Technological Forecasting & Social Change 80 (2013) 408–418

Contents lists available at SciVerse ScienceDirect

Technological Forecasting & Social Change

Adaptive Robust Design under deep uncertainty

Caner Hamarat *, Jan H. Kwakkel, Erik Pruyt

Delft University of Technology, Policy Analysis Department, PO Box 5015, 2600 GA Delft, The Netherlands

ARTICLE INFO

Article history:
Received 14 May 2011
Received in revised form 2 July 2012
Accepted 27 August 2012
Available online 8 November 2012

Keywords:
Model-based decision support
Deep uncertainty
Adaptive policy-making
Exploratory Modeling and Analysis

ABSTRACT

Developing strategies, or policies, that automatically adapt to changing conditions is called adaptive decision-making, respectively adaptive policy-making. In this paper, we propose an iterative computational model-based approach to support adaptive decision-making under deep uncertainty. This approach combines an adaptive policy-making framework with a computational approach to generate and explore thousands of plausible scenarios using simulation models, data mining techniques, and robust optimization. The proposed approach, which is very useful for Future-Oriented Technology Analysis (FTA) studies, is illustrated on a policy-making case related to energy transitions. This case demonstrates how the performance of a policy can be improved iteratively by exploring its performance across thousands of plausible scenarios, identifying problematic subsets that require improvement, identifying adaptive high leverage actions with which the adaptive policy needs to be extended until a satisfying dynamic adaptive policy is found for the entire ensemble of plausible scenarios. The approach is not only appropriate for energy transitions; it is also appropriate for any long-term structural and systematic transformation characterized by dynamic complexity and deep uncertainty.

1. Introduction

Conceptual, formal, and computational models are commonly used to support decision-making and policy-making [1–5]. The term 'model' refers here to a representation of the most crucial aspects of a system of interest for extracting usable information [6]. The term 'decision-making' is used here for the act or process of making strategies or conscious decisions by an individual or group of actors, and 'policy-making' for the act or process of designing policies by those in charge of designing (public) policy. Hence, decision-making is more general than, and to some extent includes, policy-making. Although the approach proposed in this paper applies equally well to long-term decision-making as to policy-making, we will, from here on, consistently refer to 'policy-making' and 'policies', for our work mainly focuses on policy-making and the case we use to illustrate the approach here relates to policy-making for stimulating energy transitions.

Although some uncertainty, defined here as any type of aberration from utter certainty [4], is mostly taken into account in traditional model-based policy-making, it mainly includes what is known and certain. However, uncertainty is prevalent in complex systems and policy-making related to complex issues. Policy failures are often attributable to the omission of uncertainties in policy-making [7]. Policies that would be optimal for one particular scenario often fail in most other scenarios. And policies that are optimal for dynamically complex issues at a particular point in time often fail at other moments in time. Hence, in case of complex issues under uncertainty, there is a strong need for policies that are designed to adapt over time to new circumstances and surprises, i.e. adaptive policies, and to perform acceptably well in all circumstances, i.e. robust adaptive policies [7,8].

In order to develop policies under uncertainty, analysts often use techniques such as exploratory scenarios [9], Delphi surveys [10], and the analysis of wild cards and weak signals [11]. Characteristic for these techniques is that they aim at charting the

* Corresponding author. Tel.: +31 15 27 88080; fax: +31 15 27 86233.
E-mail address: c.hamarat@tudelft.nl (C. Hamarat).

0040-1625/$ – see front matter © 2012 Elsevier Inc. All rights reserved.
http://dx.doi.org/10.1016/j.techfore.2012.10.004

boundaries of what might occur in the future. Although useful, these traditional methods are not free of problems. Goodwin and Wright [12, p. 355] argue that "all the extant forecasting methods – including the use of expert judgment, statistical forecasting, Delphi and prediction markets – contain fundamental weaknesses". Popper et al. [13] state that the traditional methods "all founder on the same shoals: an inability to grapple with the long-term's multiplicity of plausible futures".

Modeling used for policy-making under uncertainty long faced the same inability to grapple with the long-term's multiplicity of plausible futures. Although testing parametric uncertainty is a standard practice in modeling, and the importance to present a spectrum of runs under very different hypotheses covering the range of their variation was recognized decades ago [14, p. 149], modelers were until recently unable to truly overcome this inability due to computational barriers encountered when dealing with complex systems [8]. Adaptive foresight studies would also hugely benefit from enhanced computational assistance [15].

If uncertainties are not just parametric, but also relate to functional relations, model hypotheses and aspects, model structures, mental and formal models, worldviews, modeling paradigms, the effects of policies on modeled systems, and the lack of consensus on the valuation of model outcomes, i.e. in case of 'deep uncertainty', then traditional modeling and model-based policy-making tends to fail. Deep uncertainty pertains according to Lempert et al. [8] to those "situations in which analysts do not know, or the parties to a decision cannot agree on, (1) the appropriate conceptual models which describe the relationships among the key driving forces that shape the long-term future, (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes". Deep uncertainty pertains, in other words, from a modelers' perspective to situations in which a multiplicity of alternative models could be developed for how (aspects of) systems may work, many plausible outcomes could be generated with these models, and outcomes could be valued in different ways, but one is not able to rank order the alternative system models, plausible outcomes, and outcome evaluations in terms of likelihood [16]. Hence, all alternative system models, plausible scenarios, and evaluations require consideration, without exception, and none should be treated as the single best model representation, true scenario, or correct evaluation. It is clear that there is a strong need for policy-making approaches that allow for dealing with deep uncertainty, i.e. with many different kinds of uncertainties, multiple models, a multiplicity of plausible scenarios and evaluations of these scenarios [17].

In this paper, we propose an iterative model-based approach for designing adaptive policies that are robust under deep uncertainty. The approach starts from a conceptualization of the decision problem and the identification of the key uncertainties. Next, an ensemble of models is developed that explicitly allows for the exploration of the uncertainties. The behavior of the ensemble is analyzed and troublesome or advantageous (combinations of) uncertainties are identified, stimulating policy design. Iteratively, the initial design is fine-tuned until there are no remaining troublesome (combinations of) uncertainties or the policy is deemed satisfactory based on other grounds. This approach thus explicitly uses the multiplicity of plausible futures for policy design, addressing one of the shortcomings of many traditional approaches and practices, i.e. the poor utilization of the potential to be prepared for uncertainties and surprises of future developments [18]. The systemic characteristic of the proposed approach enables a holistic and systemic exploration of the future, which is of great importance in FTA [19].

The proposed approach is illustrated by means of a long-term policy-making case related to the transition of energy system toward sustainability. Energy systems are complex, their development over time is dynamically complex, and many aspects related to these systems and their future developments are deeply uncertain. Current attempts at steering the transition toward a more sustainable and cleaner configuration are static and may not be very effective and efficient in various futures, i.e. they may not be robust. This energy transition case is therefore used for illustrating how this approach could be used for policy-making, and more generally, decision-making under deep uncertainty.

