lifetime of a technology	15 − 50 years for different technologies
Initial Decommissioned Capacity	Initial values of the total decommissioned capacities of the technologies	10 − 10 million MW for different technologies
Planning and Construction Period	Average period for planning and constructing new capacity for a technology	1 − 5 years for different technologies
Progress Ratio	Ratio for determining cost reduction due to learning curve	70% − 95% for for different technologies
Initial Cost	Initial cost of installing new capacity of a technology	€500000 − €10 million per MW
Economic Growth	Change in the ratio of economic growth factor	randomly fluctuating btwn -0.01 − 0.035
Preference Structures	Preferences that influence new commissioning capacity of a technology	against unknown, expected progress, CO_2 emissions, Cost per MWe
Delay order of lifetime	Time delays for decom. of installed capacity	Different orders of time delay

Table 6: Uncertainties of the electricity transition case

6.3.2 Uncertainties

The uncertainties to be explored in this study are shown in Table 6. Uncertainties considered include both parametric uncertainties (i.e. initial values), model structure uncertainties. Initial values for capacities, cumulatively decommissioned capacities, and marginal costs of new capacity for each technology are explored. Additionally, parameters such as lifetimes of technologies and average planning and construction periods are analyzed. Structural uncertainties explored include learning effects and structures that enable to switch between different lookup functions. In our analysis, there are also switch structures that are either 1 or 0 for enabling technologies 3 and 4 and for enabling different preference structures. When the switch for a particular structure is 1, it means that the corresponding structure is active and vice versa. We generated 10.000 computational experiments using Latin Hypercube Sampling.

6.3.3 Results

In order to identify the causes for undesirable dynamics, it is necessary to find simultaneous combinations of values for input variables that result in similar characteristic values for the outcome variables. For this, we use in this paper the Patient Rule Induction Method (PRIM) (Friedman and Fisher 1999; Lempert et al. 2006; Groves and Lempert 2007). PRIM can be used if one seeks a set of subspaces of the input variable space within which the values of output variables are considerably different from the average value over the entire input domain. In the context of this paper, the input space is the uncertainty space. Thus, we use PRIM to find subspaces in the global uncertainty space that result in highly desirable or undesirable outcomes.

The analysis of the results without the introduction of any policy action revealed that the main driver for a failing transition, understood as a fraction of new technologies lower than 0.6, was a long life time of the existing dominant technology. Therefore, a basic policy would be to increase the decommissioning of the old dominant technology, thus effectively shortening its lifetime in all cases.

The efficacy of this basic policy is again assessed over the 10000 computational experiments. An analysis of these results shows that there are two main vulnerabilities, namely a poorly performing technology 2 and a mismatch between the economic dynamics and the investment in new technology. To address these two vulnerabilities, two corresponding adaptive actions that are only triggered if needed and associated trigger values are specified: (1) a subsidy for the costs of new technologies if they are coming close to the cost of the dominant technology, and (2) stopping the commissioning of technology 2 and replacing it with additional commissioning for Technology 3 and 4 if technologies 3 and 4 show more potential than technology 2.

