A Multi-Pathfinder for Developing Adaptive Robust Policies in System Dynamics

Caner Hamarat[*], *Erik Pruyt, Erwin T. Loonen*

Abstract

Adaptivity is essential for dynamically complex and uncertain systems. Adaptive policymaking is an approach to design policies that can be adapted over time to how the future unfolds. It is crucial for adaptive policymaking to specify under what conditions and how to adapt the policy. The performance of adaptive policy is critically depended on the proper timing of the actions. This paper illustrates that robust optimization can be used as decision support aid for appropriate specification of conditions to ensure adaptivity of policy under uncertainty. Furthermore, multiplicity of divergent objectives of different stakeholders is also important for policy support in dynamic systems. To address this issue, multi-objective optimization algorithms are good candidates for a proper solution. In this paper, we outline how to use multi-objective robust optimization in System Dynamics to support adaptive policy design. The outlined approach results, rather than a single set of conditions, in multiple alternative conditions under which to adapt policy. Thus, better informed policy debate on trade-offs is possible. The approach is illustrated through a SD model about the transition toward renewable energy systems in the EU. The study aims to propose a model-based simulation approach with multi-objective robust optimization for supporting informed adaptive policymaking.

Keywords

Adaptive policymaking, deep uncertainty, robust optimization, multi-objective optimization

Introduction

Dynamic complexity and deep uncertainty are common characteristics of many complex systems. Due to increasing complexity and uncertainty of today's world, policymaking becomes challenging. Most traditional approaches for policymaking perform unsatisfactorily. The reason is that their reliance on predictions results in static policies, which are designed and fixed only according to best estimates about the future. Due to their nature, static policies are ineffective and inappropriate for dealing with complexity and uncertainty. For this reason, there is a strong need for innovative approaches to deal with uncertainty and complexity. Under deep uncertainty, adaptivity and flexibility are extremely important and should be taken into consideration in policy design (Neufville and Scholtes, 2011). A possible planning approach is to include adaptivity and flexibility into policy design for developing long-term adaptive policies.

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The idea of adaptivity dates back to almost a century ago. Dewey (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 and 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. (Walker, Rahman, and Cave, 2001) developed a structured, stepwise approach for dynamic adaptation which is called adaptive policymaking. This approach suggests 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.

In order to design an adaptive and flexible policy, it is essential to make intelligent decisions on whether and/or when to activate necessary actions. Robust optimization (Rosenhead, Elton, and Gupta, 1972) can be of great use in order to determine whether and/or when to activate actions. For robust adaptive policy design, it is important to take the multiplicity of different objectives into account, instead of designing a policy based on a single objective (Kasprzyk *et al.*, 2013) (Haasnoot *et al.*) (McInerney, Lempert, and Keller, 2012). In this paper, we outline how adaptive policymaking can be supported through multi-objective robust optimization. We apply the outlined approach to a case study of developing an adaptive policy for steering the transition of the EU energy system towards a more sustainable functioning.

Methodology

The Adaptive Robust Design approach

There is a growing literature on the need for adaptive planning because of deep uncertainty. A wide variety of approaches and analytical tools are being put forward to support the design of adaptive plans. One example is Adaptive Policymaking (Walker *et al.*, 2001), which is a generic approach for designing dynamic robust long-term plans under deep uncertainty.

Exploratory Modeling and Analysis (Agusdinata, 2008; Bankes, 1993) is a computational approach to support the design of long-term plans under deep uncertainty. EMA 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 analyse 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, the Adaptive Robust Design approach (Hamarat, Kwakkel, and Pruyt, 2012) consolidates EMA into the adaptive policymaking for creating a more operational approach. It 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 Figure 1).