The rest of the paper is organized as follows. Section 2 introduces an adaptive policy-making framework and our Adaptive Robust Design approach. Section 3 contains the energy transition case and the illustration of our approach to it. Section 4 includes the discussion. Concluding remarks are made in Section 5.

2. Methodology: the adaptive policy-making framework and the Adaptive Robust Design approach

2.1. The adaptive policy-making framework

Under deep uncertainty, predictive approaches are likely to result in policies that perform poorly. In response, an alternative policy-making paradigm has emerged. This paradigm holds that, under deep uncertainty, policy-making needs to be dynamic with built-in flexibility [8,15,20–24]. The initial ideas for this paradigm were developed almost a century ago. Dewey [25] put forth an argument proposing that policies be treated as experiments, with the aim of promoting continual learning and adaptation in response to experience over time [26]. Policy learning is also a major issue in evolutionary economics of innovation [27–29]. Early applications of adaptive policies are also found in the field of environmental management [30,31], where policies are designed from the outset to test clearly formulated hypotheses about the behavior of an ecosystem being changed by human use [32]. A similar attitude is also advocated by Collingridge [33] with respect to the development of new technologies. Given ignorance about the possible side effects of technologies under development, he argues that one should strive for correctability of decisions, extensive monitoring of effects, and flexibility. More recently, Brans et al. [34] and Walker et al. [24] developed a structured, stepwise approach for dynamic adaptation. Walker et al. [24] advocate that policies should be adaptive: one should take only those actions that are non-regret and time-urgent and postpone other actions to a later stage. In order to realize this, it is suggested that a monitoring system and a pre-specification of responses when specific trigger values are reached should complement a basic policy. The resulting policy is flexible and adaptive to the future as it unfolds.

Fig. 1 shows a framework that operationalizes the high level outline of adaptive policy-making. In Step I, the existing conditions of an infrastructure system are analyzed and the goals for future development are specified. In Step II, the way in which this is to be achieved is defined. This basic policy is made more robust through four types of actions, which are specified in Step III, namely by mitigating actions to reduce the certain adverse effects of a policy; hedging actions to spread or reduce the negative impacts of uncertain adverse effects of a policy; seizing actions to profit from opportunities; and shaping actions to reduce the likelihood that an external condition or event that could make the policy fail will occur, or to increase the chance that an external condition or event that could make the policy succeed will occur. Even with the actions taken in Step III, there is still the need to monitor the performance of the policy and take action if necessary. This is called contingency planning, and is implemented in Step IV. Signposts specify information that should be tracked in order to determine whether the policy is progressing toward success. Critical values of signpost variables (triggers) are chosen, beyond which actions should be implemented to ensure that the policy keeps moving the system at a proper speed in the right direction. There are four different types of actions that can be triggered by a signpost: defensive actions are taken to reinforce the basic policy, preserve its benefits, or meet outside challenges in response to specific triggers that leave the basic policy unchanged; corrective actions are adjustments to the basic policy; capitalizing actions aim at taking advantage of opportunities that improve the outcomes of the basic policy; and a reassessment of the policy is initiated when the analysis and assumptions critical to the policy's success have lost validity.

In a recent special issue of *Technological Forecasting and Social Change* on adaptivity in decision-making, the guest editors conclude that “Adaptive policy-making is a way of dealing with deep uncertainty that falls between too much precaution and acting too late. While the need for adaptation is increasingly acknowledged, it is still a developing concept, and requires the further development of specific tools and methods for its operationalization” [7]. More specifically, for adaptive policy-making to become a useful policy-making approach, it is necessary to specify in more depth how the various steps could be carried out and which methods and techniques could be employed in each of the steps. That is, adaptive policy-making needs to move from being a high level concept captured in a flowchart, to being a detailed policy-making approach. A possible qualitative approach for

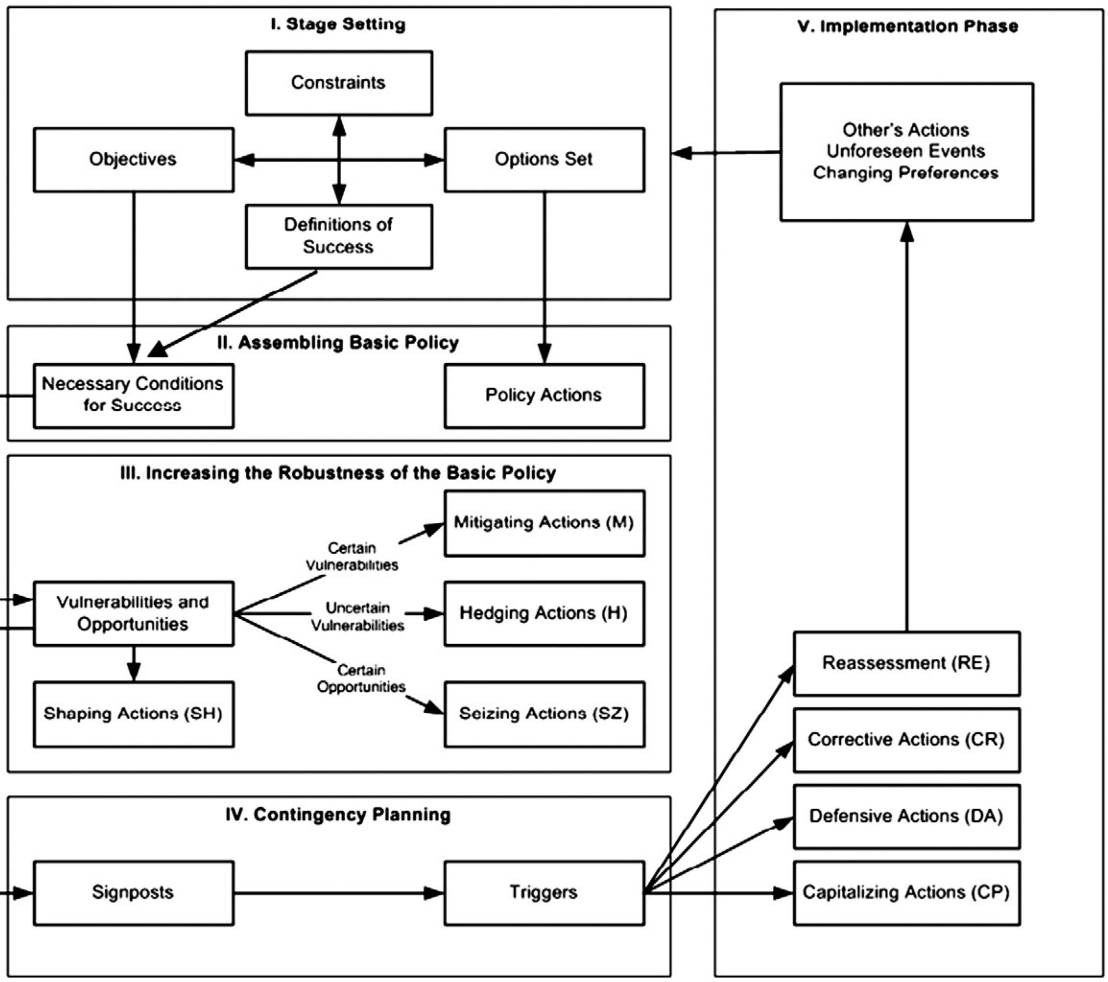

Fig. 1. Steps of the Adaptive Policy-Making Framework.
Source: [1].

operationalizing the Adaptive Policy-Making Framework is through structured workshops [35]. A possible quantitative approach for operationalizing the Adaptive Policy-making Framework is by using Exploratory Modeling and Analysis [36–38]. This computational approach, which we call the Adaptive Robust Design (ARD) approach, is proposed and illustrated below.

