Simulation Modelling Practice and Theory 46 (2014) 25–39

Contents lists available at ScienceDirect

Simulation Modelling Practice and Theory

journal homepage: www.elsevier.com/locate/simpat

An exploratory approach for adaptive policymaking by using multi-objective robust optimization

Caner Hamarat [a,*], Jan H. Kwakkel [a], Erik Pruyt [a], Erwin T. Loonen [b]

[a] Delft University of Technology, The Netherlands
[b] GEN Nederland, The Netherlands

ARTICLE INFO

Article history:
Available online 29 March 2014

Keywords:
Adaptive policymaking
Deep uncertainty
Multi-objective robust optimization
Simulation optimization
Complex systems
Exploratory modeling and analysis

ABSTRACT

Developing robust policies for complex systems is a profound challenge because of their nonlinear and unpredictable nature. Dealing with these characteristics requires innovative approaches. A possible approach is to design policies that can be adapted over time in response to how the future unfolds. An essential part of adaptive policymaking is specifying under what conditions, and in which way, to adapt the policy. The performance of an adaptive policy is critically dependent on this: if the policy is adapted too late or too early, significant deterioration in policy performance can be incurred. An additional complicating factor is that in almost any policy problem, a multiplicity of divergent and potentially conflicting objectives has to be considered. In this paper we tackle both problems simultaneously through the use of multi-objective robust simulation optimization. Robust optimization helps in specifying appropriate conditions for adapting a policy, by identifying conditions that produce satisfactory results across a large ensemble of scenarios. Multi-objective optimization helps in identifying such conditions for a set of criteria, and providing insights into the tradeoffs between these criteria. Simulation is used for evaluating policy performance. This approach results in the identification of multiple alternative conditions under which to adapt a policy, rather than a single set of conditions. This creates the possibility of an informed policy debate on trade-offs. The approach is illustrated through a case study on designing a robust policy for supporting the transition toward renewable energy systems in the European Union. The results indicate that the proposed approach can be efficiently used for developing policy suggestions and for improving decision support for policymakers. By extension, it is possible to apply this methodology in dynamically complex and deeply uncertain systems such as public health, financial systems, transportation, and housing.

1. Introduction

Policymaking for complex adaptive systems requires dealing with dynamic complexity and deep uncertainty. Complex adaptive systems are composed of interacting heterogeneous agents that act independently, interact with each other, and adapt their behavior over time [1,2]. Out of these interactions emerge global regularities that show dynamic behavior over time due to the intrinsic adaptations taking place by the individual heterogeneous agents. The result of this is that when

* Corresponding author. Address: Jaffalaan 5, 2628 BX Delft, The Netherlands. Tel.: +31 15 278 8080; fax: +31 15 278 6233.
E-mail address: c.hamarat@tudelft.nl (C. Hamarat).

http://dx.doi.org/10.1016/j.simpat.2014.02.008
1569-190X/

making policy for complex adaptive systems, one is confronted by intrinsic unpredictability [1]. Various traditional approaches have been proposed to improve policymaking. There are two main analytical reasons why traditional approaches for policymaking mostly do not perform satisfactory when applied to complex adaptive systems. First, traditional planning approaches start from predicting the future and preparing a plan for meeting this future [3]. Second, the typical plan is static and not designed to be changed over time [4–7]. Due to their nature, static policies based on predictions of the future are ineffective and inappropriate for dealing with complexity under uncertainty. Hence, there is a need for innovative approaches for dealing with complexity and uncertainty, especially deep uncertainty.

Arguable

Deep uncertainty is encountered when the different parties to a decision do not know or cannot agree on the system model that relates consequences to actions and uncertain model inputs [8], or when decisions are modified over time [9]. In these cases, it is possible to enumerate the possibilities (e.g. sets of model inputs, alternative relationships inside a model, etc.), without ranking these possibilities in terms of perceived likelihood or assigning probabilities to the different possibilities [10].

Policies that can be adapted over time in response to how the uncertainties resolve have been suggested as a way of improving the performance of policies in the presence of deep uncertainty [11]. The idea of adaptivity dates back almost a century ago. Dewey [12] suggested that policies could be used as experiments that can stimulate learning and adaptation, allowing the policy to evolve based on experience [13]. Early applications of adaptive policies can be found in the field of environmental management [14,15]. Policies are designed from the outset to test well-formulated hypotheses about how the behavior of an ecosystem will react to human actions [16]. A similar attitude is also advocated by Collingridge [17] 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.

Over the last few years, substantial work has been done on the design of adaptive policies in a variety of policy domains. In transport policy, [5,18,19] all put forward adaptive planning approaches for airports, [20–22] put forward adaptive policies for the implementation of intelligent speed adaptation measures, and more broadly [23] outlines the benefits of adaptive policies for transport policy in general. In water resources management, examples of adaptive policymaking include [24–26]. In climate adaptation, [27–33] all argue for adaptive policies. A common theme running through this work in different policy domains is that one should take only those actions that are non-regret and time-urgent and postpone other actions to a later stage [34]. However, in none of this work so far, a method has been put forward for identifying when to adapt the policy [11,35,36].

It has been argued that computational modeling approaches are promising for designing adaptive policies [1,29,37]. Various model-based decision support techniques have been put forward that can be used to support the design of adaptive policies. These include Robust Decision Making (RDM) [8,32,38], info-gap decision theory [39], real options [4] and Adaptive Robust Design [36]. There is an emerging literature comparing and contrasting these different approaches [24,25,34,40].

Here, we focus on Adaptive Robust Design, which in essence combines RDM with an explicit framework for adaptive policies [34,36]. This approach starts 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 cases, where each case represents a realization of one specific future. Subsequently, (5) using scenario discovery [41], this ensemble of cases is analyzed in order to identify troublesome and/or promising regions across the outcomes of interest, as well as the combination of uncertainties that cause these troublesome and promising regions. The next steps are: (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 Fig. 1).

Of central importance to adaptive policymaking is the idea that future actions are activated only if and when necessary. That is, the design of a monitoring system with associated trigger values for activating pre-specified actions is at the heart of adaptive policymaking. The outlined approach can be used to identify the conditions under which changes in the policy are required. However, this leaves unresolved the question at which trigger values actions should best be activated. The challenge here is finding an appropriate balance between activating actions too early and too late. Specifying appropriate trigger values is further complicated by the presence of different stakeholders with different preferences. A good trigger value for one actor might be far from ideal for another. This paper builds on [36] and specifically addresses the problem of specifying good trigger values in the presence of multiple stakeholders with different preferences.

When a simulation model is used to find the optimum input parameters of a given system to determine expected performance, this is called simulation optimization [42,43]. The literature on model-based decision support for adaptive policymaking has until very recently ignored the use of simulation optimization. It has been argued that optimization is impossible because of uncertainty and the presence of multiple stakeholders with diverging preferences [44]. Kasprzyk et al. [45] used a simulation optimization approach to identify feasible designs, the robustness of which was subsequently tested using RDM; and Matrosov et al. [24] compared economic optimization with RDM and argued that these approaches should somehow be combined. In this paper we build on this work. We argue that the problem caused by uncertainty can be addressed through the use of robust optimization and adopting a multi-objective optimization approach can alleviate the problem caused by the presence of multiple stakeholders with diverging preferences. More specifically, we argue that