Figure 8 shows the performance envelope for doing nothing, the basic policy, and the basic policy with the additional dynamic actions. The envelopes are based on the 10000 experiments and are generated by identifying the maximum and minimum value at each time step. Figure 8 also
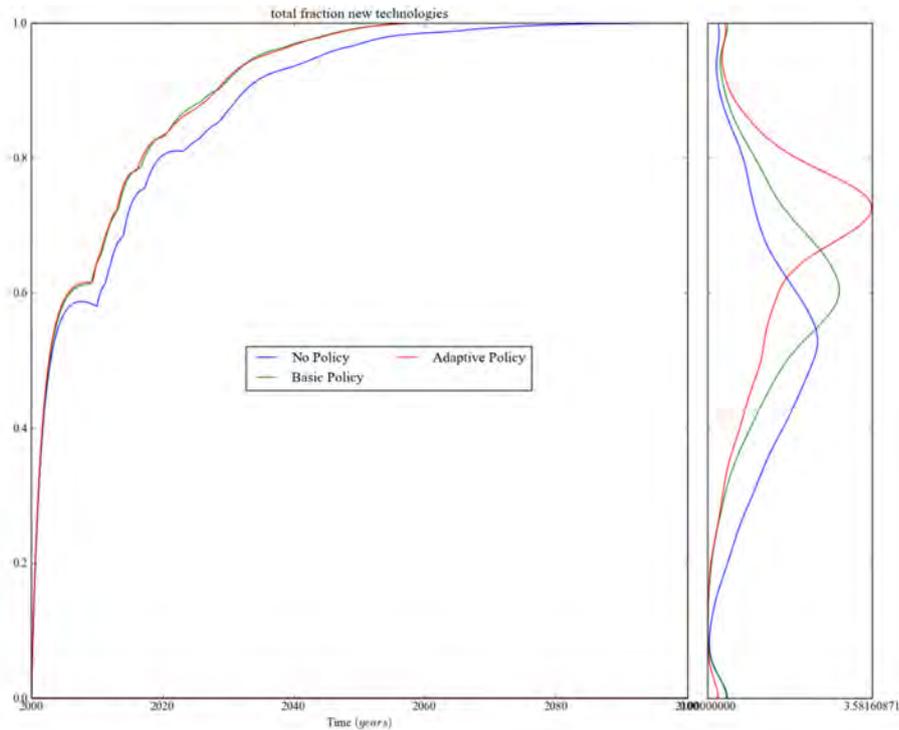
Figure 8: Performance envelopes for the two policies and doing nothing and Gaussian Kernel Density estimates for the terminal values

shows a Gaussian Kernel density estimate of the terminal values, assuming that each computational experiment is equiprobable. In case of no policy, the majority of runs results in a terminal value of around 0.5. The introduction of the basic policy is able to move this up to around 0.6. The additional adaptive actions result in a further increase up to 0.7 for most of the cases. This shows that the resulting final policy is effective in increasing the extent of the transition towards more sustainable functioning. However, the figure also shows that there is a long tail with cases where the transition is less successful. A further analysis of this tail revealed that these cases are characterized by a substantial increase in the degree of sustainability of the old dominant technology – which is fine too.

7 An Updated Picture of the Field

Following Forrester's call for a 'broader and deeper debate about [the] underlying philosophy [of System Dynamics], the contrast with alternative philosophies, the nature of knowledge, the role of subjective and observational information, and the criteria for judging validity' (Forrester 1980, p15) and Lane's example, Pruyt (2006) looked closely at the nature of System Dynamics, the basic assumptions underlying System Dynamics, and classifications of different System Dynamics strands, among else in a paradigmatic table developed starting from the paradigmatic framework of Tashakkori and Teddlie (1998) from the social and behavioral sciences. Table 7 displays the paradigmatic framework extended by Pruyt (2006), which is extended here with another paradigmatic position for the System Dynamics strand described in the current paper.

This paradigmatic table could be seen as an evolving non-exhaustive device to structure thinking, and position philosophical theories, method(ologie)s, techniques and tools. Although paradigms and paradigmatic frameworks are nothing but artifacts of the human mind, they are important because they could be used to support and influence thinking, and because they (in)directly

impact the real world:

> 'Different modeling paradigms cause their practitioners to define different problems, follow different procedures, and use different criteria to evaluate the results. Paradigms deeply bias the way modelers see the world and thus influence the contents and shapes of models.' (Meadows and Robinson 1985, p20)

Different paradigmatic frameworks could be (and are) proposed for different purposes and in specific contexts, and these frameworks could and should be extended and adapted when justified.

Pruyt (2006) added an intermediary paradigm to the paradigmatic table, the *critical realist* paradigm, which could as well have been labelled the 'mainstream System Dynamics paradigm'. This set of (intermediary) basic assumptions corresponds well to mainstream System Dynamics. Since the set of paradigmatic assumptions underlying ESDMA seems very similar but also sufficiently different from the set underlying mainstream System Dynamics as well as the other consistent sets, we added the 'Exploratist paradigm' to provide a paradigmatic home for ESDMA.