2.2. The Adaptive Robust Design approach

EMA is a methodology that uses computational experiments to combine plausible models and other uncertainties in order to generate a large variety of scenarios that are in turn used to analyze complex uncertain systems, support the development of long-term strategic policies under deep uncertainty, and test policy robustness over. EMA could also be used to develop adaptive policies under deep uncertainty since it allows for generating and exploring a multiplicity of plausible scenarios by sweeping multi-dimensional uncertainty space. EMA could then be used to identify vulnerabilities and opportunities present in this ensemble of scenarios, paving the way for designing targeted actions that address vulnerabilities or seize opportunities. The efficacy of the resulting policies could then be tested over the entire ensemble of scenarios. Moreover, EMA could be used to identify conditions under which changes in a policy are required. That is, it could help in developing a monitoring system and its associated actions. It thus appears that EMA could be of use in all adaptive policy-making steps.

Hence, our Adaptive Robust Design (ARD) approach starts along the lines of the EMA methodology with: (1) the conceptualization of the problem, (2) the identification of uncertainties (and certainties), and (3) the development of an ensemble of models that allows generating many plausible scenarios. It then proceeds with: (4) the generation of a large ensemble of scenarios, (5) the exploration and analysis of the ensemble of scenarios obtained in Step 4 in order to identify troublesome and/or promising regions across the outcomes of interest, as well as the main causes of these troublesome and promising regions, (6) the design – informed by the analysis in Step 5 – of policies for turning troublesome regions into unproblematic regions, (7) the implementation of the candidate policies in the models, (8) the generation of all plausible scenarios, subject to the candidate policies, (9) the exploration and analysis of the ensemble of scenarios obtained in Step 8 in order to identify troublesome and/or promising regions across the outcomes of interest, as well as the main causes of densely concentrated troublesome and/or promising regions, etc. Steps 5–8 should be iterated until an adaptive policy emerges with robust outcomes (see in Fig. 2).

The identification of troublesome and/or promising regions is crucial for this approach to be efficacious. These sub-regions of the uncertainty space represent combinations of uncertainties that either have highly negative or highly positive effects. The troublesome regions and the promising regions correspond respectively to vulnerabilities and opportunities in the adaptive policy-making framework. If uncertainties have a positive or negative effect across all the regions, then they are typically best addressed in the basic policy or through actions aimed at enhancing the robustness of the basic policy, while uncertainties of relevance only in particular regions are typically better handled through monitoring and associated corrective, defensive, or capitalizing actions.

In order to identify the troublesome and promising regions, we use an adapted version of the Patient Rule Induction Method (PRIM) [39–42] – one that can deal with categorical and continuous uncertainties – which allows distilling uncertainty sub-spaces with high positive match ratios for a pre-specified binary classification function and with high relative masses (above a pre-specified threshold relative to the total scenario space). PRIM is particularly valuable for discovering troublesome subspaces of the multi-dimensional uncertainty space, and hence, for developing specific adaptive actions for adaptive policies. PRIM has been used in combination with EMA by other authors [40–42]. Those applications, however, aimed at translating the troublesome regions back to qualitative scenarios that could then be presented to a decision maker. Here, the troublesome and promising regions identified with PRIM are used directly for designing adaptive policies and the corresponding monitoring systems.

The approach for developing adaptive policies as presented here shares characteristics with 'Robust Decision Making (RDM)' [8,41,43,44]. Like in RDM, we emphasize the iterative character of policy formation. However, by connecting this to a particular framework for the design of adaptive policies, our approach is more specific on the various ways in which uncertainties can be handled through policies. Related to this, the approach focuses not solely on the negative side of the uncertainties, but also

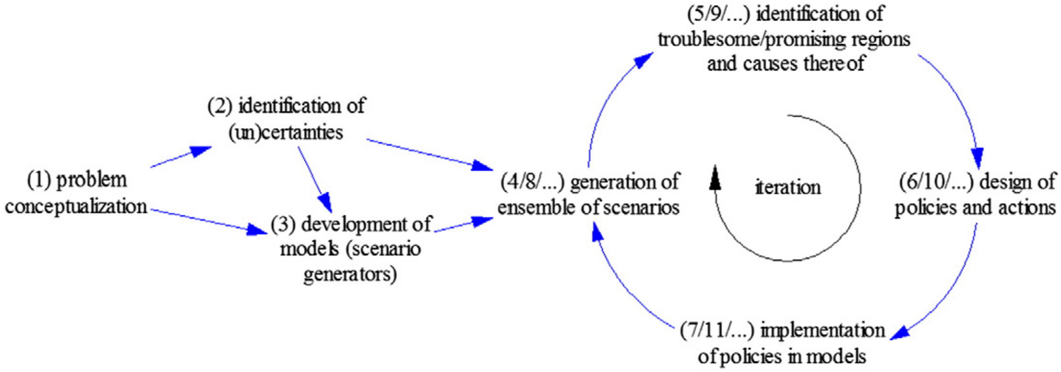

Fig. 2. Iterative Adaptive Robust Design process.

explicitly considers the opportunities that uncertainties can present. Another difference is that RDM relies on the notion of regret and uses a modified version of the expected utility framework [44], our approach does not entail such a stance. Finally, in the exemplary paper on RDM [41], there is a need for significant computational power due to sampling techniques used, whereas through the utilization of computationally more efficient methods such as PRIM, more efficient sampling techniques can be employed.

3. Illustration: Adaptive Robust Design in case of energy transitions

In order to illustrate how the ARD approach helps in designing adaptive policies, we present an illustrative case study about developing an adaptive policy for stimulating the transition of the electric power generation sector toward a more sustainable one. Transitions are large systematic societal transformations that, in general, are characterized by long periods over which they play out. Energy transitions are characterized by many deep uncertainties related to transition mechanisms, to the various competing technologies, and to human and organizational decision-making [45]. Here we focus on the competition between technologies.