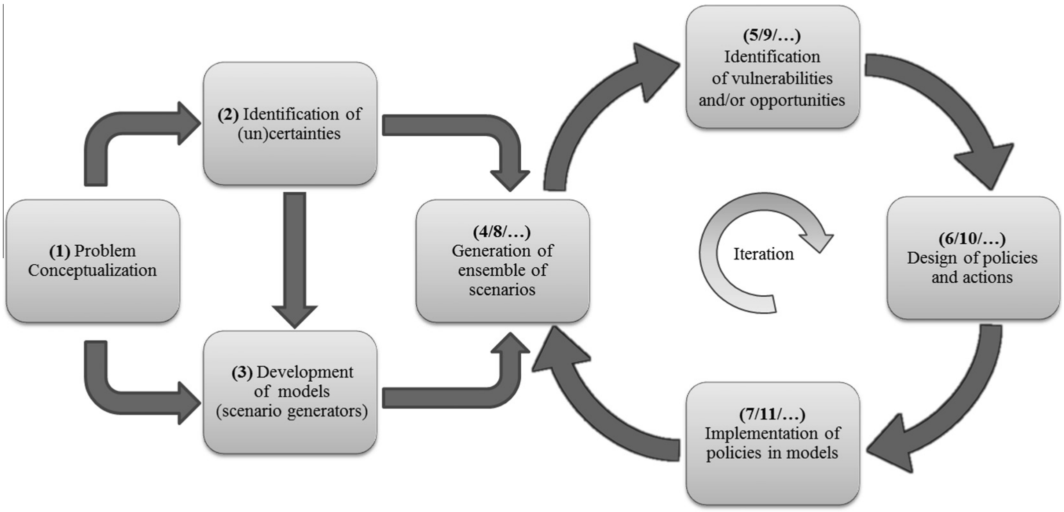

Fig. 1. The iterative Adaptive Robust Design process.

the problem of identifying when to adapt a policy can be addressed through multi-objective robust optimization. We demonstrate this multi-objective robust optimization approach with a case study of the design of an adaptive policy for steering the transition of the EU energy system towards a more sustainable functioning. Our work thus differs from [45] in that we include the robustness analysis inside the simulation optimization approach, and as such we follow the suggestion of [24] on combining simulation optimization and RDM.

The rest of this paper is structured accordingly. Section 2 presents more details on the methodology. Section 3 introduces details on the case and simulation model used. Section 4 presents the results. Section 5 contains our concluding remarks.

2. Methodology

Add to the report

Vulnerabilities and opportunities are central concepts in adaptive policy making. In order to design robust policies, it is crucial to identify combinations of uncertainties that have a substantial positive (opportunity) or negative (vulnerability) influence on the degree of goal achievement. Targeted actions can then be designed to either take advantage of the opportunity, or reduce the effect of the vulnerability. Such actions can be taken immediately, or at some future point in time when the conditions warrant it. The Patient Rule Induction Method (PRIM) [46–48] can be used for discovering vulnerabilities and opportunities. PRIM can be used for data analytic questions, where the analyst tries to find combinations of values for input variables that result in similar characteristic values for the outcome variables. Specifically, one seeks one or more subspaces of the model input space within which the value of an outcome of interest is considerably different from its average value over the entire model input space. PRIM describes these subspaces in the form of hyper-rectangular boxes of the model input space. It has been shown that the results of PRIM could be enhanced significantly by preprocessing the data with Principal Component Analysis (PCA) [49]. In this paper, we use PCA PRIM for identifying vulnerabilities and opportunities.

The adaptive part of an adaptive policy or plan takes the form of a monitoring system that specifies what information should be tracked, and under which pre-specified conditions pre-specified actions will be taken [5,19]. A signpost is the information which is tracked to decide whether it is necessary to take actions and a trigger is the critical value of a signpost that triggers to take actions. These signposts and triggers are defined during the contingency planning phase in adaptive policymaking. The efficacy of an adaptive plan hinges on the care with which the contingency planning is carried out. In the current adaptive policymaking literature, the values used for triggers are mostly based on logical guesses, expert opinions, or historical data [50]. Given the importance of the monitoring system for the overall efficacy of an adaptive policy, there is a need for a more substantial way of determining appropriate trigger values. The use of optimization can be a possible solution for this problem.

Optimization is widely used in every aspect of policymaking and in fields ranging from engineering to science, and from business to daily life. Optimization mostly refers to finding the optimum solution among a set of plausible alternatives under given constraints. However, this approach might be misleading for policymaking under deep uncertainty where optimizing a single goal is not the main aim [51]. Under deep uncertainty, one best solution among a set of possible alternatives without violating the given constraints, i.e. an optimal solution, usually does not exist [51,52]. A field within optimization that allows to overcome the difficulties posed by uncertainty is robust optimization [53]. Robust optimization methods aim at finding optimal outcomes in the presence of uncertainty [54–56]. Adaptive policymaking requires proper handling of both parametric and structural uncertainties in order to develop robust policies. Therefore, robust optimization methods can be of great use for adaptive policymaking [57].

The use of computational simulations for analyzing dynamic systems helps gather significant information about the system of interest [58]. More specifically, simulation is used for evaluating the performance of complex systems [59]. In the simulation optimization field, several approaches have been proposed [60–62], although many of them assume a certain or fixed environment [56]. However, improper handling of uncertainty may result in undesirable solutions. Given an uncontested objective function, uncertainty can affect either or both the constraints and the score on the objective function [57,63]. Several approaches have been proposed to handle uncertainty in simulation optimization [56,64–66]. The basic idea shared by these approaches is that the uncertainties are somehow directly incorporated in the optimization problem. There are at least three distinct ways in which this can be done [66], namely (i) the direct simulation approach where the robustness measures are calculated by repeatedly running the simulation model (e.g. [67]); (ii) the metamodel approach where the results of a simulation model are approximated using a metamodel (e.g. [56,64,68]); and (iii) the stochastic approximation approach where the values of the random functions are used directly in the optimization algorithm [69]. In this paper, we adopt a direct simulation approach and are interested in the situation where the uncertainty affects the objective function.

What is robustness

In robust optimization, robustness can be operationalized in many different ways. Rosenhead et al. [52] understand robustness as flexibility, that is, as leaving options open. Other ways of operationalizing robustness include Wald's minimax criterion, which chooses the decision alternative that minimizes the maximum risk [70]; minimax regret [71], which results in choosing the solution with the least maximum regret [8]; and various forms of satisficing [72], such as risk discounting, and certainty equivalents [52]. With the direct uncertainty treatment, Adaptive Robust Design resembles Monte-Carlo strategies where simulation techniques are used to obtain objective function values [63].

Within the literature on computational support for designing adaptive policies, robustness has been defined in a number of ways such as the first order derivative of the objective function [73]; as reasonable performance over a wide range of plausible futures [36,74]; as regret [8,75]; and as sacrificing a small amount of optimal performance in order to be less sensitive to violated assumptions [74]. This last definition bears a large similarity to the local robustness model employed in info-gap decision theory [39]. Another approach, used for robust parameter design, is the signal-to-noise ratio, which can be simplified as mean divided by standard deviation [76,77]. Later, we will use an approach that is very similar to signal-to-noise ratio for our robustness scores.

How to merge stuff

For complex and uncertain systems where decision making involves multiple stakeholders, it may be treacherous to design plans that are based on a single objective or objectives that are imprecisely merged into a single objective. Multi-objective optimization helps to grasp the multiplicity of different and possibly conflicting objectives. For mostly, there is no single solution for a multi-objective optimization problem because of trade-offs between the different objectives. If it is possible to assign precise and uncontested weights to the different objectives, then it might be possible to merge multiple objectives into a single overarching objective. However, it is often difficult to decide on the appropriate weights for different objectives in complex and uncertain systems, in particular when various stakeholders are involved. An alternative approach is to find a set of solutions that are not dominated. A given solution is non-dominated if there does not exist a solution that performs better on all criteria. These solutions are called Pareto optimal and the result of the optimization is not a single optimal solution but a set of solutions that, together, form the Pareto front. Multi-objective optimization has been used before for simulation optimization [68,78–80].