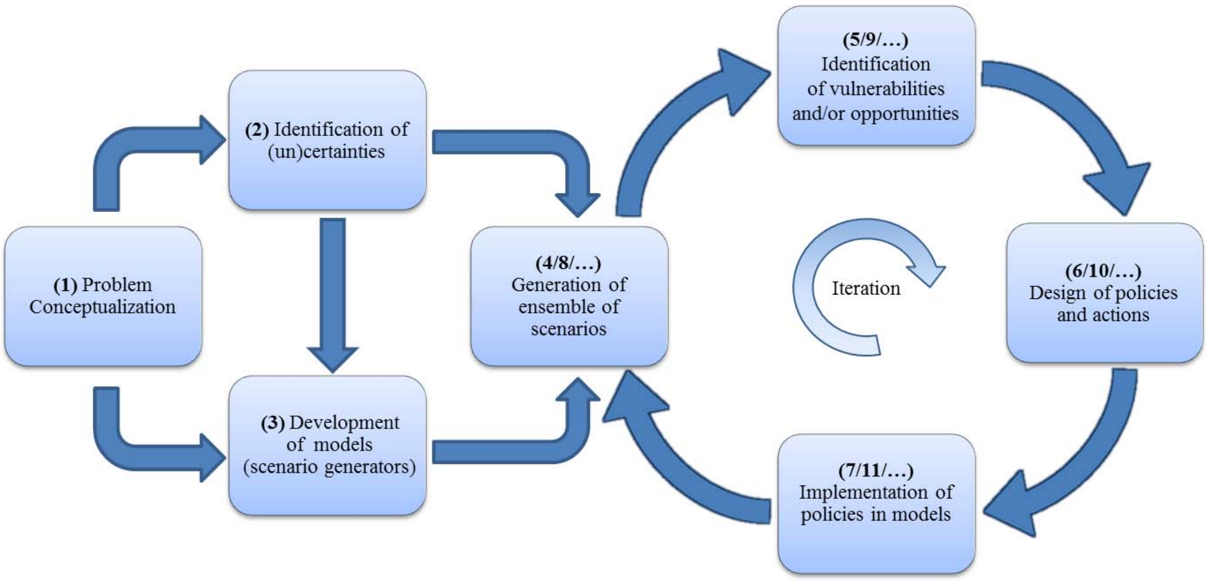

Figure 1: The Iterative Adaptive Robust Design process

Computerized Decision Support

Discovering Vulnerabilities and Opportunities

Vulnerabilities and opportunities are central concepts in adaptive policy making. In order to be able to design robust policies, it is crucial to identify problematic and/or promising regions that can be targeted more effectively. Actions that are targeted at the regions of interest are either taken now or in the future to address vulnerability or to take advantage of an opportunity.

In this study, Patient Rule Induction Method (PRIM) (Friedman and Fisher, 1999; Groves and Lempert, 2007; Kwakkel, Auping, and Pruyt, 2012; Lempert *et al.*, 2006) is used for discovering vulnerabilities and/or opportunities. PRIM 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). An extension of PRIM by using Principal Component Analysis (PCA) (Dalal *et al.*, 2013), an orthogonal transformation procedure, allows a better identification of regions of interest. In this study, the PCA PRIM is used for identifying regions of interest for designing targeted actions.

The specification of when to activate which actions

The adaptive part of adaptive policymaking takes the form of a monitoring system that specifies what information should be tracked, and under which pre-specified conditions addition, pre-specified actions will be taken. These signposts and triggers is a crucial part of the contingency planning and the efficacy of an adaptive plan hinges on the care with which this contingency planning is done. The values used for triggers are mostly based on logical guesses, expert opinions or historical data. However, they should be determined more intelligently for improving the monitoring system, which means that the performance of the policy design. The use of optimization can be a possible solution approach for such a problem.

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 and Nemirovski, 1998, 2000; Bertsimas and Sim, 2004). To this purpose, robust optimization methods can be of great use for adaptive policymaking.

For complex and uncertain systems, it is treacherous to design plans that are based on a single objective or objectives that are imprecisely merged into a single one. Multi-objective optimization helps to grasp the multiplicity of different and possibly conflicting objectives. In this study, a well-established multi-objective optimization technique NSGA-II is used, namely the Nondominated Sorting Genetic Algorithm-II (Deb *et al.*, 2002). In this study, the triggers are used as the input parameters to be optimized. The result is a Pareto front that includes possible Pareto solutions that each is specified by the trigger values.

Optimization methods can be utilized for improving policy design in system dynamics models (Coyle, 1985). A possible way of using optimization in SD is through the automated specification of parameters in the model (Yucel and Barlas, 2011). However, it is crucial to take the multiplicity of objective into account. The use of multi-objective optimization methods has not been investigated thoroughly in the system dynamics literature. There are few studies that aim to combine multi-objective optimization and system dynamics (Duggan, 2005) (Duggan, 2008b) (Duggan, 2008a) (Eksin, 2008).

EU Energy Case

Background

For 2020, the European Union (EU) has certain targets for the reduction on carbon emissions and the share of the renewable technologies in the energy system (Commission, 2007; European Commission, 2010). The main aim is to reach 20% reduction in the carbon emission levels compared to 1990 levels and to increase the share of the renewables at least to 20% by 2020. However, the energy system includes various uncertainties related to technology lifetimes, economic growth, costs, learning curves, investment preferences and so on. For instance, precise lifetimes of technologies are not known and expected values are used in planning decisions. Furthermore, it is deeply uncertain how the economic growth, which has a direct influence on the energy system, will evolve. Thus, it is of great importance to take these uncertainties into consideration when analyzing the energy system.

In order to meet the goals for 2020, an Emissions Trading Scheme (ETS) for limiting the carbon emissions in the EU was initiated (Commission, 2003). ETS imposes a cap-and-trade principle that sets a cap on the allowed greenhouse gas emissions and an option to trade allowances for emissions. However, the current emissions and the share of the renewables do not give hope for the future targets. It is necessary to take more actions for steering the transition toward a cleaner energy production. This requires a better handling of the uncertainties in the energy system and more robust policies that can promote the renewable technologies.

In this study, a System Dynamics model about the EU energy systems is used for illustrative purposes. The model represents the whole power sector in the EU and considers congestion on interconnection lines by distinguishing different regions of the EU. Nine power generation technologies are included and these are: wind, PV solar, solid biomass, coal, natural gas, nuclear energy, natural gas with Carbon Capture and Sequestration (CCS), coal gasification with CCS and large scale hydro power. The model includes the main endogenous causal relations such as technological battlefield for investment, market supply-demand dynamics, cost mechanisms and interconnection capacity dynamics. An aggregated level causal loop diagram is illustrated in Figure 2, which includes the main causal loops that drive the main dynamics of the model. Not only endogenous mechanisms but also various exogenous uncertainties do exist in the energy systems. Further details about the model can be found in (Loonen, Pruyt, and Hamarat, 2013). The uncertainties to be explored will be explained in detail in the next section.