Exploratism is ontologically pluralistically realistic, but epistemologically constructivist. Operationally, it is very quantitative (computational), but in terms of interpretation is it really very qualitative. Causal relations are considered uncertain, some even unknowable, and so are models. Models are at most plausible. Hence, the broadest set of plausible models needs to be used in order to generate the widest set of plausible behaviors over time. The type of uncertainty focussed on is deep uncertainty. And robustness of policies is tested over the entire uncertainty space.

8   Concluding Remarks – Reinventing and Redefining SD

We believe we need to expand SD practices, investigate and question the basic assumptions underlying SD approaches, try out new foci and uses, and develop new multi-methods, tools, and techniques. We should let a thousand blossoms bloom, and invest heavily in some really promising areas. The alternative would be to defend the SD bastion of old. However, isolated improvement may lead to further introversion, further development of what is already well developed, but also to overall stagnation for dealing with ever more complex and uncertain issues, leading to losing the battles that really matter, and –ultimately– to the end of SD as the most practical and relevant means for dealing with dynamically complex issues. Hence, we may need extroversion and introspection in order for the SD field to grow stronger and larger.

In terms of extrospection, we may need to closely watch and embrace the most useful and promising developments in interesting fields like Data Mining, GIS, EMA, et cetera, and by doing so turn the art of SD into the computational science of SD, or at least part of the SD field. Because other SD uses and approaches have their rightful place too.

In terms of introspection, we think that some essential SD characteristics of old, may, given the current and near future state of science and computing, become less essential for the practice of SD, whereas other characteristics and ideas may require much more emphasis and development into what they were intended for in the first place.

In that respect, we believe that SD models should not necessarily be purely endogenous. In ESDMA it actually makes sense to 'pollute' SD models with 'open' elements (time series, shocks, et cetera) to bring in exogenous uncertainty, as well as with elements to include uncertainty in the internal functioning of models.

The original idea to resort to qualitative modes of behavior as a way of dealing with the unavoidability of uncertainty may require rethinking too. Interpreting model outcomes in terms of modes of behavior may serve many goals but may not be satisfactory in many cases to real-world policymakers. And with today's computing power and techniques, we finally have the means to go beyond modes of behavior for dealing with ubiquitous uncertainties.

The same is true for the use of a reference case: base or reference cases do not exist under deep uncertainty, there are at most base ensembles, and with today's computing power and advanced visualization and analysis techniques, there is no need for a single reference case nor for a very limited number of scenarios.

	Positivism	Post-positivism	Critical Realism	Exploratism	Pragmatism	Transformative-Emancipatory-Critical Parad.	Interpretivism
Ontology	monistic realistic	realistic	monistic realistic	pluralistic realistic	irrelevant	idealistic	idealistic
Ont. stability	stable	stable	rather stable	stable & unstable	irrelevant		–
Epistemology	empiricist (positivist)	moderately empiricist (probabilistic)	constructivist (group) & rationalist (ind. judgment)	constructivist	pragmatist	sceptic / relativist ('just power')	constructivist
Axiology	value-free	controllable value-ladenness	concerned by value-ladenness	concerned by value-ladenness	unconcerned by value-ladenness	non-neutral, value-ladenness	value-bound
Methodology	purely quantitative	primarily quantitative	quantitative *and* qualitative	quantitative (means) *and* qualitative (end)	quantitative *and* qualitative	qualitative, quantitative, mixed	qualitative
Logic	deductive	primarily deductive	deductive *and* inductive	deductive *and* inductive	deductive *and* inductive	deductive *and* inductive	inductive
Causality	knowable real causes	reasonably stable causal relationships (not necessarily used)	causality is key to understanding of real world	un/certain causal relationships, some of which unknowable	maybe causal relationships but not exactly knowable		indistinguishable causes and effect
Onto. & epist. Uncertainty	Marginal uncertainty	Shallow uncertainty	Medium uncertainty	Deep uncertainty	Deep uncertainty	(?)	Recognized ignorance
Appropriateness models & results	refutable but not refuted	validated models, results closest to real world	do models lead to real insight & understanding?	widest set of plausible models and behaviors	closest to goal or own value system?	advancing justice, democracy & oppressed?	confidence in constructed model
Future?	Prediction is possible	Probabilistic prediction / forecast	Forecast = impossible Fore/Insight = poss.	Fore/Insight & ensemble forecast = possible			Any fore/insight/ prediction = imp.
Appropriateness policies & strategies	optimal strategy	probably optimal or most appropriate strategy	potential to structural transformation?	truly effective across all plausible behaviors (ie robust) & triggered only if really necessary	close to goal or own value system	advancing justice, democracy & oppressed?	Any strategy if voluntarily agreed upon by all
Quantitative SD strands	X	Austere SD, Policy Engineering	Mainstream SD	ESDMA	Pragmatist SD	Modeling as Radical Learning (?)	Holon Dynamics,
Qualitative SD strands	X	CLD of real world	Consensual GMB to approach real world	GMB to elicit largest diversity of models	GMB for negotiated solution	GMB for CGCC	GMB for joint construction of meaning
Examples	X	Homer, Lyneis,...	Meadows, Forrester,...	(Auping et al. 2012) (Logtens et al. 2012)	Barton	Taket, Mertens	Vennix

