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Optimal Adaptive Policymaking under Deep Uncertainty? Yes we can!

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Abstract. *Uncertainty manifests itself in almost every aspect of decision making. Adaptive and flexible policy design becomes crucial under uncertainty. An adaptive policy is designed to be flexible and can be adapted over time to changing circumstances and unforeseeable surprises. A crucial part of an adaptive policy is the monitoring system and associated pre-specified actions to be taken in response to how the future unfolds. However, the adaptive policymaking literature remains silent on how to design this monitoring system and how to specify appropriate values that will trigger the pre-specified responses. These trigger values have to be chosen such that the resulting adaptive plan is robust and flexible to surprises in the future. Actions should be neither triggered too early nor too late. One possible family of techniques for specifying triggers is optimization. Trigger values would then be the values that maximize the extent of goal achievement across a large ensemble of scenarios. This ensemble of scenarios is generated using Exploratory Modeling and Analysis. In this paper, we show how optimization can be useful for the specification of trigger values. A Genetic Algorithm is used because of its flexibility and efficiency in complex and irregular solution spaces. The proposed approach is illustrated for the transitions of the energy system towards a more sustainable functioning which requires effective dynamic adaptive policy design. The main aim of this paper is to show the contribution of optimization for adaptive policy design.*

Keywords. *Adaptive policymaking, Exploratory Modeling and Analysis, optimization.*

1 Introduction

Adaptive policymaking is an approach for developing policies that can be adapted over time to surprises caused by uncertainty. Adaptivity and flexibility are of great importance under deep uncertainty and should be taken into consideration in policy design (Neufville & Scholtes, 2011). This can be achieved through for example real options (Neufville, 2003) or contingency planning (Kwakkel et al., 2010). In either case, the specification of the conditions under which the option or contingency action is to be used is of crucial importance to achieve dynamic adaptive robustness.

Robust optimization is a methodology that is commonly used for optimizing under uncertainty. Uncertainty is prevalent in almost all steps of policymaking, so also for trigger values. In this paper, we argue that robust optimization can be employed for optimizing these trigger values in order to achieve a robust adaptive policy. In a recent study, we have proposed an iterative approach for adaptive policy design under uncertainty (Hamarat et al., Forthcoming). In this paper, this iterative policy design approach is combined with robust optimization for optimizing the trigger values. So, we show how optimization can be effectively used in adaptive policymaking.

The proposed approach is illustrated through a case which focuses on the transition of an energy generation system toward more sustainable functioning. In today's mostly fossil-based energy system, there is a need for effective policies for steering the transition toward sustainable and cleaner energy technologies. The case is used to illustrate how our proposed approach can be used in guiding and shaping structural and systemic societal transformations.

The organization of the rest of the paper is as follows: Section 2 introduces adaptive policymaking under uncertainty and optimization. In Section 3, Exploratory Modeling and Analysis, Computer Aided Dynamic Adaptive Policy Design and Optimization by means of Genetic Algorithms are explained. The case and the results can be found in Section 4. Discussion of the results and conclusions are provided in Section 5.

2 Problem Description

2.1 Adaptive Policymaking under Uncertainty

Uncertainty manifests itself in almost every aspect of policymaking. Unforeseen events due to uncertainty can affect the performance of a policy dramatically. For instance, designing a static policy based on a best estimate future will most likely perform poorly in an uncertain and complex future (Walker et al., 2010). For an uncertain and complex future, adaptivity and flexibility should be the main aim for designing robust policies (Lempert et al., 2003; Neufville & Odoni, 2003; Neufville & Scholtes, 2011; Schwartz & Trigeorgis, 2004; Swanson et al., 2010; Walker et al., 2001).

Various approaches for designing adaptive policies have been put forward. The initial ideas for this paradigm were founded almost a century ago. Dewey (1927) 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 (Busenberg, 2001). Early applications of adaptive policies can be found in the field of environmental management (Holling, 1978; McLain & Lee, 1996). Policies are designed from the outset to test clearly formulated hypotheses about the behavior of an ecosystem being changed by human use (Lee, 1993). A similar attitude is also advocated by Collingridge (1980) 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, Walker et al. (2001) developed a structured, stepwise approach for dynamic adaptation. This approach advocates that plans should be adaptive: one should take only those actions that are non-regret and time-urgent and postpone other actions to a later stage.