Pareto optimal concept

A general formulation of the multi-objective optimization problem is shown in Eq. (1), where Ω is the total decision space, x the decision vector of decision variables in the decision space, F the multi-objective function, f_i the ith objective function, c_i the ith constraint function, ε the set of equality constraints, and $\mathcal{X}$ the set of inequality constraints.

$$\boxed{\begin{array}{ll} \mathit{minimize}_{x\in\Omega} & F(x) = [f_1(x), f_2(x), \ldots, f_m(x)] \\ \mathit{subject\ to} & c_m(x) = 0, \forall m \in \mathcal{E} \\ & c_n(x) \leq 0, \forall n \in \mathcal{X} \end{array}} \tag{1}$$

Eq. (1): The general multi-objective optimization problem (adapted from [81]).

Several approaches have been developed to solve multi-objective optimization problems such as the weighted sum approach, the utility function method, the lexicographic method, goal programming, and Successive Pareto Optimization [82,83]. Downsides of these approaches include the need for inter-criteria information, and the fact that they generate only a single solution at a time [84]. Evolutionary algorithms that simultaneously generate populations of candidate solutions address both points. Such a population-based approach can be used for generating the solutions on the Pareto front in a single run of an evolutionary algorithm [85]. To this purpose, evolutionary algorithms can be beneficial for solving multi-objective optimization problems [81,84]. In this study, a well-established multi-objective evolutionary optimization technique, the Nondominated Sorting Genetic Algorithm-II (NSGA-II) [86], is used.

In short, we are arguing that the problem of identifying appropriate conditions for adapting a policy can be identified through multi-objective robust optimization. In this application, the decision space Ω is formed by the set of triggers, each of which can be subject to one or more constraints c_i. The multi-objective function F specifies the robustness for the different outcomes of interest. In this paper we use a signal-to-noise ratio as our robustness metric, but there is no principal reason that other metrics could not be used instead. This metric is computed over a specific number of scenarios. Similar approaches have been applied in other fields such as environmental systems and engineering design [45,87]. The result of solving this optimization problem is an approximation of the Pareto front, containing a set of Pareto optimal, i.e. non-dominated, trigger values.

3. The EU energy case

3.1. Background

The European Union (EU) has targets for the reduction in carbon emissions and the share of renewable technologies in the total energy production by 2020 [88]. The main aim is to reach 20% reduction in carbon emission levels compared to 2010 levels and to increase the share of renewables to at least 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 conditions, which have 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, and preparing policies for meeting the EU targets.

In order to meet the 2020 goals, the EU adopted the European Emissions Trading Scheme (ETS) for limiting the carbon emissions [88]. 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, current emissions and shares of renewables show a fragile progress of reaching the 2020 targets. It is necessary to take additional actions for steering the transition toward cleaner energy production. This requires a better handling of the uncertainties in the energy system and more robust policies that can promote renewable technologies.

3.2. The model

In this study, a System Dynamics [89–91] model is used for simulating the plausible futures of the EU electricity system. The model represents the power sector in the EU and includes congestion on interconnection lines by distinguishing seven different regions in the EU. These are northwest (NW), northeast (NE), middle (M), southwest (SW), southeast (SE) of Europe, United Kingdom and Ireland (UKI) and Italy (I). Nine power generation technologies are included. 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 endogenously includes mechanisms and processes related to the competition between technology investments, market supply–demand dynamics, cost mechanisms, and interconnection capacity dynamics. Not only endogenous mechanisms but also various exogenous variables are included. Fig. 2 shows the main sub-models that constitute this model at an aggregate level. These are installed capacity, electricity demand, electricity price, profitability, and levelised costs of electricity. At an aggregated level, there are two main factors that drive new capacity investments: electricity demand and expected profitability. An increase of the electricity demand leads to an increase in the installed capacity, which will affect the electricity price. This will cause a rising demand, in turn resulting in more installed capacity. On the other hand, decreasing electricity prices will lead to lower profitability and less installed capacity, which will result in electricity price increases. Each sub-model has more detailed interactions within itself and with the other sub-models and exogenous variables and these causal relationships drive the main dynamics of the EU electricity system.

Fig. 2 is a graphical representation of the causal relationships in the model. In order to run computational simulations, these relationships are translated into a system of differential equations, which are implemented in Vensim [92]. The model includes 33 ordinary differential equations, 499 auxiliary equations, and 632 variables. In this study, we are particularly interested in certain outputs and inputs. The output variables that we are interested in are the fraction of renewable technologies, the fraction of carbon emission reduction and the average total costs of electricity production. The differential equations for these outputs are given in Eq. (2). It is beyond the scope of this paper to include all the equations and variables separately. More detail on the model can be found in [93], including detailed descriptions of each equation and variable.

$$
\begin{aligned}
&\text{Fraction of renewable technologies} = \frac{\sum_{i=1}^{7}\sum_{j_r=1}^{4}\left(\text{Power production}_{i,j}\right)}{\sum_{i=1}^{7}\sum_{j=1}^{9}\left(\text{Power production}_{i,j}\right)}\\
&\text{Fraction of carbon emission reduction} = \frac{\sum_{i=1}^{7}\sum_{j=1}^{9}\left(\text{Carbon intensity}_{i,j}\times\text{Power production}_{i,j}\right)\text{ in 2010}}{\int_{2010}^{2050}\sum_{i=1}^{7}\sum_{j=1}^{9}\left(\text{Carbon intensity}_{i,j}\times\text{Power production}_{i,j}\right)dt}\\
&\text{Average total costs of electricity production} = \frac{\int_{2010}^{2050}\sum_{i=1}^{7}\sum_{j=1}^{9}\left(\text{Producer costs}_{i,j}+\text{Policy costs}_{i,j}\right)dt}{\int_{2010}^{2050}\sum_{i=1}^{7}\sum_{j=1}^{9}\left(\text{Power production}_{i,j}\right)dt}\\
&\forall i = 1,2,\ldots,7\ (\mathit{Regions\ in\ EU})\\
&\forall j = 1,2,\ldots,9\ (\mathit{Technologies\ used})\\
&\forall j_r = 1,2,3,4\ (\mathit{Renewable\ technologies}: \mathit{Wind}, \mathit{PV}, \mathit{hydro}, \mathit{biomass})\\
&t \in [2010,2050]
\end{aligned}
\tag{2}
$$

Eq. (2): The equations for the output variable of interest.