3.1. Introduction to the energy transition case

In order to achieve a sustainable future, there is a strong need for a transition in many domains, including transportation, housing, water and energy [46]. Energy is a crucial domain in which a fundamental transition toward clean generation technologies is desirable [47] for environmental and security reasons. The current energy system is mainly dominated by fossil energy generation technologies which are being challenged by rapidly evolving emerging technologies. Although new sustainable energy technologies are entering the market, their contribution to the total amount of energy generation is still relatively small. Transition of the energy system toward sustainability depends on the developments related to new technologies.

Such developments are typically characterized by non-linearity and uncertainty regarding technological characteristics and market adoption [48,49]. For example, precise lifetimes of technologies are not known and expected values are used in planning decisions. Also, since the installation of new capacity mostly happens in large chunks, planning is complex and happens under uncertainty, and construction times are open to surprises affecting the actual completion time. Other important uncertainties are related to learning effects on costs and technological performance. Costs and technological performance, and expectations related to them, in turn influence the adoption and survival of technologies during the transition. These uncertainties play a crucial role and need to be taken into account when analyzing the dynamics of energy transitions and when trying to influence them by means of adaptive policies.

Table 1
Overview of the uncertainties.

Uncertainties	Description	Type	Range or categories
Initial capacities	Starting value of the installed capacity of a technology	Parametric	Varying between 1 and 16,000 MW for different technologies
Lifetimes	Expected lifetime of a technology	Parametric	Varying between 15 and 50 years for different technologies
Delay orders of lifetimes	Orders of the decommissioning delays	Categorical	1st, 3rd, 10th, 1000th
Initial decommissioned capacities	Initial values of the total decommissioned capacities of the technologies	Parametric	Varying between 10 and 10,000,0000 MW for different technologies
Planning and construction periods	Average period for planning and constructing new capacity for a technology	Parametric	Varying between 1 and 5 years for different technologies
Progress ratios	Ratio for determining cost reduction due to learning curve	Parametric	Varying between 70% and 95% for four different technologies
Initial costs	Initial investment cost of new capacity of a particular technology	Parametric	Varying between €500,000 and €10 million per MW
Economic growth	Economic growth rate	Parametric	Randomly fluctuating between −0.01 and 0.035 (smoothed concatenation of 10-year random growth values)
Investment preference structures	Preference criteria and weights for investing in new capacity of each of the technologies	Parametric weights and categorical switches	Preference for (more) familiar technologies [called here the Preference 'Against unknown']; preference for (higher) expected progress; preference for (higher) 'CO_2 avoidance'; preference for (lower) 'Cost per MWe'

In order to explore the problem and the uncertainties of energy transitions, a System Dynamics [50,51] model developed for exploring the dynamics of energy system transitions [3] is used in this study. The SD model incorporates, at a high level of aggregation, the main structures driving the competition among four energy technologies. Technology 1 represents old dominant non-renewable technologies. The other three technologies are at the start of the simulation relatively new, more sustainable, and more expensive. Since fast and relatively simple models are needed for 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 mechanisms such as total energy demand, investment costs and the effect of learning curves on costs. A more detailed explanation of the model can be found in [3]. And the uncertainties taken into consideration and their corresponding ranges are displayed in Table 1.

3.2. The ARD process illustrated

3.2.1. No policy

In order to explore the behavior of the simulation model over a wide variety of conditions, we utilize a workbench that is written in Python [52] which controls Vensim through its Dynamic Link Library [53,54]. Using Latin Hypercube Sampling (LHS) [55], a 'no policy' ensemble of 10,000 simulations was generated. In the model used, at least one preference criterion must be activated (switch value equal to 1) for each run, else the run needs to be excluded: out of 10,000 simulations, 651 cases were excluded for that reason. Fig. 3 shows the results of 1000 randomly selected cases out of the remaining 9349 runs in the post-processed 'no policy' ensemble. The figure shows the behavior over time for the outcome indicator 'fraction of new technologies of total energy generation' as well as the Gaussian Kernel Density Estimates (KDEs) [56] of the end states.

These results show that the fraction of new technologies seems to be concentrated around 60% of total generation capacity by the simulated year 2100, which means that over the 100 year simulation time, the fraction of new technologies remains below 60% for about half of the runs. If the goal is an energy transition toward sustainability, then this ensemble as a whole is unlikely to be acceptable and requires policy intervention. Hence, we use PRIM to identify relatively large regions in the uncertainty space that generate relatively high concentrations of undesirable results, and the combinations of uncertainties and their values that lead to these regions. To this end, the end states for the total fraction of new technologies are classified as 1 if the fraction is below 0.60 and 0 otherwise. Using PRIM, three troublesome uncertainty sub-spaces that contain at least 70% of the cases of class 1 are identified. These regions are characterized by specific combinations of uncertainties: Table 2 shows the full range of the uncertainties (first row), and the uncertainty ranges for each of these troublesome regions (other rows). Since PRIM seeks for regions in the uncertainty space with specific characteristics, not all of the uncertainties but only the uncertainties that determine the sub-spaces are shown. The lower range of the 'lifetime of Technology 1' is relevant for all three sub-spaces, i.e. the adoption of new sustainable technologies is hampered – in combination with the other uncertainties of the sub-spaces – by longer lifetimes of the dominant technology. Although a low performance of Technology 2 on the 'CO_2 avoidance' criterion, a high performance of Technology 1 on the 'expected cost per MWe' criterion, a short lifetime for Technology 3, and a short planning and construction time for Technology 1 also hinder the transition toward sustainability, none of these uncertainties and their ranges are as unambiguous as the lifetime of Technology 1 (for all regions, not the lower ranges). Shortening the lifetime of Technology 1 therefore seems to be a promising basic policy, i.e. a policy that will be implemented in any case from the start.

3.2.2. Basic policy

Shortening the lifetime of Technology 1 could be achieved by increasing its decommissioning, for as long as the fraction of new technologies remains below a particular target fraction, say 0.8, assuming that 80% is a reasonable target for the fraction of sustainable technologies. To assess the performance of this basic policy, the same 9349 experiments used for exploring the no policy case are now executed with the basic policy. Fig. 4 displays the envelopes spanning the upper and lower limits of the total