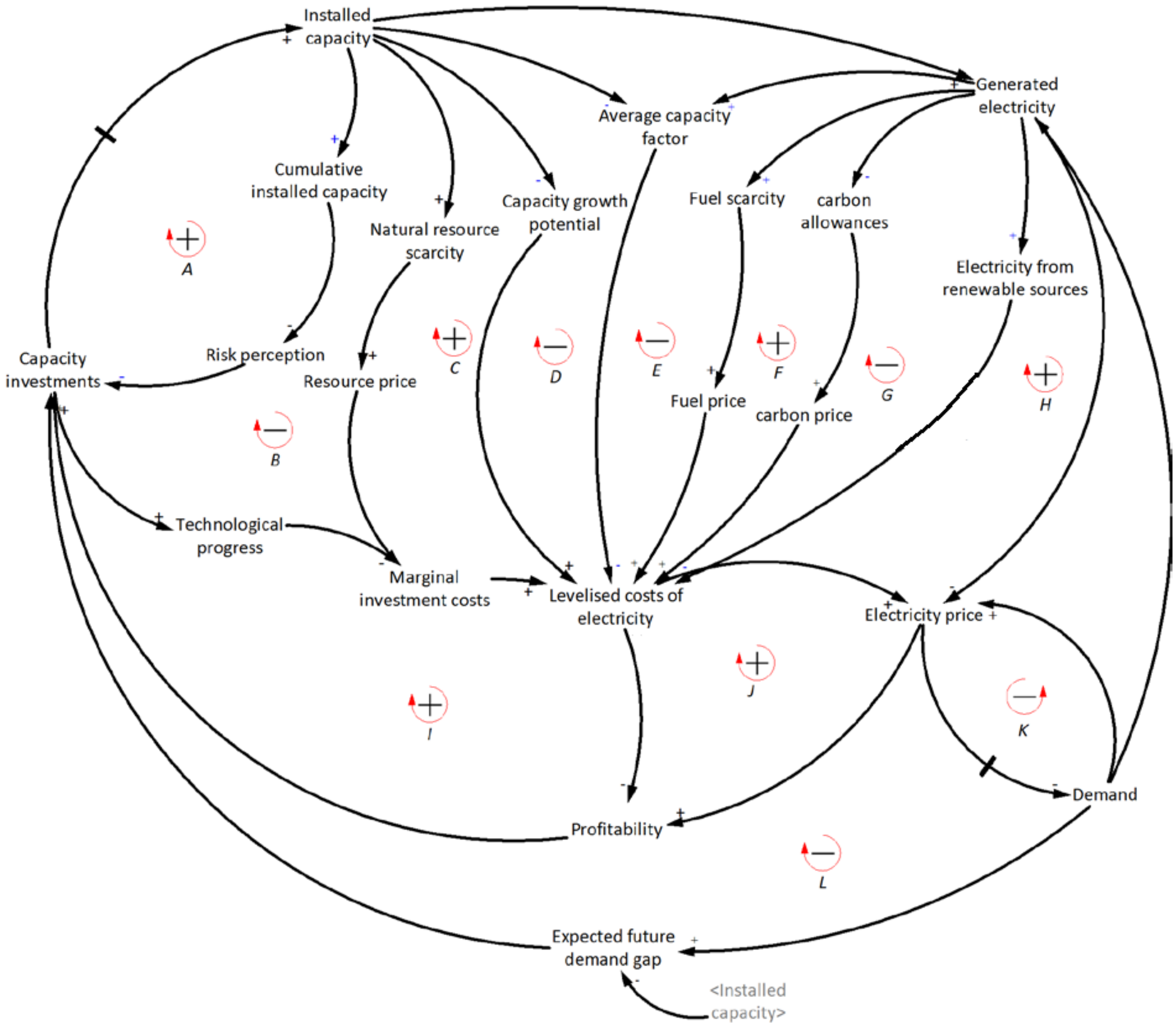

Figure 2: Aggregated Causal Loop Diagram of the main dynamics

Uncertainty Specification

In order to explore the uncertainty space, not only parametric but also structural uncertainties are included in the analysis. For exploring structural uncertainties, several possible behaviors are identified and a switch mechanism is used for switching between different behaviors. For example, 6 different plausible economic development trends are defined and there is a switch that helps us explore the different economic growth scenarios. Similarly, switches are used for electrification rate and physical limits. Remaining uncertainties have parametric characteristics and they are explored over pre-defined ranges. Table 1 provides an overview of the uncertainties that are analyzed and their descriptions. In total, there are 46 uncertainties to be explored in this study.