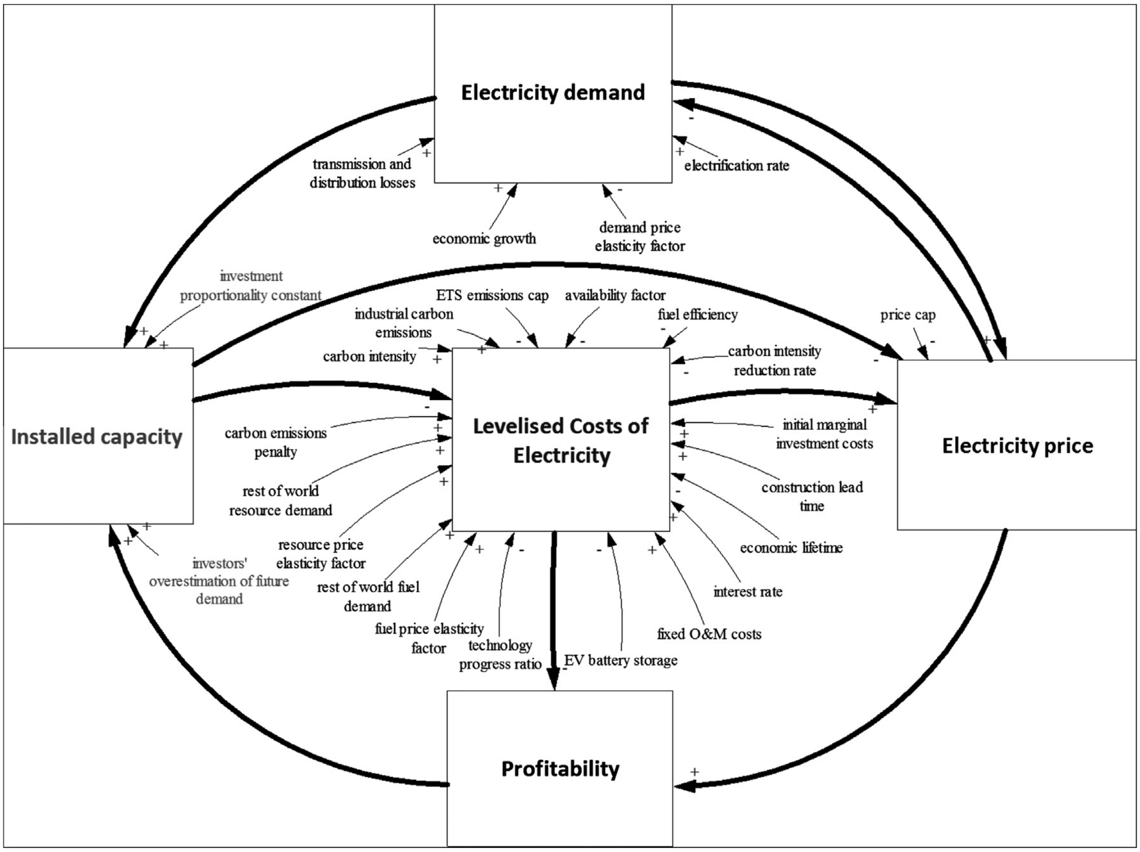

Fig. 2. The main causal loop diagram of the EU energy model.

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 costs will decrease with increasing experience. Different progress ratios are explored for each technology
Economic growth	It is deeply uncertain how the economy will develop over time. Six possible developments of economic growth behaviors are considered
Electrification rate	The rate of electrification of the economy is explored by means of six different electrification trends
Physical limits	The effect of physical limits on the penetration rate of a technology is unknown. Two different behaviors are considered
Preference weights	Investor perspectives on technology investments are treated as being 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 (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 many EU countries is expected between 2013 and 2050. The time of the nuclear ban is varied between 2013 and 2050
Price – demand elasticity	A parametric range is considered for price – demand elasticity factors

From a range of various deeply uncertain inputs, we are interested in exploring and analyzing their influence on the key output variables. In order to explore the uncertainty space, not only parametric but also structural uncertainties are included in the analysis. For exploring structural uncertainties, several alternative model formulations have been specified and a switch mechanism is used for switching between these alternative formulations. Parametric uncertainties are explored over pre-defined ranges. Table 1 provides an overview of the uncertainties, 46 in total, that are analyzed and their descriptions.

4. Results

4.1. From ETS toward an adaptive policy

ETS is currently used in Europe to reduce carbon emissions. It introduces an annual cap on the maximum amount of emissions and the option for trading these carbon emission rights. The results of the ETS policy so far leave much to be desired. This creates the need to explore plausible futures under this policy and identify ways of complementing this policy in pursuit of the desired CO_2 reduction.

Using a workbench written in Python [94] which controls Vensim [92], the model has been simulated 10,000 times to generate an ensemble of cases, generating time series between 2010 and 2050. Each case is a selection of 46 different uncertainties and certain assumptions about the future state of the system via Latin Hypercube Sampling [95]. The results of the ETS policy under uncertainty indicate that it is difficult to meet the 2020 targets through ETS only. For most futures, the fraction of renewables remains around 25% and the carbon emissions reduction fraction is around 10%; well short of the 20% target. It is obvious that there is a need for further actions in order to achieve a sustainable energy future.

Through scenario discovery using PCA PRIM, we identify the key vulnerabilities and opportunities of the ETS policy, in light of which the ETS policy can be redesigned. Although this analysis did not produce useful information with respect to vulnerabilities, there are useful findings related to opportunities that could be taken 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 to 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 stronger learning effects for renewables are opportunities for achieving a more sustainable functioning. Hence, in order to improve the ETS system, three adaptive actions are added to the current ETS policy.

(1) *Action 1* aims at accelerating the phase out of the old non-renewable technologies. The gap between the desired and the current level of the renewable fraction is tracked. The desired level is assumed to be 80%. This action introduces an additional decommissioning flow, factored by the gap, for non-renewable technologies.

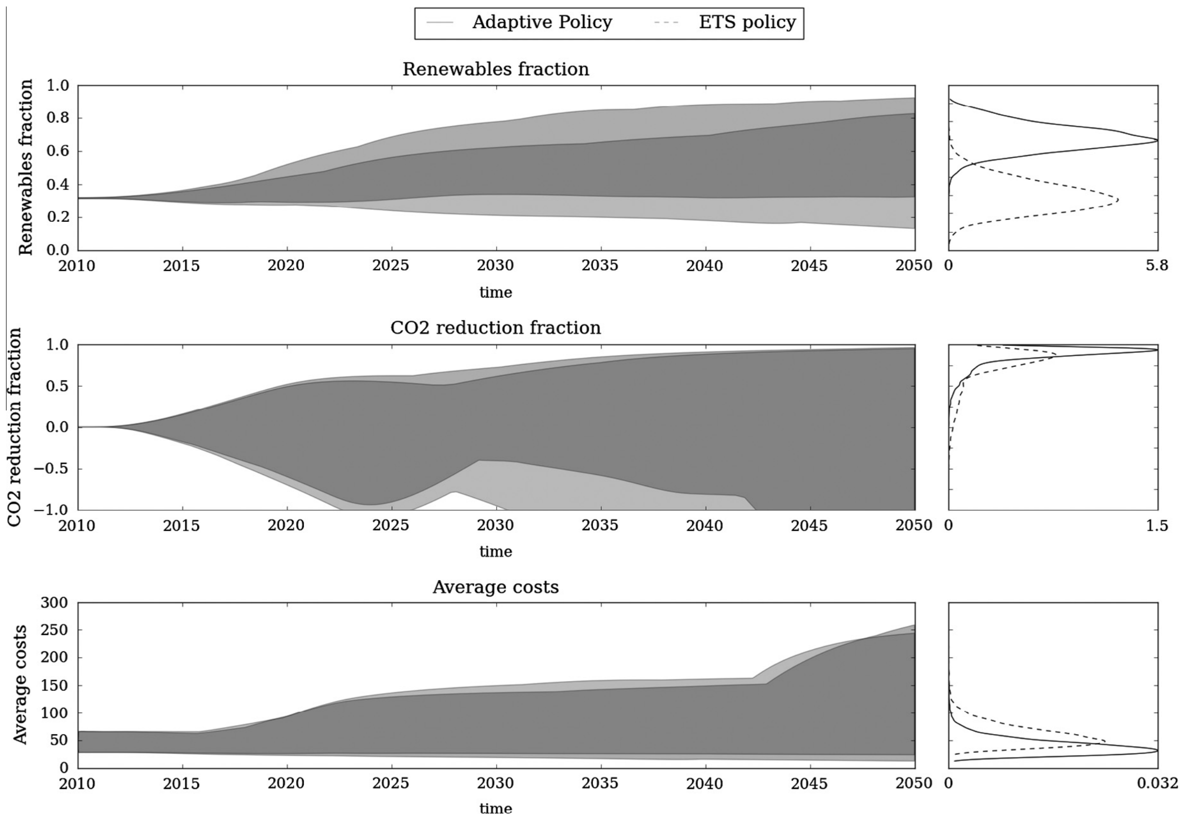

Fig. 3. Comparison of ETS and adaptive policies.