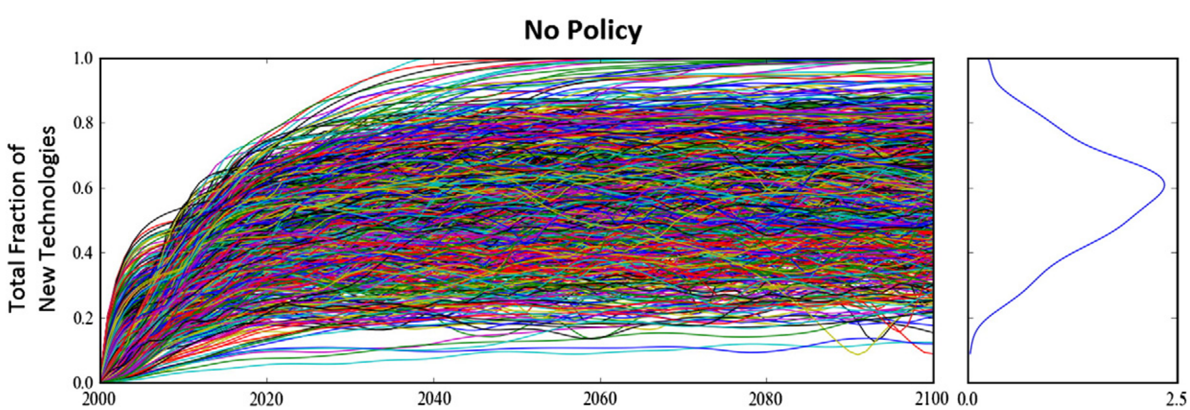

Fig. 3. Total fraction of new technologies for the 'no policy' ensemble.

Table 2
PRIM results for the no policy ensemble.

	Preference against unknown		Average planning and construction period Tech. 1		Lifetime of Technology 1		Lifetime of Technology 3		CO_2 avoidance performance of Technology 2		Expected cost per MWe performance of Technology 1	
	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
Original	2	5	1	5	30	50	15	40	1	5	1	2
Region1	2	5	1	5	34.4	50	15	37.5	1	4.2	1.1	1.8
Region2	2	5	1	4.8	33.7	50	15	37.5	1	4.4	1.1	2
Region3	2.9	4.9	1	4.5	32.6	50	16.3	40	1	5	1.2	2

fraction of new technologies for the no policy ensemble (in blue) and the basic policy ensemble (in green) as well as the KDEs of the end states of all runs in the respective ensembles.

The upward shift of the sustainable fraction in Fig. 4 means that the need for new capacity resulting from the additional decommissioning of Technology 1 is to a large extent filled by new technologies. Hence, the basic policy stimulates the transition from Technology 1 to new technologies, at least to some extent. Although there is an improvement in terms of the fraction of sustainable technologies, there is still a room for further improvement. Many runs still end below the 60% new technologies threshold. For this reason, we applied PRIM once more with the same classification rule in order to identify troublesome regions for the basic policy.

The basic policy aimed at increasing the decommissioning of the dominant technology, since all PRIM boxes indicated decreasing the negative effect of the lifetime of Technology 1 would help to increase the fraction of new technologies. The second iteration PRIM results show there are three very different troublesome regions in the basic policy ensemble: the first region relates to the performance of the technologies on the CO_2 avoidance criterion, the second region relates to the underperformance of Technology 2, and the third region is determined by uncertainties related to economic growth and expected progress.

3.2.3. Contingency planning

To redesign and improve the basic policy, it is necessary to analyze the characteristics of the PRIM regions to identify the vulnerabilities that generate the undesirable outcomes. The main drivers of the first region are the CO_2 avoidance performance values for Technologies 1, 2, and 3. If the CO_2 avoidance performance of the dominant technology is high, while it is low for the new technologies, then transition toward new technologies is limited. Additionally, the region shows that higher performance for expected cost per MWe of the dominant technology also limits the transition. This outcome is not undesirable: it means that the old dominant technology outperforms the other technologies in terms of expected investment costs *and* CO_2 avoidance, which, in our case (not considering long term security of supply), serves the same goal as the transition. Hence, it is not necessary to design a strategy for this region; this uncertainty sub-space consists of acceptable scenarios in terms of CO_2 avoidance even though the transition to new technologies is limited.

The second region is mainly driven by uncertainties related to Technology 2. A shorter lifetime, lower performance of CO_2 avoidance, and longer planning and construction period for Technology 2, lead to low fractions of sustainable technologies. The results indicate that Technology 1 becomes more preferable than Technology 2, which is initially the main alternative to Technology 1. In this situation, a reasonable defensive action would be to focus on the other sustainable technologies, in order to promote the transition toward these technologies instead. To address this vulnerability, a signpost tracking the progress of Technologies 2, 3 and 4 could be used. The point where the performance of Technology 3 or 4 equals the performance of Technology 2 could be the trigger for

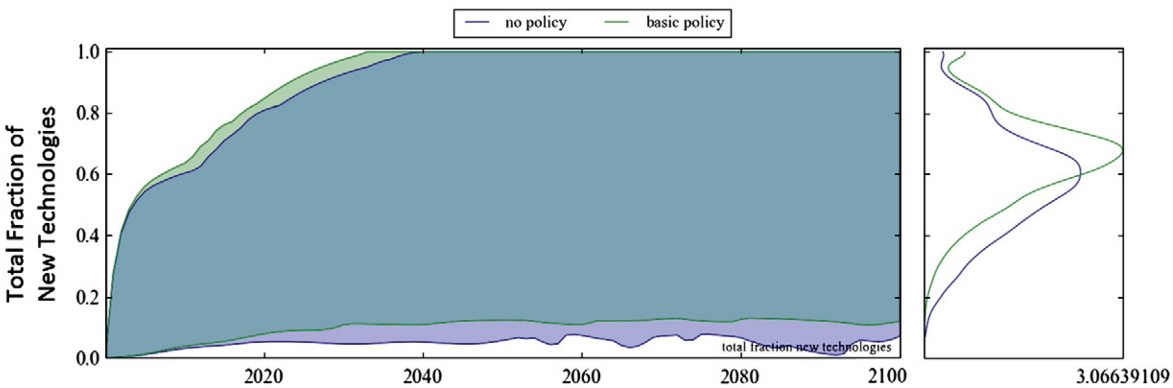

Fig. 4. Comparison of no policy and basic policy for total fraction of new technologies.

this signpost. Using this trigger, the corrective action would be to stop investing in Technology 2 and to shift investments to Technologies 3 and 4 instead. So, we modified our basic policy by adding the monitoring and corrective actions and reran the experiments. Although there is not a clear improvement in terms of total fraction of new technologies, the installed capacities of Technologies 3 and 4 increase. This means that the defensive action developed for the second region served its purpose by steering the commissioning toward Technologies 3 and 4.