Table 1: Specification of the uncertainties to be explored

Name	Description
Economic lifetime	For each technology, the average lifetimes are not known precisely. Different ranges for the economic lifetimes are explored for each technology.
Learning curve	It is uncertain for different technologies how much cost will be decreased by increasing experience. Different progress ratios are explored for each technology.
Economic growth	It is deeply uncertain how the economy will develop over time. 6 possible growth behaviors are considered.
Electrification rate	The rate of the electrification of the economy is explored by including 6 different electrification trends in the uncertainty exploration.
Physical limits	The effect of the physical limits on the penetration rate of a technology is unknown. 2 different behaviors are considered in the analysis.
Preference weights	Different investor's perspectives on technology investments are deeply uncertain. Growth potential, technological familiarity, marginal investment costs and carbon abatement are possible decision criteria.
Battery storage	For wind and PV solar, the availability of the battery storage is difficult to predict. A parametric range is explored for this uncertainty.
Time of nuclear ban	A forced ban for nuclear energy in the EU is expected between 2013 and 2050. The time of nuclear ban is ranged between 2013 and 2050.
Price – demand elasticity	A parametric range is considered for price – demand elasticity factors.

Objectives

For the multi-objective optimization, it is necessary to identify the objectives to be used for the optimization. In this study, we use three objectives that are as follows: (1) the fraction of the renewable technologies over the total energy system, (2) the fraction of carbon emissions reduction in 2050 compared to 2010 levels and (3) average total costs of electricity production. The EU has specific targets for the share of renewable technologies and the reduction fraction of carbon emissions by 2020. To that purpose, the first two objectives are chosen to be included in the optimization. It is obvious that these two objectives have similar trends. So, another objective, which is thee average total costs of electricity generation, is included for the multi-objective optimization. While the first two objectives are to be maximized, this last cost related objective is to be minimized.

Analysis

From ETS toward an adaptive policy

The ETS is currently in practice around Europe for reducing the carbon emissions. It introduces an annual cap on the maximum amount of emissions and the option for trading these carbon emissions. The ETS policy does not reveal promising results so far and it needs further analysis to explore the plausible futures under this policy. Using a workbench that is written in Python (Van Rossum, 1995) which controls Vensim (Ventana Systems Inc., 2010, 2011), an ensemble of 10,000 simulations by Latin Hypercube Sampling (Pilger, Costa, and Koppe, 2005; Seaholm, Ackerman, and Wu, 1988) is generated which consists of 46 different uncertainties. The results indicate that it is almost impossible to meet the 2020 targets by only using ETS policy. For most possible futures, the fraction of renewables remains around 40% and the carbon emissions reduction fraction is around 30%. It is obvious that there is a need for further actions to take in order to achieve a sustainable energy future. By using PCA PRIM, the opportunities and vulnerabilities of the ETS policy can be used for designing targeted adaptive actions to improve the policy design. Although PCA PRIM does not reveal useful vulnerability information, there are useful findings related to opportunities to take advantage of. PCA PRIM is used to identify the opportunities that can lead to futures where the fraction of renewables is higher than 40%. These opportunities are mainly related with the technology lifetimes and the learning curves of the technologies. To be more precise; longer lifetimes of renewables, shorter lifetimes of non-renewables (especially coal and gas) and better learning curves for renewables are the opportunities that can help promote the sustainability.

In order to improve the policy design, some adaptive actions are added to the current ETS policy. The first adaptive action is related with accelerating the phasing out of the old non-renewable technologies. A desired renewable fraction level of 80% and the gap between the desired and the current level is tracked. An additional decommissioning flow which is factored by this gap is introduced for the non-renewable technologies. The second action aims to make the renewable technologies more cost-attractive by introducing a subsidy fraction on the marginal investment costs of renewable technologies. This action introduces a subsidy of 25% for a period of 10 years when the costs of renewable technologies are close to the most expensive non-renewable with proximity of 125%. The last adaptive action is about introducing an additional decommissioning. A forecast of the renewables fraction for 10 years ahead is made and if the gap between the desired fraction and this forecast is bigger than a certain trigger value of 10%, then 25% additional decommissioning is introduced.

The resulting policy with these adaptive actions is called as the adaptive policy. For testing the performance of the adaptive policy, it is also run for the same ensemble of 10,000 simulations. There is a remarkable improvement in the policy performance with the introduction of the adaptive policy design. Figure 3 shows a comparison of the ETS policy (in blue) and the adaptive policy (in green) for the carbon emissions reduction fraction, average total costs and the renewables fraction. The figures represent the envelopes which spans the upper and lower limits for 10,000 simulations over time and the density estimates of the end states of all runs in the respective ensembles. It can be observed that the adaptive policy improves the fraction of renewables dramatically from 40% on average to 70%. Similarly, there are clear improvements in terms of the carbon emissions reduction fraction and the average total costs.