(2) *Action 2* aims at making the renewable technologies more cost-attractive by introducing a subsidy fraction on the marginal investment costs of renewable technologies. The costs of the most expensive non-renewable technology and the renewable technologies are monitored. If the cost of a renewable is close to the most expensive non-renewable, here within 25% (proximity), then a subsidy of 25% is introduced for 10 years.
(3) *Action 3* aims at sustaining the targeted renewable fraction in the future. A forecast of the renewable fraction for 10 years ahead is made. A desired fraction is also assumed to be 80%. If the gap between the desired fraction and the forecast is bigger than the trigger level of 10%, non-renewable technologies are decommissioned with an additional percentage of 25%.

The resulting policy with these adaptive actions is called the adaptive policy. For testing the performance of the adaptive policy, it is again run for the same ensemble of 10,000 computational experiments. There is a remarkable improvement in policy performance. Fig. 3 compares the ETS policy (in dark gray and dashed line) and the adaptive policy (in light gray and solid line) for three outcomes: the carbon emissions reduction fraction, average total costs, and the renewables fraction. The figure shows the envelopes of the outcomes (left) which span the upper and lower limits for 10,000 simulations over time and the Kernel Density Estimates [96] of the terminal values in 2050 (right) in the respective ensemble. The adaptive policy improves the fraction of renewables dramatically from 40% to 50% on average in 2020 and to 70% in 2050. Similarly, there are clear improvements in terms of the fraction of carbon emissions reduction and average total costs.

Table 2
List of triggers and their descriptions.

Trigger	Brief description
Action 1	
Desired fraction (*df*)	Desired fraction of renewable technologies
Additional decommissioning (*ad*)	Additional fraction of non-renewable technologies to be decommissioned
Action 2	
Subsidy factor (*sf*)	Additional fraction of subsidy for renewables
Subsidy duration (*sd*)	Duration for how long the subsidy for the renewables will be active
Proximity (*pr*)	Proximity of cost to the cost of the most expensive non-renewable technology
Action 3	
Decommissioning factor (*dcf*)	Fraction to be decommissioned for non-renewables when the gap between desired and forecasted fraction for renewables is above the Trigger
Forecast time horizon (*fth*)	Time horizon over which the forecast for the level of renewable fraction is done
Trigger (*tr*)	Proximity of the forecasted renewable fraction to the desired fraction

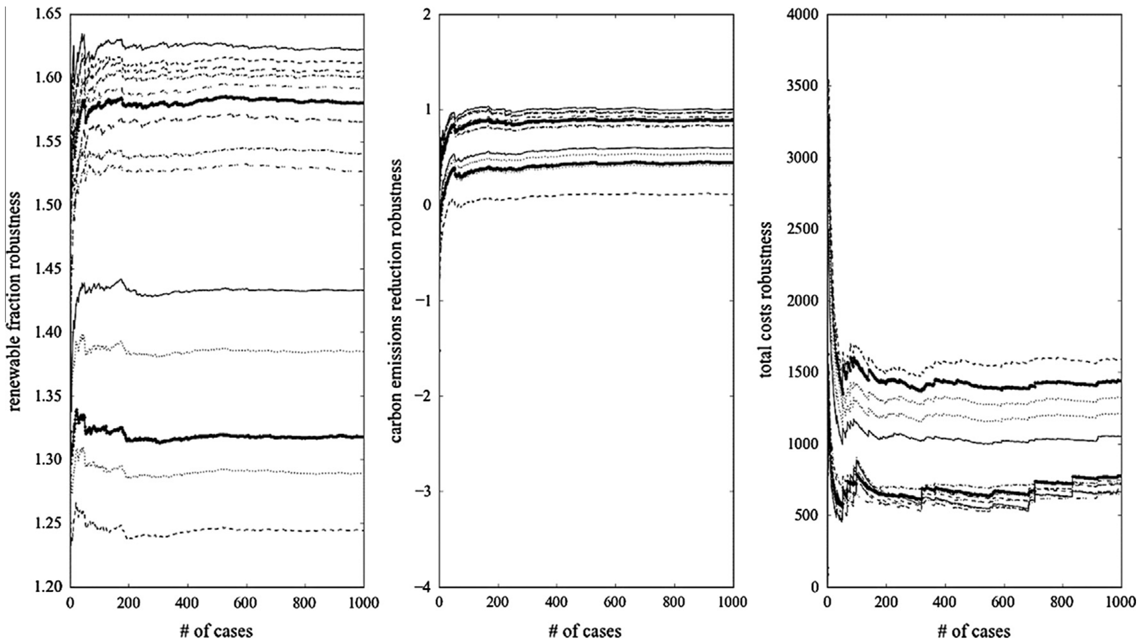

Fig. 4. Robustness check.

4.2. Fine-tuning the trigger values

For the multi-objective robust optimization, we use three objectives: (1) the fraction of renewable technologies, (2) the fraction of carbon emission reduction in 2050 compared to 2010, and (3) the average total costs of electricity production. The simulation model used in this study produces the values for these three objectives. The EU has specific targets for the share of renewable technologies and the reduction fraction of carbon emissions by 2020. Hence, these are the first two objectives. They are to some extent dependent and/or similar. However, the average total cost of electricity generation is dissimilar. While the first two objectives are to be maximized, the third objective is to be minimized.

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 is of a crucial importance for the performance of the adaptive policy. In the adaptive ETS policy, there are 8 triggers. In Table 2, these triggers are given together with their brief descriptions and it also shows which trigger is part of which action.

The robustness metric used here is based on the idea of increasing the expected outcomes of a given policy while making them more insensitive, i.e. certain, no matter how various uncertainties play out. The goal is thus to increase the certainty about the expected outcomes across many plausible scenarios. More formally, this means that there is an expected value and dispersion around this value. In this paper, in case of maximizing, we define robustness as the mean divided by the standard deviation. The higher the mean, the higher the metric. The smaller the standard deviation, the higher the metric. This will not work in case of minimizing, so there we use the mean multiplied by the standard deviation. The lower the mean, the lower the metric. The lower the standard deviation, the lower the metric. In order to calculate such a robustness metric, each candidate needs to be evaluated using many simulations.

Combining the foregoing description of the outcomes of interest and the decision space, we get the multi-objective optimization problem shown in Eq. (3). We have three objective functions. The first two are to be maximized and the third one is to be minimized. The objective function f_i show how the robustness metrics are calculated. For these functions, a correction factor of 1 is added to the means and standard deviations to prevent division by zero. l_p is the decision space and consists of the triggers specified in Table 2. The set of constraints in Eq. (3) shows the boundaries within which the triggers will be optimized.

$$
\begin{array}{lll}
\textit{maximize} & F(l_p) = (f_{frac}, f_{carbon}, -f_{costs}) & \\
\textit{where} & l_p = \begin{bmatrix} p_{df} \\ p_{ad} \\ p_{sf} \\ p_{sd} \\ p_{pr} \\ p_{dcf} \\ p_{fth} \\ p_{tr} \end{bmatrix} & \\
 & f_{frac}(y_{frac}) = \dfrac{(\mu_{frac}+1)}{(\sigma_{frac}+1)} & \\
 & f_{carbon}(y_{carbon}) = \dfrac{(\mu_{carbon}+1)}{(\sigma_{carbon}+1)} & \\
 & f_{costs}(y_{costs}) = (\mu_{costs}+1) * (\sigma_{costs}+1) & \\
\textbf{subject to} & c_{df}: \quad 0.5 \le p_{df} \le 1.0 & \\
 & c_{ad}: \quad 0.0 \le p_{ad} \le 0.75 & \\
 & c_{sf}: \quad 0.0 \le p_{sf} \le 0.5 & \\
 & c_{sd}: \quad 0.0 \le p_{sd} \le 20.0 & \\
 & c_{pr}: \quad 1.0 \le p_{pr} \le 2.0 & \\
 & c_{dcf}: \quad 0.0 \le p_{dcf} \le 0.5 & \\
 & c_{fth}: \quad 10.0 \le p_{fth} \le 40.0 & \\
 & c_{tr}: \quad 0.0 \le p_{tr} \le 1.0 &
\end{array}
\tag{3}
$$

Eq. (3): The mathematical formulation of multi-objective optimization.