A central idea in these approaches is the combination of time urgent actions to be taken immediately with pre-specified action taken in response to how the future unfolds. The correct specification of when to respond with these pre-specified actions is essential for a robust and adaptive policy design. To this purpose, signposts to track specific information can be defined for monitoring the system. Specific values of these signposts are called triggers and they are triggered when pre-specified conditions occur in the system (Kwakkel, et al., 2010). However, the literature remains silent on the monitoring system and the specification of trigger values. A common approach is to consult for expert opinions or to estimate values based on historical trends. These approaches are open to surprises caused by uncertainty and can lead to poor policy performances. For this reason, it is crucial to use more intelligent and robust methods for specifying trigger values. The use of optimization can be a possible solution approach for such a problem.

2.2 Robust Optimization

Optimization is widely used in every aspect of policymaking and in various fields ranging from engineering to science and from business to daily life. Optimization is mostly referred as finding the optimum solution among a set of plausible alternatives under certain constraints. It is the common practice to use optimization for predictive purposes, aiming for a *single best* solution. However, this predictive approach might be misleading under uncertainty for policymaking, where often an optimum single goal is not the main aim (Bankes, 2011). A field in optimization to overcome the difficulty of uncertainty is robust optimization. Robust optimization methods aim at finding optimal outcomes in the presence of uncertainty about input parameters (Ben-Tal & Nemirovski, 1998, 2000; Bertsimas & Sim, 2004). To this purpose, robust optimization methods can be of great use for adaptive policymaking.

There is an enormous variety of different techniques and methods in the optimization literature. Among various optimization techniques, Genetic Algorithm (GA) is a commonly used heuristic method. GA is flexible and efficient in complex and irregular solution spaces. It mimics the evolution process and tries to find the fittest survivor. In GA, a candidate solution is represented as a chromosome where each allele of the chromosome is a decision variable. Each trigger value can be considered as a decision variable that these trigger values form a candidate policy. So, Genetic Algorithm can be used for the specification of trigger values in adaptive policymaking.

3 Methodology

3.1 Exploratory Modeling and Analysis

Exploratory Modeling and Analysis (EMA) is a research methodology that uses computational experiments to analyze complex and uncertain systems and support long-term strategic decision making under deep uncertainty (Agusdinata, 2008; Bankes, 1993). EMA can be contrasted with the use of models to predict system behavior, where models are built by consolidating known facts into a single package (Hodges & Dewar, 1992). In predictive modeling, a single best estimate model is used as a surrogate for the actual system. Where applicable, this consolidative methodology is a powerful technique for understanding the behavior of complex systems. Unfortunately, for many systems of interest, the construction of a model that may be validly used as surrogate is simply not a possibility (Cambell et al., 1985; Hodges & Dewar, 1992). For many systems, a methodology based on consolidating all known information into a single model and using it to make best estimate predictions can be highly misleading. However, models can be constructed that are consistent with the available information, but such models are not unique. Rather than specifying a single model and falsely treating it as a reliable image of the system of interest, the available information is consistent with a set of models, whose implications for potential decisions may be quite diverse. A single model run drawn from this potentially infinite set of plausible models is not a "prediction"; rather, it provides a computational experiment that reveals how the world would behave if the various guesses made in any particular model about the various unresolvable uncertainties were correct. By conducting many such experiments, EMA provides insights and understanding about the system functions and effectiveness/robustness of policies despite the presence of deep uncertainty. EMA is not a modeling technique by itself, but it is a methodology for building and using models under deep uncertainty.

3.2 Computer Aided Dynamic Adaptive Policy Design

EMA could be used to develop dynamic adaptive policies. EMA allows for the explicit representation and exploration of a multiplicity of plausible futures under deep uncertainty. Thus, EMA can be used to identify the vulnerabilities and opportunities that this ensemble of futures holds, paving the way for designing targeted policies that address vulnerabilities or seize opportunities. The efficacy of these policy designs can then be tested against the ensemble of futures. Moreover, EMA can be used to identify conditions under which changes in a policy are required. That is, it can help in developing the monitoring system and its associated actions. It thus appears that EMA can be of use in all the steps of the design phase of a dynamic adaptive policy.