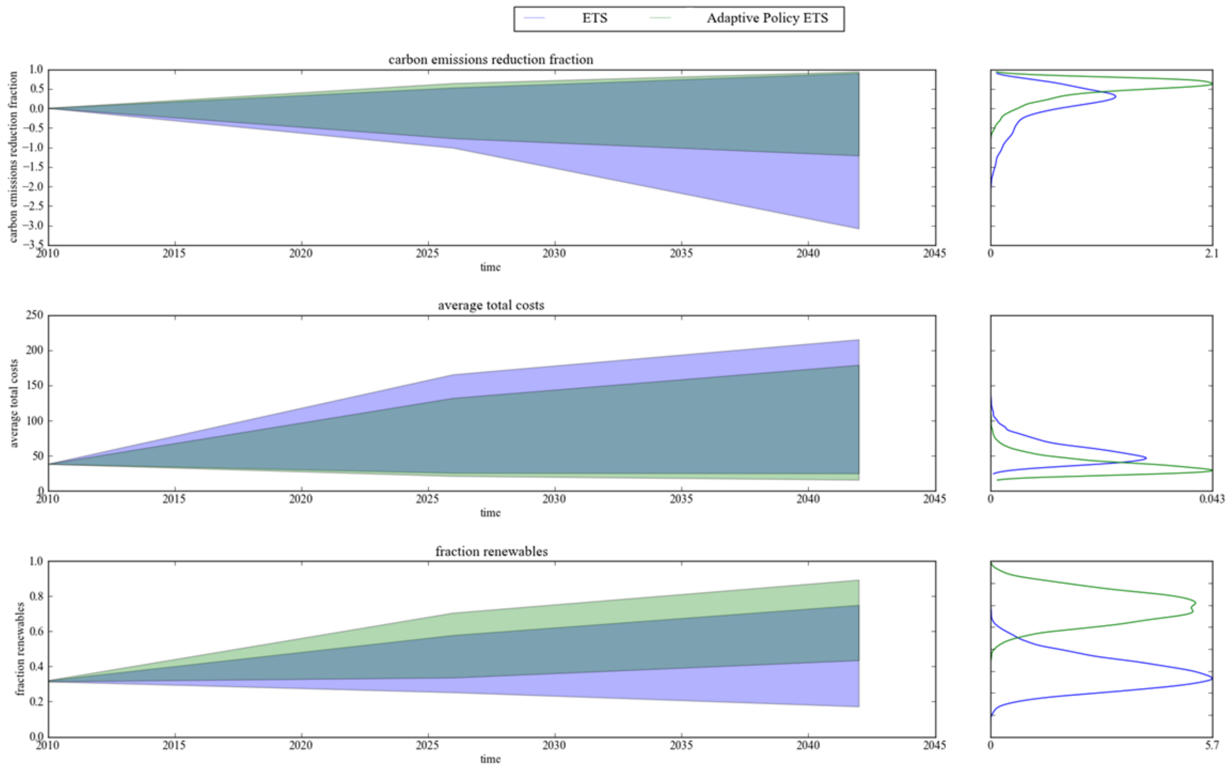

Figure 3: Comparison of ETS and Adaptive policies

Fine-tuning the trigger values

In order to design an adaptive policy, signposts and triggers are used for ensuring the adaptivity and flexibility of the policy. The specification of the triggers has a crucial importance for the performance of the adaptive policy. To specify these triggers more intelligently, optimization could be of great use. To this purpose, multi-objective robust optimization is used in this study, more specifically NSGA-II algorithm is used (Deb *et al.*, 2002). In our adaptive policy design, there are 8 different triggers to be used as the input parameters of the optimization algorithm. The triggers and their associated ranges can be found in Table 2.

Table 2: Triggers and their ranges for the optimization

Name	Range
Desired Fraction	0.5 – 1.0
Additional Decommissioning	0.0 – 0.75
Subsidy Factor	0.0 – 0.5
Subsidy Duration	0 – 40
Proximity	1 – 2
Decommissioning Factor	0.0 – 1.0
Time Ahead	10 – 40
Trigger	0.0 – 1.0

It is crucial to decide on how to characterize robustness for the multi-objective robust optimization. In this paper, we define the robustness in a manner similar to signal-to-noise ratio, which is the mean divided by the standard deviation. This robustness metric enables us to increase the mean while minimizing the perturbations. However, this can only work for maximization, not for minimization. Instead of mean divided by the deviation, the mean multiplied by the standard deviation is used for minimization purposes. In order to operationalize such robustness metric, each candidate needs to be evaluated using many simulations.

The NSGA-II algorithm is executed for a pre-defined number of 25 generations with a population size of 100. The three objectives are as follows: (1) Maximize the fraction of renewables, (2) maximize the fraction of carbon emissions reduction and (3) minimize the average total costs of electricity. For the objectives to be maximized, the robustness score is computed as the average divided by the standard deviation for 500 cases that will be used for the optimization. For the minimization objectives, the robustness score equals the average times the standard deviation.

Figure 4 shows the number of changes to the set of Pareto front solutions, including both additions and removals. For the first 10 generations, there is a considerable change in the number of Pareto solutions. After 15 generations, no change is observed which can be interpreted that the Pareto front is stabilized and converged to a solution.