The robustness metric is calculated over a series of computational experiments. Choosing the number of experiments is important and requires trading off computational time and accuracy. To this purpose, a stability check is performed to have a better understanding of the appropriate number of experiments to be used. Fig. 4 shows the robustness scores for the three objectives as a function of the number of computational experiments over which the scores are calculated. Again, these computational experiments are generated by sampling across the 46 different uncertainties (see Table 1). As can be seen, after around 500 experiments, the robustness score stabilizes for all objectives. This means that using more than 500 experiments does not add value to the optimization. Thus, for each candidate solution during the optimization, we calculate the mean and the standard deviation for the robustness scores for three objectives over 500 different experiments.

In this study, we use the System Dynamics model for the computational experiments. Each computational experiment specifies a single simulation with this model. The robustness scores f_i are calculated over 500 experiments. These 500 experiments cover the space spanned by the 46 different uncertainties (see Table 1) and are generated using Latin Hypercube Sampling [95]. This means that for a single evaluation of the objective function, the simulation model is run 500 times.

In this study, we use a real-coded NSGA-II because the triggers have real values. The triggers form the chromosomes, where each chromosome represents a policy setting. We use a binary tournament selection operator in combination with a crowded-comparison operator for the selection criterion [86]. This crowding distance mechanism preserves diversity among non-dominated solutions. The genetic operators used are binary simulated crossover and polynomial bounded mutation [97]. The NSGA-II algorithm is executed for a pre-defined number of 80 generations with a population size of 200, crossover rate of 0.8 and mutation rate of 0.05. To check convergence, Fig. 5 shows the number of additions as a solid line and removals as a dashed line to an archive of Pareto front solutions. As can be seen, the additions are almost stabilized and not many new solutions are being included in the Pareto front from the 65th generation on. Although the removals also seem to be stabilizing, around the 65th generation, there is a big number of removals from the Pareto front. However, the total number of changes to the Pareto front does not fluctuate dramatically for the last 15 generations.

Fig. 6 shows a 3D representation of the robustness scores of the three objectives that are normalized between 0 and 1. The gray dots represent the dominated non-Pareto solutions and the black ones the solutions on the Pareto front, which is composed of 98 Pareto solutions. It can be observed how the optimization algorithm has evolved from the initial non-Pareto

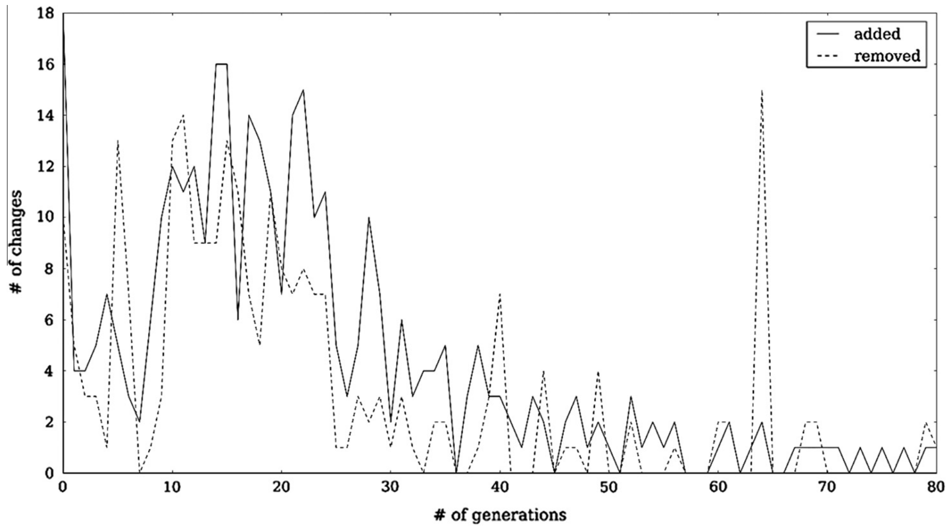

Fig. 5. Changes to the Pareto front over the generations.

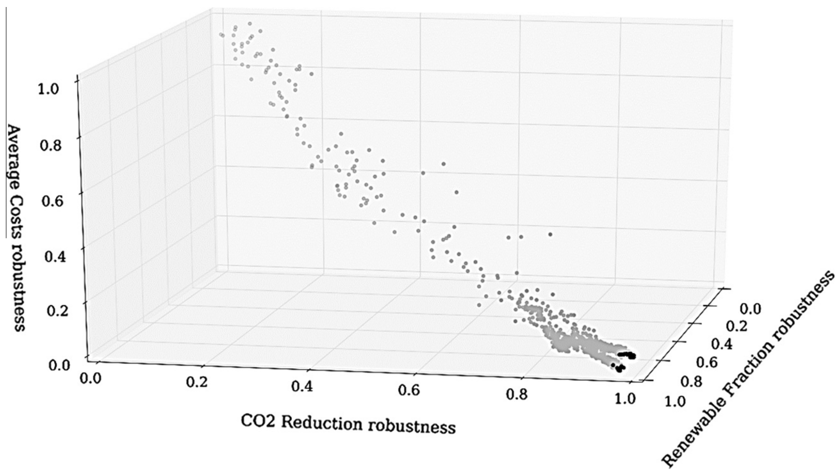

Fig. 6. Non-Pareto solutions in gray and Pareto front in black (normalized btw. 0–1).

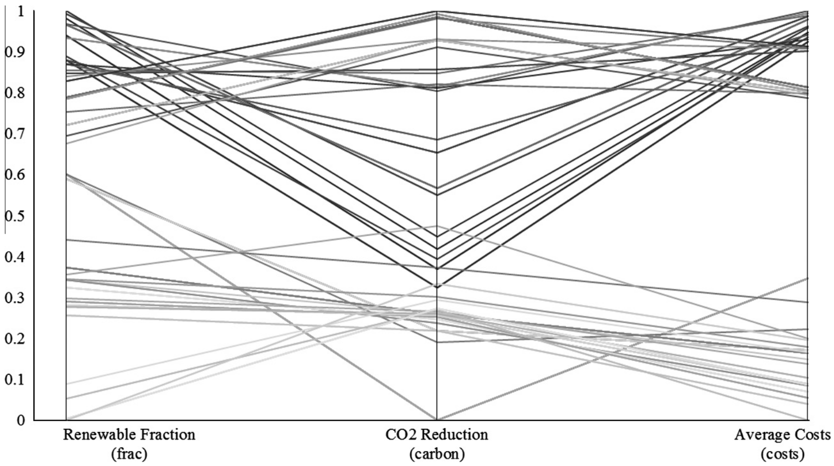

Fig. 7. The scores for the solutions in the Pareto approximate set, visualized on a parallel coordinates plot.

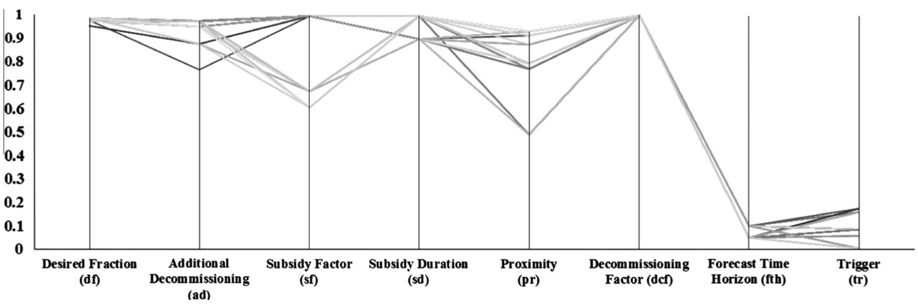

Fig. 8. The values of the decision levers for the solutions in the Pareto approximate set, visualized on a parallel coordinates plot.

solutions toward a Pareto front by following the gray dots converging to the black dots in Fig. 6. As expected, it is easy to see the tradeoff between the renewables and emissions objectives and the cost objective from these results.