Here, an iterative approach we call Computer Aided Dynamic Adaptive Policy Design (CADAPD) has been proposed (Hamarat, et al., Forthcoming):

1. conceptualization of the problem,
2. identification of the uncertainties,
3. development of an ensemble of models for exploring the uncertainties,
4. running the computer model(s) without introducing any policies in order to generate the ensemble of futures,
5. analysis of the results obtained from Step 4 in order to identify the vulnerabilities and opportunities,
6. design of candidate policies for addressing vulnerabilities and seizing opportunities,
7. testing of candidate policies across the ensemble of futures,
8. iteration through Steps 5-7 until a satisfying policy emerges.

3.3 Genetic Algorithm

Genetic Algorithms (GA) are optimization methods based on natural selection as can be observed in biological systems (Fraser & Burnell, 1970; Holland, 1975). This approach requires constructing an initial population composed of chromosomes, where each chromosome represents a candidate solution. Next, the fitness of each population member is assessed using a user specified objective function. In light of the fitness scores of the current population members, the next generation is created. For creating the next generation, the new members are reproduced from those selected through evolutionary processes such as crossover and mutation. Once the next generation is created, the fitness calculations are computed again for the new population members. This process of fitness evaluation and reproduction of new generation is repeated until a pre-specified termination criterion is met. Possible termination criteria include reaching a desired solution, a fixed number of iterations, and convergence of the fitness scores.

GA are commonly used for solving decision making problems due to their flexibility and efficiency in complex and irregular solution spaces (Chambers, 1999). We argue that GA can be efficiently used in CADAPD for optimizing trigger values. The chromosome structure for representing a candidate solution can be easily used for representing a set of trigger values as a candidate policy setting. In this case, each genome of a chromosome will be a trigger value and each chromosome will represent is a complete representation of the monitoring system. So, GA can be employed for optimizing the set of trigger values.

The trigger values for the various actions in a monitoring system should be robust across the ensemble of plausible futures. The criterion used for performance calculation in robust optimization is quite important. There are different criteria such as minimizing the maximum regret (minimax), maximizing the minimum gain (maximin) or maximizing the maximum gain (maximax) (Winston & Goldberg, 2004). GA is often used for robust optimization (Herrmann, 1999; Li et al., 2005; Maruyama & Igarashi, 2008). In this study, a cardinality criterion, which is the number of cases above a certain threshold, is utilized. We start by generating a population of trigger values. Each population member is a set of trigger values for the actions in the monitoring system. The performance of each population member is evaluated according to the cardinality criterion over a fixed number of plausible futures.

4 The Case

4.1 Energy Transitions

We use an energy transitions case to demonstrate the outlined approach. Transition studies aim at analyzing the underlying mechanisms that drive transitions, and developing methods for steering the transition toward the desired goals (Loorbach et al., 2010). Energy systems are a crucial domain in which a fundamental transition toward cleaner energy production is necessary (Loorbach, et al., 2010). The current energy system is mainly based on fossil energy generation. Although new sustainable energy technologies are entering the market, their contribution to the total amount of energy generation is still relatively small.

System Dynamics (SD) is a modeling method for understanding the behaviors of nonlinear, dynamically complex systems, and for policy analysis and design (Forrester, 1961; Sterman, 2000). In order to explore the problem and the uncertainties, a System Dynamics model developed for exploring the dynamics of energy systems transitions illustrated in (Pruyt et al., 2011) 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 is the old dominant technology that is non-renewable and mainly fossil fuel based. The other three technologies are new –more or less- sustainable technologies. 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, cost of commissioning capacity of a technology and the effect of learning curves on costs. A more detailed explanation about the model can be found in (Pruyt, et al., 2011). The uncertainties considered in the model include both parametric uncertainties (e.g. initial values) and model structure uncertainties (e.g. different mixes of decision criteria). A detailed description of the uncertainties taken into consideration and their corresponding ranges can be found in (Hamarat, et al., Forthcoming).