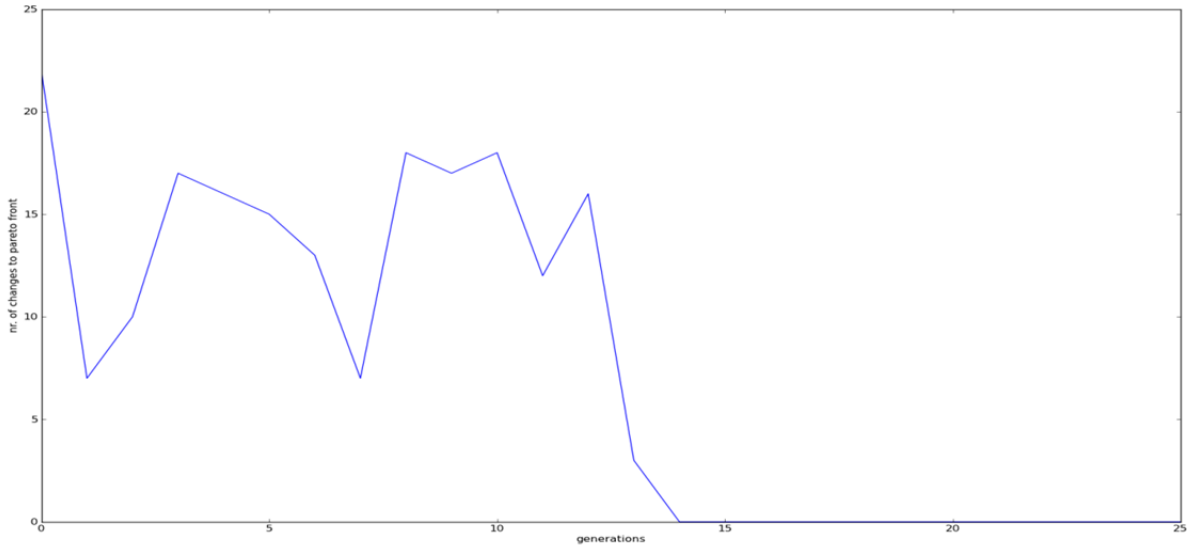

Figure 4: Changes to the Pareto front over the generations

In Figure 5, a 3D representation of the scores of the three objectives that are normalized between 0 and 1 is provided. The blue dots represent the dominated solutions and the red ones are the solutions on the Pareto front. As can be seen from the figure, the solutions converge toward a front where the renewables fraction and the carbon emissions reduction fraction have higher scores by trading off the score of the average total costs. There are 27 solutions on the Pareto front. As expected, it is easy to see the tradeoff between the renewables and emissions objectives and the cost objective (Appendix A). The figure illustrates that there is a minimum cost limit that cannot be beaten.

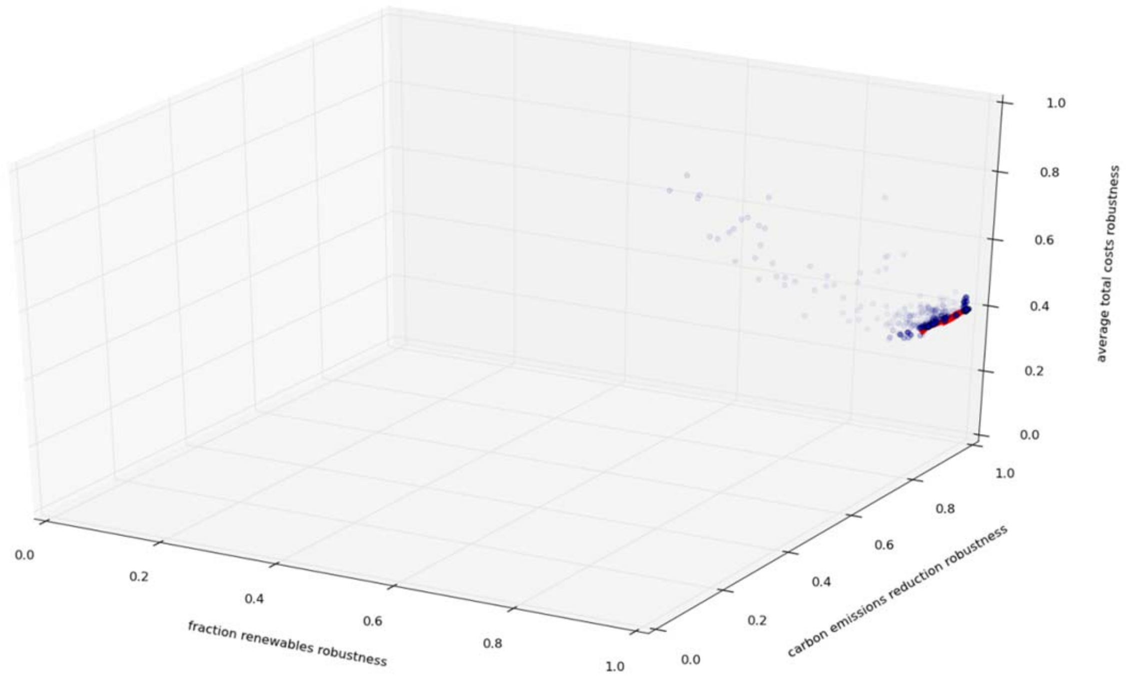

Figure 5: Non-Pareto solutions in blue and Pareto Solutions in red (normalized btw. 0-1)

In order to have a better understanding, it is useful to see the input parameters for the Pareto front. Figure 6 illustrates the parallel coordinates for the 28 Pareto solutions and their corresponding values for the eight triggers. To have better visualization, the values are scaled between 0 and 1 and their original values can be found on Table 3. The figures show that when the amount of additional decommissioning is too small, it is mostly in combination with smaller trigger values. This means that if there is less additional decommissioning of the non-renewable technologies, then there must be as little as possible deviation from the desired fraction of renewables.