Table 7: The extended paradigm table representing the positivist, postpositivist, critical realist, exploratist, pragmatist, transformative-emancipatory-critical, and constructivist paradigms based on (Pruyt 2006), (Tashakkori & Teddlie, 1998, table 2.1 p23), and (Mertens, 2002, p140–142)

Deep uncertainty also puts another question on the table: whether developing and using one plausible SD model is enough. If a model is just plausible, then maybe other plausible models need to be made as well, before robustness could be tested properly. That brings us to the ontological-epistemological stance of traditional SD and the mainstream attempts to try to integrate very different perspectives into one and the same model (Pruyt 2006). From our point of view, it would make more sense to model different perspectives separately, to design policies that are acceptable for all perspectives, and to test policies over all perspectives/models.

Hence, we may need to question the basic ontological-epistemological assumption of traditional SD, move beyond the concept of modes of behavior for dealing with uncertainty. And above all else do we need excellent SD education beyond the introductory level, even beyond the most advanced traditional courses in SD.

In this paper, we reviewed one promising strand of SD, namely ESDMA. ESDMA makes SD more generally applicable, ie it extends the usefulness of SD from dynamically complex issues to *deeply uncertain* dynamically complex issues.

ESDMA also operationalizes the concept of policy robustness by allowing testing robustness of policies and comparing policies over the entire multi-dimensional uncertainty space. Small, manageable and partly open SD models are most appropriate for ESDMA, making another case for small SD-like models (Ghaffarzadegan et al. 2011).

ESDMA is as much about analysis as it is about modeling, which is why much of the current effort is into developing analytic tools to analyze outcomes and models (via the model outcomes). The current analytic tools already generate a wealth of analytical and policy relevant insights, partially filling another gap in traditional SD, namely the lack of advanced analysis of model outcomes (and models).

Since ESDMA allows exploring policy robustness over the entire uncertainty/scenario space and design of adaptive policies addressing the entire scenario space, it actually makes the job of policymakers much lighter. On the one hand, that is also true for the analyst: more analytic tools are available to perform policy relevant analyses. On the other hand however does it actually make the job of a modeler and analyst more difficult, since a larger tool set needs to be mastered, multiple plausible models may need to be developed, analyses need to be performed systematically, complex outputs need to be interpreted, and policies need to be designed iteratively and compared with all other policies.

Another complicating factor is the fact that easy software for doing all of the above is not commercially available yet. Our software, which requires python coding skills, makes it accessible and useable to a select few only. But even if the software would become available to all, then system dynamicists also need advanced education in data mining, time series clustering, formal modeling techniques, and the like.

Moreover, ESDMA modelers need to have more than just modeling and basic analytic skills: process skills, facilitator skills, modeling skills, programming skills, sampling skills, advanced analytic skills, communication skills are all needed – in other words, super(wo)men or well-functioning teams covering the whole skill set may be required.

Finally, it is our experience that just ESDMA may not be enough. Policymakers need to become part of the ESDMA and need to experience uncertainty first hand before being aligning heart and mind. New types of workshops like EGMSS and ESG are thus needed to complement the analytic results and policy advice. In all, there is still a lot of work to be done before the computational science of SD will be the (state of the) art of SD.

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