4.2 Policy Descriptions

Starting without introducing a policy, the analysis based on a previous study (Hamarat, et al., Forthcoming) show that the transition towards sustainability is hampered by a long lifetime of the dominant technology 1 (Hamarat, et al., Forthcoming). 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 ensemble of plausible futures. 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 vulnerabilities, two adaptive actions that are only triggered if needed and associated trigger values are specified: (1) a subsidy for the costs of new technologies, and (2) stopping the commissioning of technology 2 and replacing it with additional commissioning for Technology 3 and 4. In Action 1, the costs of Technologies 2, 3 and 4 are monitored and if they are close enough to the cost of Technology 1, a subsidy for their costs are introduced over a period of 10 years. The trigger value for this action is the proximity of the cost of the new technologies to the cost of technology 1. There are three trigger values for this action because each of the new technologies is monitored separately. Action 2 monitors the performances of Technologies 2, 3 and 4 based on the learning curves, CO_2 emission levels and the expected costs. Monitoring these indicators, if the overall performance of Technologies 3 or 4 is close enough to the performance of Technology 2, then the commissioning of Technology 2 is diverted towards

Technology 3 and 4. For this action, only one trigger value is used and its value is the proximity factor of the performances. This set of four trigger values is used as input for the optimization to achieve an adaptive policy with optimized trigger value parameters for two adaptive actions.

To optimize the adaptive policy, we use Pyevolve (Perone, 2009) for implementing GA. Our decision variables for GA are the four trigger values to form a candidate policy setting. The GA is ran for 100 generations and with a population size of 50 for each generation. Each candidate is tested over 1000 experiments that are generated using Latin Hypercube Sampling (LHS) by exploring over the uncertainties. These 1000 experiments span the uncertainty space so each candidate is tested across an ensemble of plausible futures. The number of experiments where the end states for the total fraction of new technologies are above 0.60 determines the fitness score of the candidate. This robust optimization approach of testing over a large number of experiments and calculating the fitness based on a cardinality criterion makes our adaptive policy robust and flexible for a variety of cases. Other GA parameters used are as follows: crossover rate of 0.75 and mutation rate of 0.05. The final fitness of the best candidate found by GA is 0.84. This means that about 840 of the 1000 cases are above the sustainable fraction level of 0.60. The optimized trigger values obtained from GA are used as new parameters for the adaptive policy and this modified policy is called as the optimized adaptive policy.

In this study, there are four policy options to be analyzed: no policy, the basic policy, the adaptive policy with user specified trigger values, and the optimized adaptive policy. As the outcome of interest, we used the fraction of the new sustainable technologies over the total energy generation. By exploring the uncertainties specified, 10000 experiments were generated using LHS, and the performance of each policy option was assessed over these experiments. Fig. 1 shows the results for four policy options. The left side of the figure illustrates the envelopes of upper and lower limits over a time horizon of 100 years for each design. The right side of the figure shows a Gaussian kernel density estimate of the end states.

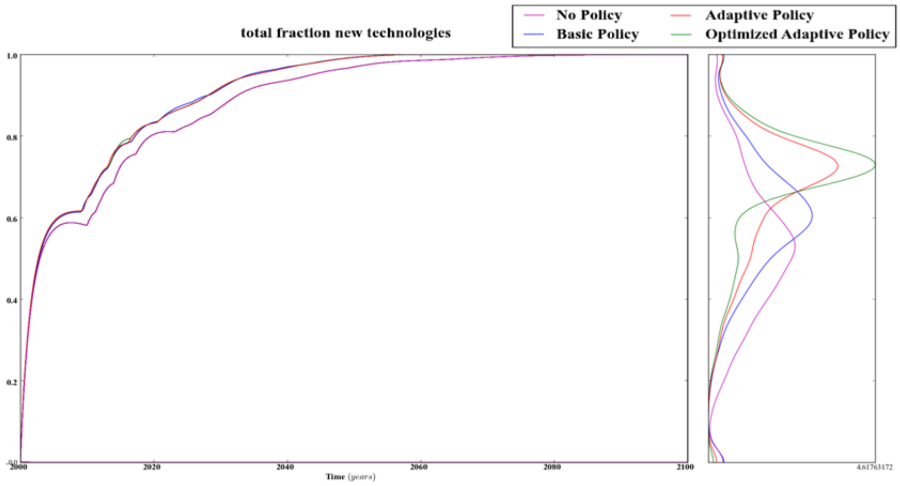

Fig. 1. Comparison of No Policy, Basic, Adaptive and Optimized Adaptive Policy

When there is no policy (purple line), the runs are concentrated around a fraction of 0.5. Introducing the basic policy improves the performance substantially to a level of 0.6 but this level is still not good enough. The adaptive policy with the monitoring system and user specified triggers has a considerable effect on the fraction of new technologies, which is around a fraction of 0.8. A further improvement can be reached when the trigger values are optimized. The optimized policy also seems to reach a fraction level around 0.8. However, focusing on the difference between the red (adaptive) and the green (optimized) lines, there is a clear shift upwards by the introduction of optimized policy. A number of the adaptive policy cases that are below a level around 0.6 are pushed to a level around 0.8 by the introduction of optimized adaptive policy. In other words, there is an improvement of performance in the level of individual scenarios, and thus over the ensemble of scenarios.