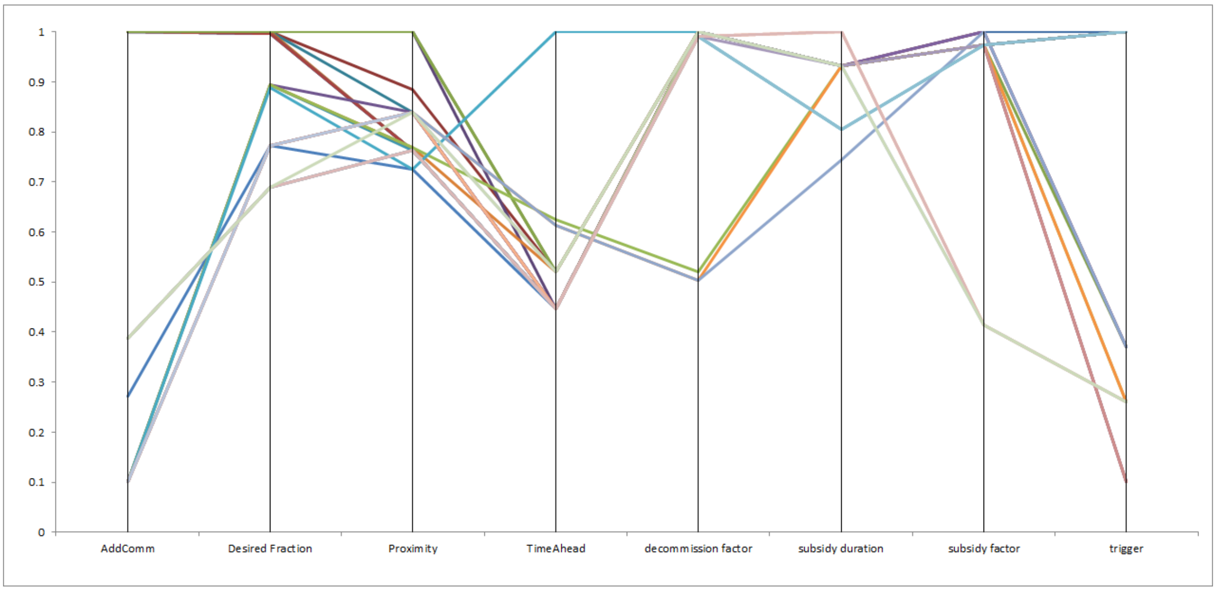

Figure 6: Parallel Coordinates for the Pareto front of the first optimization (normalized)

Discussions

This study illustrates how multiobjective robust optimization could of great use for supporting policy design in dynamic systems. In the presence of multiple, possibly, conflicting objectives, it is hard to design policies that satisfy all of the objectives and tradeoffs are inevitable. This approach helps identify multiple alternative policies, instead of a single “best” policy suggestion. Thus, it creates room for a better informed policy debate on tradeoffs.

An essential contribution of using robust optimization for adaptive policymaking is the intelligent specification of the policy levers, namely triggers. Initially, these parameters were assigned values by using guesses according to historical data, expert opinion or common sense. The resulting adaptive policy is more robust to uncertainty and outperforms the basic ETS policy (See Figure 3). However, it might be possible to specify the triggers more effectively for further improvement of the policy design. The values assigned by the optimization algorithm shows that the trigger values can be determined more intelligently. Figure 7 shows a comparison of the adaptive policy and one of the policy solutions on the

Pareto front identified by the robust optimization. It is obvious that robust optimization helps improve the policy design by specifying the values more intelligently.