The third region shows that certain combinations of economic growth factors and preference for the expected progress criterion may also hinder the energy transition. Each of the economic growth parameters indicated in the third region corresponds to the value of economic development for ten years and together they constitute the overall behavior of economic development over 100 years. Although it is difficult to interpret the combination of these economic growth parameters, one could conclude that certain combinations of these parameters hinder the breakthrough of new technologies. Since the way in which economic development is represented in this model creates cyclic behavior, a possible corrective action could be to partly decouple the adoption of new technologies from the economic cycle with the help of subsidies and additional commissioning of new technologies. For this purpose, we use the investment cost of new technologies as a signpost. A possible defensive action would be to subsidize one or more sustainable technologies for some time to make them competitive. Hence, the costs of Technologies 2, 3 and 4 are monitored over time and when their costs are close enough to the cost of the dominant technology, a 20% cost reduction of the new technologies is triggered over a period of 10 years. To further address this vulnerability, we also add a hedging action to the basic policy in the form of additional commissioning of Technologies 3 and 4 in their early years. These actions together aim at making the sustainable technologies more cost efficient once their costs are reasonably affordable levels, and to promote the transition toward new technologies in their early years. The economic action is successful in promoting sustainable technologies and increasing the total fraction after the first 10 years (around 2020). The adoption of the new technologies in later years is also higher than under the basic policy, suggesting that these cost reductions are effective.

To improve the performance of the adaptive policy even further, the triggers used for adaptivity were optimized using robust optimization [57–59]. Using the trigger values optimized over the entire ensemble for the actions previously discussed significantly improves the adaptive policy. Fig. 5 shows a comparison in terms of the *total fraction of new technologies* of the 'no policy' ensemble, the 'basic policy' ensemble, and this 'adaptive policy' ensemble over the same uncertainty space, i.e. using the same experimental design.

It shows that the 'adaptive policy' ensemble, although hardly improving the extremes, outperforms the 'basic policy' and 'no policy' ensembles on this key performance indicator: the adaptive policy is a better guarantee for a successful transition under deep uncertainty, without forcing a transition to new technologies upon situations that do not require a transition to take place (e.g. in case of a cheap and environmentally friendly dominant technology) or for which a transition would be overly expensive.

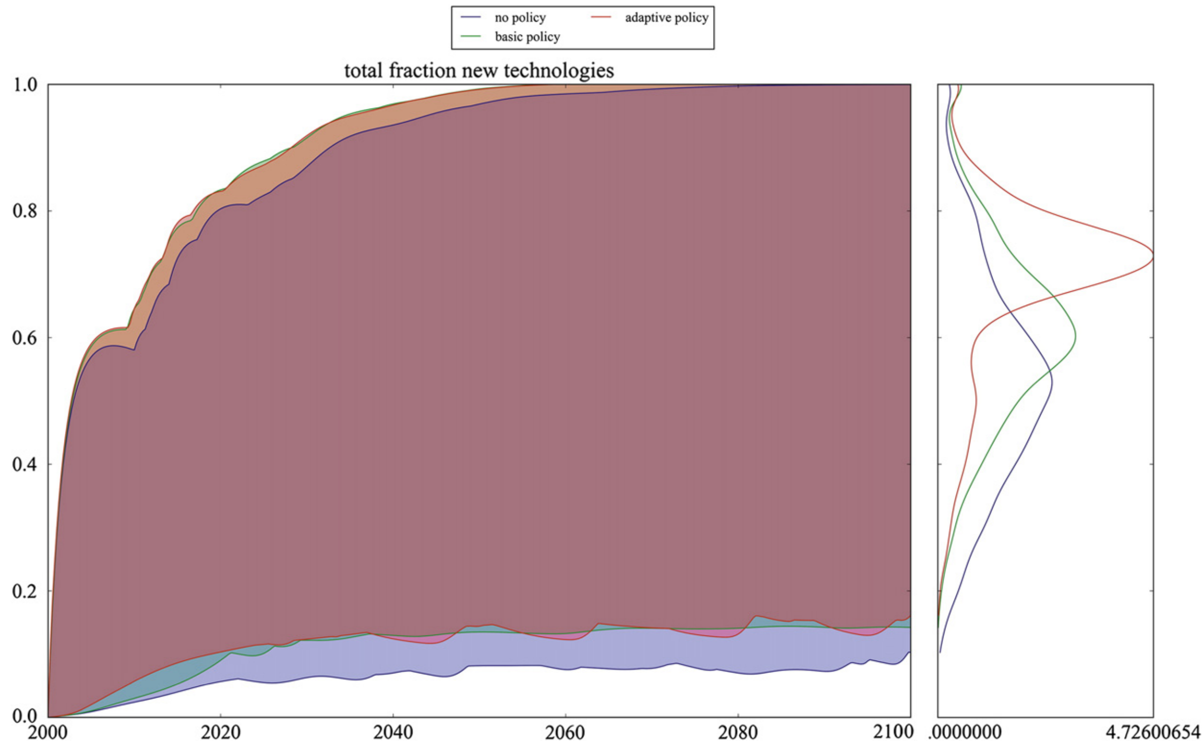

Fig. 5. Comparison of no policy, basic policy and adaptive policy for total fraction of new technologies.

4. Discussion and implications for Future-Oriented Technology Analysis (FTA)

In this paper we proposed an iterative computational approach for designing adaptive policies that are robust under deep uncertainty. The proposed approach has been illustrated on an energy transition case. Several of our findings warrant further discussion.

An important issue relates to the hedging action and the monitoring of the costs. Fig. 5 shows that these actions are effective in the early years, but lose their effect after 2020 due to the time-restricted nature of the hedging action. However, it is not possible to conclude that this reduction in effectiveness is caused only by the nature of the hedging action. To reveal the underlying mechanism leading to a decline after 2020, it is necessary to identify those runs that improve around 2020 and then collapse. A modified classification in combination with PRIM could be utilized for such an analysis.

This study also has implications for Future-Oriented Technology Analysis (FTA). Transitions represent large structural and systematic transformations and the transition toward a more sustainable energy generation system is a grand societal challenge. This study shows how EMA and the proposed iterative Adaptive Robust Design approach can be employed for shaping and steering transitions toward more sustainable energy systems. Thus, this study is in line with the purpose of FTA projects that aim at developing long-term, adaptive, and robust policies for socio-economic and technological changes (i.e. energy transitions). This study illustrated the potential of EMA for FTA as suggested by Porter et al. [17].

Uncertainties and surprises are inevitable and intrinsic to FTA projects. The adequate handling of uncertainty is thus of prime importance. Using FTA for planning for action is one area where the handling of uncertainty is crucial. Here, the goal should be to aim for plans that are adequate across the multiplicity of plausible future worlds. This paper shows a way in which EMA can be utilized to support the iterative development and refinement of adaptive policies in light of a clear exploration of the multiplicity of plausible futures. That is, the paper offers a new technique for FTA practitioners in their work of supporting long-term planning.

Another important challenge in many FTA projects is supporting a multi-actor process. Different perspectives, different worldviews or different mental models of various stakeholders are usually the norm in FTA projects and may result in situations where the results of FTA projects are contested by one or more of the actors involved in the process if the diversity of views and/or actors is not properly cared for. Here, EMA can be of use, since EMA allows incorporating a multiplicity of perspectives, worldviews, mental models or quantitative models. That is, EMA could be used to support an inclusive modeling process from the start, where different beliefs about how a system functions, or which aspects of a problem are important, are explicitly taken into account and assessed for their consequences.