In order to understand the optimized adaptive policy better, Fig. 3 shows a boxplot of the trigger values showing when and how often they are triggered. Action 2, replacement of Technology 2 with Technology 3 or 4 according to the performance, is instantly activated for almost all of the cases. This means that this action should be included in the basic policy and Technology 2 should not be invested in. In other words; with learning effects, competition between (renewable) technologies and under deep uncertainty, investments should be concentrated and spread at the same time. On the other hand, subsidy triggers of Action 1are activated after around 10-15 years and even for some of the cases, they are triggered at a much later stage. So, it is more appropriate to keep this action as a part of the contingency plan.

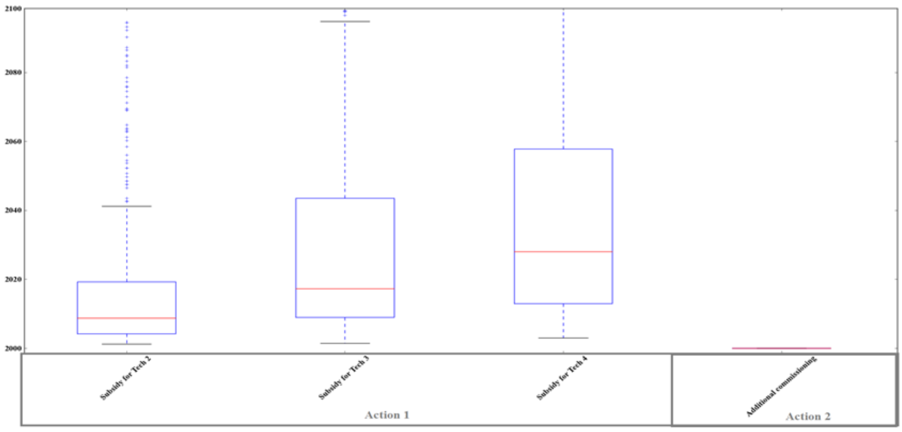

Fig. 2. Boxplot for the activation times of adaptive actions

5 Concluding Remarks

This study presents how optimization can be effectively used in adaptive policymaking. The approach is illustrated on a case about the transition towards a more sustainable energy system. (Hamarat, et al., Forthcoming) proposed an iterative adaptive policy design approach in a recent study to develop adaptive policies under deep uncertainty. In this paper, this iterative approach is combined with optimization to improve the performance of adaptive policymaking by optimizing the trigger value specification. With the optimized trigger values, the monitoring system will be improved so that the adaptive actions can be taken on time and if needed.

In the previous study (Hamarat, et al., Forthcoming), the analysis resulted in an adaptive policy that is a combination of a basic policy and a contingency plan with two adaptive actions to be taken according to user-specified trigger values. Using robust optimization, new optimized values are specified for these trigger values. This optimized policy shows that shifting one of the adaptive actions of the previous study from the contingency plan to the basic plan results in an improvement of individual scenarios and hence, the ensemble performance.

Robust optimization is an optimization methodology for optimizing robustness under uncertainty. A crucial concept in robust optimization is the choice of robustness calculation. In this study, we also employ a robust optimization method for calculating the fitness of a candidate solution according to a cardinality criterion. However, there are other criteria such as minimax, maximax or maximin. Maximin is a common approach used in robust optimization where we look for the worst cases for each candidate solution and try to maximize the worst cases. Since the choice of optimization criterion can have a great importance on the solution, other possible criteria should also be considered and tested.

Another issue for future research is the number of cases to be used for robustness calculation. In order to find the most robust policy setting, each candidate policy design is tested against a certain number of cases. The average value of the end states for the sustainable fraction over these cases is used to compute the fitness of a candidate solution. A small number of cases will not be determining whereas a higher number is computationally exhaustive. For this reason, the number of cases to be tested should be selected properly to increase the performance of the optimization.

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