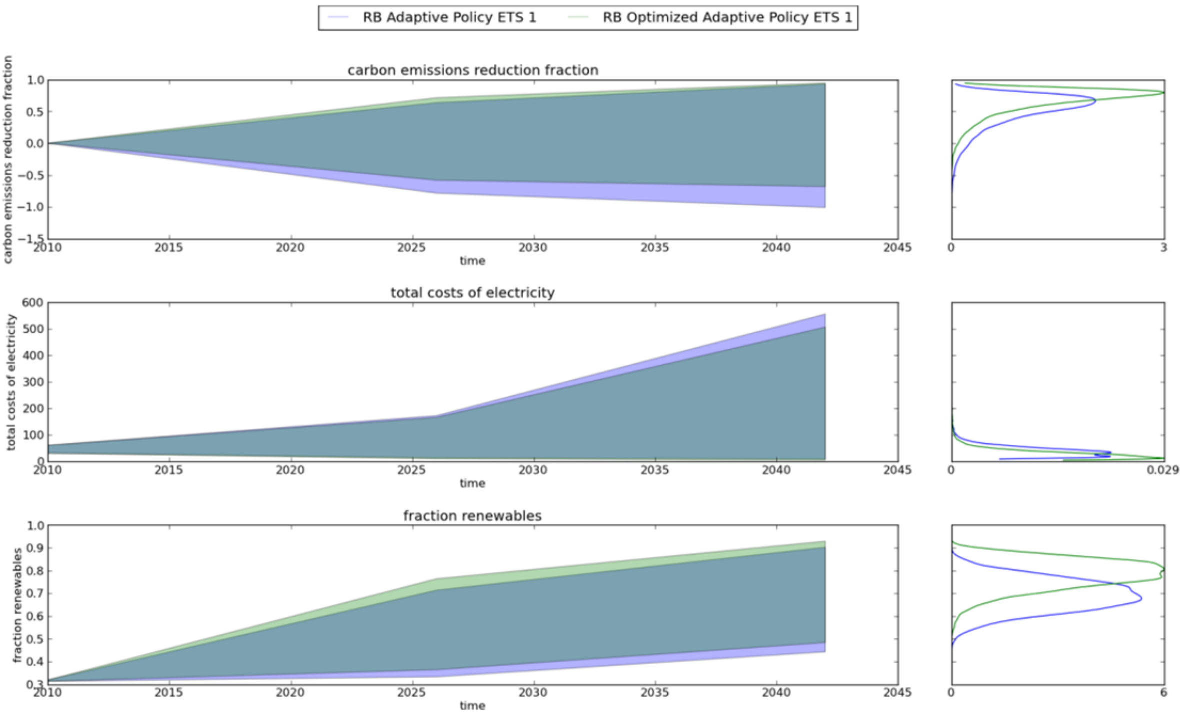

Figure 7: Comparison of adaptive policy and optimized policy

The choice of robustness metric has an important influence on the Pareto solutions identified by the multiobjective robust optimization. In this study, we have used a robustness score based on the mean divided by the standard deviation for maximization, and the mean multiplied by the standard deviation for minimization. However, it is possible to get different results by using different metrics. In our study, we choose to use a robustness score that aims to maximize the average over a certain number of cases and minimize the deviation. For instance, a regret-based metric, where the aim is to minimize the maximum regret, can lead to different results.

Multiobjective optimization and robust optimization are already computationally exhaustive techniques separately. It becomes time and resource consuming when they are merged together. This computational constraint limits the scope of the analysis. For instance, it is essential to work with relatively small, less detailed models. However, sometimes it might be essential to have quick results if, for instance, it is necessary to make a decision quickly. For such conditions, it might be better to take advantage of faster and quicker techniques such as Multi-Criteria Decision Analysis (MCDA).

Conclusions

Policymaking under deep uncertainty and dynamic complexity is a challenging task. A possible approach for dealing with deep uncertainty is the adaptive policymaking. In a recent paper (Hamarat *et al.*, 2012), an Adaptive Robust Design approach for developing adaptive policies under deep uncertainty is proposed. However, that approach does not explicitly consider the multiplicity of different objectives. Most policy problems include multiple parties/stakeholders/actors having multiple, potentially, conflicting objectives. So, there is a need for methods dealing with multiple objectives. To this purpose, we use multiobjective optimization together with the Adaptive Robust Design approach.

The proposed approach in this paper is illustrated through a case study that deals with the possible futures of the EU energy market. There is a strong need for more innovative policies than the current ETS policy to promote the transition toward renewable technologies. The results indicate that the proposed approach can be efficiently used for developing policy suggestions and for improving the decision support for policymakers in dynamically complex systems. Multiobjective optimization can be effectively utilized for improving the policy design in system dynamics.

Acknowledgements

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APPENDIX A

Table 3: Scores of the solutions on the Pareto front

fraction renewables score	carbon emission reduction score	average total cost score
1.66515958	1.09915343	581.11209943
1.66498125	1.09460053	576.53648781
1.66498125	1.09460053	576.53648781
1.66446291	1.09927693	574.40481665
1.66446291	1.09927693	574.40481665
1.66446291	1.09927693	574.40481665
1.66389957	1.09941222	581.37372016
1.66389520	1.10764117	578.27482934
1.66240633	1.10199250	577.68447679
1.65709637	1.07060308	572.92454697
1.65683552	1.06972597	572.31497905
1.65451022	1.06684621	571.74629060
1.64933297	1.04200385	565.49398064
1.64807981	1.04186434	563.90183745
1.64459214	1.04756461	569.70913003
1.64277368	1.04054030	562.94397605
1.64265164	1.05100700	571.14187547
1.63407105	1.01803123	562.88709162
1.63259528	1.02111486	561.42223050
1.63185500	1.02360786	553.88846551
1.62536401	1.01110391	552.72997174
1.62529785	1.01130922	552.83619609
1.62529590	1.01131470	552.83634577
1.62088387	0.99851711	526.44613294
1.61772058	0.99306598	524.42572492
1.59955497	0.97546140	522.72249305
1.59832603	0.97358282	521.48447148

APPENDIX B

Table 4: Upper and lower limits of the triggers for the Pareto front solutions

	Add Comm	Desired Fraction	Proximity	Time Ahead	decommission factor	subsidy duration	subsidy factor	trigger
Min	0.071	0.678	1.372	14.016	0.492	31.204	0.192	0.008
Max	0.708	0.984	1.891	31.345	0.977	41.900	0.463	0.082