5. Conclusions

We have proposed an iterative model-based approach for developing adaptive policies under uncertainty. The proposed approach, which we call Adaptive Robust Design, has been illustrated through a case about the structural and systemic transformation of energy generation systems toward a more sustainable future. Our analysis shows that ARD can be used to develop long-term, adaptive and robust policies for grand societal transformations. Furthermore, this study has shown that Exploratory Modeling and Analysis can be utilized successfully in the context of adaptive policy-making. The iterative approach for designing robust adaptive policies helps to identify and address both vulnerabilities and opportunities, resulting in a dynamic adaptive policy that improves the extent to which the energy system transits to a more sustainable functioning.

There is a growing awareness about the need for handling uncertainty explicitly in decision-making. The recent financial and economic woes have rekindled a wider interest in approaches for handling uncertainty. However, there is also a certain degree of skepticism about the extent to which models can be used for decision-making under uncertainty. In addition, all the extant forecasting methods contain fundamental weaknesses and struggle deeply in grappling with the long-term's multiplicity of plausible futures. The presented case illustrates how models can be used to support decision-making, despite the presence of a wide variety of quite distinct uncertainties and a multiplicity of plausible futures. A central idea in this approach is to use the available models differently, instead of using them in a predictive manner and ignoring many uncertainties. The models were used here to explicitly explore a plethora of uncertainties in order to assess the implications of these uncertainties for decision-making. The presented approach can easily be expanded or modified. For example, we used PRIM for the identification of both opportunities and vulnerabilities. Other rule induction methods, such as decision tree induction, Classification and Regression Trees (CART) [60], could be equally well applied to this task.

Acknowledgments

This study is part of the project “Dealing with Uncertainties in Infrastructure Planning and Design: Exploratory Modeling, Real Options analysis and Policy Design” which is supported by the Next Generation Infrastructures (NGI) Foundation.

References

[1] J.H. Kwakkel, W.E. Walker, V.A.W.J. Marchau, Adaptive airport strategic planning, Eur. J. Transp. Infrastruct. Res. 10 (2010) 249–273.
[2] E. Pruyt, C. Hamarat, The Influenza A (H1N1)v pandemic: an exploratory system dynamics approach, in: The 28th International Conference of the System Dynamics Society, System Dynamics Society, Seoul, South Korea, 2010.