The Pareto solutions in Fig. 6 show that there are two clusters of solutions. In order to have a better understanding of these clusters of solutions, we looked at the robustness scores of the Pareto front solutions and illustrated them by using a parallel coordinates plot in Fig. 7. The original robustness scores are scaled between 0 and 1 in order to visualize multiple axes with different scales together. It can be seen that the scores for the average costs form clusters around two points, whereas the renewables fraction and CO_2 reduction fraction are distributed more evenly. Hence, this suggests that there is a clear and distinct tradeoff between CO_2 reduction and the average costs.

For a better understanding of how the different solutions on the Pareto front differ, it is useful to visualize the values for the decision levers. Fig. 8 shows this in a parallel coordinates plot. The trigger values are normalized between 0 and 1 due to the scaling issue of different ranges for each trigger. The parallel coordinates in Fig. 8 show that the desired fraction (*df*), the forecast time horizon (*fth*), the decommissioning factor (*dcf*), and the subsidy duration (*sd*) are the binding constraints. In order to achieve the Pareto front, the desired fraction needs to be set to its maximum, the forecast for the renewable fraction should be restricted to a maximum of 12 years ahead, the decommissioning factor of Action 2 should be larger than 50% and the subsidy duration should at least lie between 18 and 20 years.

5. Concluding remarks

In recent years, there has been an increasing interest in adaptive policies. These are policies that are designed from the outset to be adapted over time in response to learning and new information. The efficacy of adaptive policies hinges on identifying appropriate conditions, or triggers, for adapting the policy. Here, one has to find a balance between adapting a policy too early or too late. Up till now, the literature on adaptive policies used best guesses and historic data in specifying these conditions. Given the importance of appropriate trigger for the efficacy of an adaptive policy, there is a need for a method for supporting the identification of appropriate triggers. In this paper, we have argued and demonstrated that robust multi-objective optimization is a method for this. By focusing on robustness, the presence of uncertainty is explicitly accounted for. By using a multi-objective optimization approach, the multiplicity of outcomes of interest intrinsic to multi-stakeholder

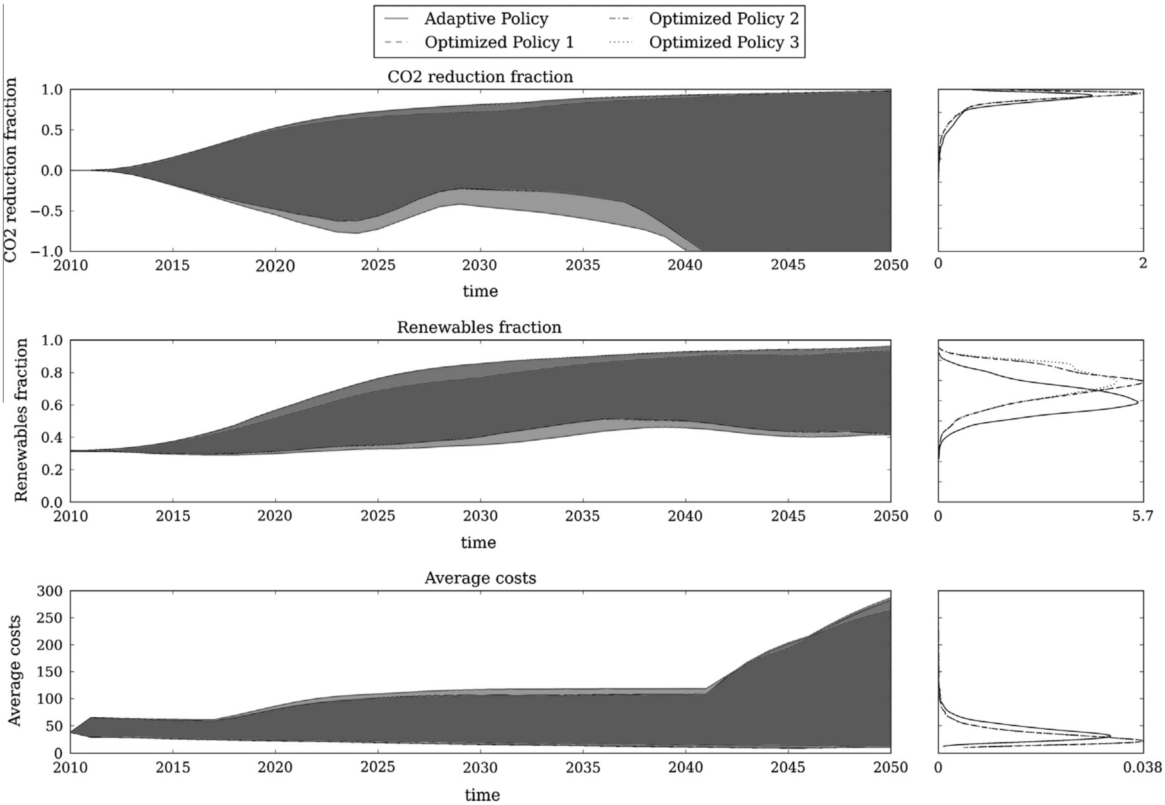

Fig. 9. Comparison of the adaptive and three optimized policies from the Pareto front.

decision problems is addressed. The outlined approach helps in identifying multiple alternative policies, instead of producing a single "best" policy. Thus, it creates room for a better-informed policy debate on trade-offs.

We demonstrated the efficacy of multi-objective robust optimization for specifying trigger values in a case study on improving the current ETS policy of the European Union. It is clear that there is a need for more innovative policies than the current ETS policy to promote the transition toward a sustainable system. We developed a basic adaptive policy using educated guesses for the different triggers. Although this adaptive policy outperformed the ETS policy, we then showed it is possible to improve the performance of this adaptive policy even further through multi-objective robust optimization. Fig. 9 shows a comparison of the adaptive policy and three solutions randomly chosen from the Pareto front identified by the multi-objective robust optimization. The solid line represents the basic adaptive policy and the dashed lines represent the three optimized policies. The results indicate that the proposed approach can be efficiently used for developing policy suggestions and for improving decision support to policymakers in energy policy. By extension, it is possible to apply this methodology in dynamically complex and deeply uncertain systems such as public health, financial systems, transportation, water resources management, climate adaptation, and housing.

The choice of robustness metric has an important influence on the Pareto solutions identified. In this study, we have used a robustness metric based on the mean divided by the standard deviation for maximization, and the mean multiplied by the standard deviation for minimization. It is plausible that if a different robustness metric had been used, the resulting trigger values would be substantially different. For instance, a regret based metric [74] can lead to different results. However, our work does not hinge on the particular robustness metric. Still, further work is needed to compare and contrast alternative robustness metrics, in pursuit of guidance on the selection of robustness metrics appropriate to the specific decision problem at hand.

Multi-objective optimization and robust optimization in isolation are already computationally intensive. Combining the two makes this even worse. Computational constraints may therefore limit the scope of the analysis. However, sometimes quick analysis is essential, for instance, if the time window for making a decision is very short. For such conditions, it might be better to take advantage of faster and quicker techniques such as Multi-Criteria Decision Analysis [98,99]. Another consequence of the time consuming nature of the outlined approach is that it becomes necessary to work with relatively small, less detailed models. This is motivated by the fact that it is better to be roughly right, than precisely wrong. In this paper, we used a System Dynamics model. Although such models are often focused on the general dynamics over time, rather than exact values, there has been some work on coupling these models to optimization algorithms for a variety of purposes including model testing [100–102], model calibration [100,102], and, most notably in this context, policy design [94,102,103].