[3] E. Pruyt, J.H. Kwakkel, G. Yucel, C. Hamarat, Energy transitions towards sustainability: a staged exploration of complexity and deep uncertainty, in: The 29th International Conference of the System Dynamics Society, Washington DC, USA, 2011.
[4] W. Walker, P. Harremoës, J. Rotmans, J. Van der Sluijs, M. Van Asselt, P. Janssen, M. Von Krauss, Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support, Integr. Assess. 4 (2003) 5–17.
[5] G. Yucel, Analyzing transition dynamics: the actor-options framework for modelling socio-technical systems, in: Policy Analysis, Delft University of Technology, Delft, 2010.
[6] P. Eykhoff, System Identification: Parameter and State Estimation, Wiley Interscience, London, 1974.
[7] W.E. Walker, V.A.W.J. Marchau, D. Swanson, Addressing deep uncertainty using adaptive policies: introduction to section 2, Technol. Forecast. Soc. Change 77 (2010) 917–923.
[8] R.J. Lempert, S. Popper, S. Bankes, Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis, RAND, Santa Monica, California, 2003.
[9] K. van der Heijden, Scenarios: The Art of Strategic Conversation, Wiley, 1996.
[10] H.A. Lindstone, M. Turoff, The Delphi Method: Techniques and Applications, Adison-Wesley, 1975.
[11] O. Saritas, J.E. Smith, The Big Picture — trends, drivers, wild cards, discontinuities and weak signals, Futures 43 (2011) 292–312.
[12] P. Goodwin, G. Wright, The limits of forecasting methods in anticipating rare events, Technol. Forecast. Soc. Change 77 (2010) 355–368.
[13] S. Popper, J. Griffin, C. Berrebi, T. Light, E.Y. Min, Natural gas and Israel's energy future: a strategic analysis under conditions of deep uncertainty, in: Technical Reports, RAND, Santa Monica, California, 2009.
[14] D.H. Meadows, J. Richardson, G. Bruckmann, Groping in the dark: the first decade of global modelling, John Wiley & Sons, Chichester, 1982.
[15] E.A. Eriksson, K.M. Weber, Adaptive foresight: navigating the complex landscape of policy strategies, Technol. Forecast. Soc. Change 75 (2008) 462–482.
[16] J.H. Kwakkel, W.E. Walker, V.A.W.J. Marchau, Classifying and communicating uncertainties in model-based policy analysis, Int. J. Technol. Policy Manag. 10 (2010) 299–315.
[17] A.L. Porter, W.B. Ashton, G. Clar, J.F. Coates, K. Cuhls, S.W. Cunningham, K. Ducatel, P.v.d. Duin, L. Georgehiou, T. Gordon, H. Linstone, V. Marchau, G. Massari, I. Miles, M. Mogee, A. Salo, F. Scapolo, R. Smits, W. Thissen, Technology futures analysis: toward integration of the field and new methods, Technol. Forecast. Soc. Change 71 (2004) 287–303.
[18] A. Volkery, T. Ribeiro, Scenario planning in public policy: understanding use, impacts and the role of institutional context factors, Technol. Forecast. Soc. Change 76 (2009) 1198–1207.
[19] C. Cagnin, M. Keenan, Positioning future-oriented technology analysis, in: C. Cagnin, M. Keenan, R. Johnston, F. Scapolo, R. Barré (Eds.), Future-Oriented Technology Analysis: Strategic Intelligence for an Innovative Economy, Springer, Berlin, 2008, pp. 1–13.
[20] L. Albrechts, Strategic (spatial) planning reexamined, Environ. Plann. B: Plann. Des. 31 (2004) 743–758.
[21] R.d. Neufville, A. Odoni, Airport Systems: Planning, Design, and Management, McGraw-Hill, New York, 2003.
[22] E.S. Schwartz, L. Trigeorgis, Real Options and Investment under Uncertainty: Classical Readings and Recent Contributions, The MIT Press, 2004.
[23] D. Swanson, S. Barg, S. Tyler, H. Venema, S. Tomar, S. Bhadwal, S. Nair, D. Roy, J. Drexhage, Seven tools for creating adaptive policies, Technol. Forecast. Soc. Change 77 (2010) 924–939.
[24] W.E. Walker, S.A. Rahman, J. Cave, Adaptive policies, policy analysis, and policy-making, Eur. J. Oper. Res. 128 (2001) 282–289.
[25] J. Dewey, The Public and its Problems, Holt and Company, New York, 1927.
[26] G.J. Busenberg, Learning in organizations and public policy, J. Public Policy 21 (2001) 173–189.
[27] J. De La Mothe, Innovation Strategies in Interdependent States, Edward Elgar Publishing Ltd., Gloucestershire, 2006.
[28] A. Faber, K. Frenken, Models in evolutionary economics and environmental policy: towards an evolutionary environmental economics, Technol. Forecast. Soc. Change 76 (2009) 462–470.
[29] L.K. Mytelka, K. Smith, Policy learning and innovation theory: an interactive and co-evolving process, Res. Policy 31 (2002) 1467–1479.
[30] C.S. Holling, Adaptive Environmental Assessment and Management, John Wiley & Sons, New York, 1978.
[31] R.J. McLain, R.G. Lee, Adaptive management: promises and pitfalls, Environ. Manage. 20 (1996) 437–448.
[32] K. Lee, Compass and Gyroscope: Integrating Science and Politics for the Environment, Island Press, Washington, 1993.
[33] D. Collingridge, The Social Control of Technology, Frances Pinter Publisher, London, UK, 1980.
[34] J.P. Brans, C. Macharis, P.L. Kunsch, A. Chevalier, M. Schwaniger, Combining multicriteria decision aid and system dynamics for the control of socio-economic processes. An iterative real-time procedure, Eur. J. Oper. Res. 109 (1998) 428–441.
[35] J.W.G.M. van der Pas, J.H. Kwakkel, B. Van Wee, Evaluating Adaptive Policymaking using expert opinions, Technol. Forecast. Soc. Change 79 (2012) 311–325.
[36] D.B. Agusdinata, Exploratory modeling and analysis: a promising method to deal with deep uncertainty, in: Technology, Policy and Management, Delft University of Technology, Delft, 2008, p. 285.
[37] E. Pruyt, J. Kwakkel, A bright future for system dynamics: from art to computational science and more, in: The 30th International Conference of the System Dynamics Society, St Gallen, Switzerland, 2012.
[38] S. Bankes, Exploratory modeling for policy analysis, Oper. Res. 41 (1993) 435–449.
[39] J.H. Friedman, N.I. Fisher, Bump Hunting in high-dimensional data, Stat. Comput. 9 (1999) 123–143.
[40] D.G. Groves, R.J. Lempert, A new analytic method for finding policy-relevant scenarios, Glob. Environ. Chang. 17 (2007) 73–85.
[41] R.J. Lempert, D.G. Groves, S.W. Popper, S.C. Bankes, A general analytic method for generating robust strategies and narrative scenarios, Manag. Sci. 52 (2006) 514–528.
[42] J.H. Kwakkel, W.L. Auping, E. Pruyt, Dynamic scenario discovery under deep uncertainty: the future of copper,Technol. Forecast. Soc. Change (in press), http://dx.doi.org/10.1016/j.techfore.2012.09.012.
[43] B.P. Bryant, R.J. Lempert, Thinking inside the box: a participatory, computer-assisted approach to scenario discovery, Technol. Forecast. Soc. Change 77 (2010) 34–49.
[44] R. Lempert, M. Collins, Managing the risk of uncertain threshold response: comparison of robust, optimum, and precautionary approaches, Risk Anal. 24 (2007) 1009–1026.
[45] E. Störmer, B. Truffer, D. Dominguez, W. Gujer, A. Herlyn, H. Hiessl, H. Kastenholz, A. Klinke, J. Markard, M. Maurer, A. Ruef, The exploratory analysis of trade-offs in strategic planning: lessons from regional infrastructure foresight, Technol. Forecast. Soc. Change 76 (2009) 1150–1162.
[46] P. Martens, J. Rotmans, Transitions in a globalising world, Futures 37 (2005) 1133–1144.
[47] D. Loorbach, N. Frantzeskaki, W. Thissen, Introduction to the special section: infrastructures and transitions, Technol. Forecast. Soc. Change 77 (2010) 1195–1202.
[48] W.J. Abernathy, K.B. Clark, Innovation: mapping the winds of creative destruction, Res. Policy 14 (1985) 3–22.
[49] A. Rip, Introduction of new technology; making use of recent insights from sociology and economics of technology, Technol. Anal. Strateg. Manag. 7 (1995) 417–431.
[50] J.W. Forrester, Industrial Dynamics, MIT Press, Cambridge, 1961.
[51] J.D. Sterman, Business Dynamics: Systems Thinking and Modeling for a Complex World, McGraw-Hill, 2000.
[52] G. Van Rossum, Python Reference Manual, CWI, Amsterdam, 1995.
[53] Ventana Systems Inc., Vensim Reference Manual, Ventana System Inc., 2011.
[54] Ventana Systems Inc., Vensim DSS Reference Supplement, Ventana Systems Inc., 2010.
[55] M.D. McKay, R.J. Beckman, W.J. Conover, A comparison of three methods for selecting values of input variables in the analysis of output from a computer code, Technometrics 21 (1979) 239–245.
[56] Eric Jones, Travis Oliphant, P. Peterson, et al., Scipy: Open Source Scientific Tools for Python, 2011.
[57] A. Ben-Tal, A. Nemirovski, Robust convex optimization, Math. Oper. Res. (1998) 769–805.
[58] A. Ben-Tal, A. Nemirovski, Robust solutions of linear programming problems contaminated with uncertain data, Math. Program. 88 (2000) 411–424.
[59] D. Bertsimas, M. Sim, The price of robustness, Oper. Res. 52 (2004) 35–53.
[60] L. Breiman, J.H. Friedman, R.A. Olshen, C.J. Stone, Classification and Regression Trees, Wadsworth, Monterey, CA, 1984.

Caner Hamarat is a PhD researcher at the Faculty of Technology, Policy and Management of Delft University of Technology. He obtained an MSc degree in Industrial Engineering from Sabanci University. His research interests are exploration and analysis of dynamically complex systems under deep uncertainty. In his PhD research, he focuses on long term decision-making under deep uncertainty using the Exploratory Modeling and Analysis method. His applied interests include climate change/energy issues, public health and health policies, financial crisis and energy systems. His current research interests are adaptive policy making and the use of optimization in policy-making.

Jan Kwakkel received a Ph.D. from Delft University of Technology. His research focused on the treatment of uncertainty in long-term airport planning. He currently works as a postdoc on the treatment of uncertainties in model-based decision support for fresh water supply in the Netherlands at Delft University of Technology. Next to this research, he also has an interest in scientometrics and tech-mining.

Erik Pruyt is the Assistant Professor of System Dynamics and Policy Analysis at the Faculty of Technology, Policy and Management of Delft University of Technology. He obtained a master's degree in Commercial Engineering and a PhD degree from the Faculty of Economics, Social and Political Sciences & Solvay Business School of the Free University of Brussels. His research focuses mainly on the multi-dimensional dynamics of complex systems, from short-term crises to long-term transitions. Applied interests include economic-financial crises, climate change and energy system transitions, and inter/national safety and security.