In this paper, we used NSGA-II for solving the multi-objective optimization problem. Although it is one of the best-known algorithms, NSGA-II can perform poorly in particular classes of problems [81]. The approach that we have presented in this paper does not necessarily rely on NSGA-II. Other more modern algorithms can be used instead of NSGA-II and might even have better performance characteristics. For example ε-NSGA-II, an extension to NSGA-II, combines ε-dominance archiving with adaptive population sizing, and time continuation, which prevents deterioration in the Pareto approximate set while maintaining diversity [104,105]. Even more sophisticated and of potential relevance are auto-adaptive algorithms such as Borg [106] which tailor the various optimization parameters and evolutionary operators to the specific problem [81,106]. Future work is needed to investigate the potential of these more recent and more sophisticated algorithms to supporting the robust adaptive design approach.

The proposed approach in this study does not aim to replace decision makers but aims to provide a better guided decision making process. The Adaptive Robust Design approach, which combines RDM with an explicit framework for designing adaptive policies [34,36], together with multi-objective robust optimization helps to design robust adaptive policies in the presence of uncertainty and a multiplicity of objectives. The identification of the Pareto front provides the decision maker with a multiplicity of choices and makes the tradeoffs between these choices transparent. As such it can be used to facilitate a process of deliberation with analysis [107].

Acknowledgements

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

References

[1] K.C. Desouza, Y. Lin, Towards evidence-driven policy design: complex adaptive systems and computational modeling, Innovat. J.: Public Sector Innovat. J. 16 (2011).
[2] J.H. Miller, S.E. Page, Complex Adaptive Systems: An Introduction to Computational Models of Social Life: An Introduction to Computational Models of Social Life, Princeton University Press, 2009.
[3] R. Quay, Anticipatory governance, J. Am. Plan. Assoc. 76 (2010) 496–511.
[4] R. de Neufville, S. Scholtes, Flexibility in Engineering Design, The MIT Press, Cambridge, Massachusetts, 2011.
[5] W.E. Walker, S.A. Rahman, J. Cave, Adaptive policies, policy analysis, and policy-making, Eur. J. Oper. Res. 128 (2001) 282–289.
[6] L. Albrechts, Strategic (spatial) planning reexamined, Environ. Plan. B: Plan. Des. 31 (2004) 743–758.
[7] R.L. Wilby, S. Dessai, Robust adaptation to climate change, Weather 65 (2010) 180–185.
[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, CA, USA, 2003.
[9] S. Hallegatte, A. Shah, R. Lempert, C. Brown, S. Gill, Investment Decision Making Under Deep Uncertainty: Application to Climate Change, The World Bank, 2012.
[10] J.H. Kwakkel, W.E. Walker, V.A.W.J. Marchau, Classifying and communicating uncertainties in model-based policy analysis, Int. J. Technol. Policy Manage. 10 (2010) 299–315.
[11] W.E. Walker, V.A.W.J. Marchau, D.A. Swanson, Addressing deep uncertainty using adaptive policies: introduction to section 2, Technol. Forecast. Soc. Chang. 77 (2010) 917–923.
[12] J. Dewey, The Public and its Problems, Holt and Company, New York, USA, 1927.
[13] G.J. Busenberg, Learning in organizations and public policy, J. Public Policy 21 (2001) 173–189.
[14] C.S. Holling, Adaptive Environmental Assessment and Management, John Wiley & Sons, New York, 1978.
[15] R.J. McLain, R.G. Lee, Adaptive management: promises and pitfalls, Environ. Manage. 20 (1996) 437–448.
[16] K. Lee, Compass and Gyroscope: Integrating Science and Politics for the Environment, Island Press, Washington, 1993.
[17] D. Collingridge, The Social Control of Technology, Frances Pinter Publisher, London, UK, 1980.
[18] R. de Neufville, A. Odoni, Airport Systems: Planning, Design, and Management, McGraw-Hill, New York, 2003.
[19] J.H. Kwakkel, W.E. Walker, V.A.W.J. Marchau, Adaptive airport strategic planning, Eur. J. Transp. Infrastruct. Res. 10 (2010) 227–250.
[20] V.A.W.J. Marchau, W.E. Walker, Dealing with uncertainty in implementing advanced driver assistance systems: an adaptive approach, Integr. Assess. 4 (2003) 35–45.
[21] J.W.G.M. van der Pas, V.A.W.J. Marchau, W.E. Walker, G.P. Van Wee, B. Agusdinata, Exploratory MCDA for handling deep uncertainties: the case of intelligent speed adaptation implementation, J. Multicr. Decision Anal. 17 (2010) 1–23.
[22] J.W.G.M. van der Pas, J.H. Kwakkel, B. Van Wee, Evaluating adaptive policymaking using expert opinions, Technol. Forecast. Soc. Chang. 43 (2012) 923–933.
[23] V.A.W.J. Marchau, W.E. Walker, R. van Duin, An adaptive approach to implementing innovative urban transport solutions, Transp. Policy 15 (2009) 405–412.
[24] E.S. Matrosov, S. Padula, J.J. Harou, Selecting portfolios of water supply and demand management strategies under uncertainty – contrasting economic optimisation and 'robust decision making' approaches, Water Resour. Manage. 27 (2013) 1123–1148.
[25] E.S. Matrosov, A.M. Woords, J.J. Harou, Robust decision making and info-gap decision theory for water resource system planning, J. Hydrol. 494 (2013) 43–58.
[26] S. Dessai, M. Hulme, Assessing the robustness of adaptation decisions to climate change uncertainties: a case study on water resources management in the East of England, Global Environ. Change 17 (2007) 59–72.
[27] M. Haasnoot, H. Middelkoop, A. Offermans, E. van Beek, W.P.A. van Deursen, Exploring pathways for sustainable water management in river deltas in a changing environment, Clim. Change 115 (2012) 795–819.
[28] M. Haasnoot, J.H. Kwakkel, W.E. Walker, J. Ter Maat, Dynamic adaptive policy pathways: a new method for crafting robust decisions for a deeply uncertain world, Global Environ. Change 23 (2013) 485–498.
[29] S. Dessai, M. Hulme, R. Lempert, R. Pielke Jr., Do we need better predictions to adapt to a changing climate?, EOS 90 (2009) 111–112
[30] J.W. Hall, S. Brown, R.J. Nicholss, N.F. Pidgeon, R.T. Watson, Proportionate adaptation, Nat. Clim. Change 2 (2012) 833–834.
[31] S. Hallegatte, Strategies to adapt to an uncertain climate change, Global Environ. Change 19 (2009) 240–247.
[32] R.J. Lempert, D.G. Groves, Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the American West, Technol. Forecast. Soc. Chang. 77 (2010) 960–974.

[33] C.P. Weaver, R.J. Lempert, C. Brown, J.W. Hall, D. Revell, D. Sarewitz, Improving the contribution of climate model information to decision making: the value and demands of robust decision making frameworks, WIREs Clim. Change 4 (2013) 39–60.
[34] W.E. Walker, M. Haasnoot, J.H. Kwakkel, Adapt or perish: a review of planning approaches for adaptation under deep uncertainty, Sustainability 5 (2013) 955–979.
[35] IISD, Designing Policies in a World of Uncertainty, Change and Surprise – Adaptive Policy-Making for Agriculture and Water Resources in the Face of Climate Change – Phase I Research Report, International Institute for Sustainable Development, Winnipeg, 2006.
[36] C. Hamarat, J.H. Kwakkel, E. Pruyt, Adaptive robust design under deep uncertainty, Technol. Forecast. Soc. Chang. 80 (2013) 408–418.
[37] S.C. Bankes, Tools and techniques for developing policies for complex and uncertain systems, Proc. Natl. Acad. Sci. USA 99 (2002) 7263–7266.
[38] R.J. Lempert, A new decision sciences for complex systems, Proc. Natl. Acad. Sci. USA 99 (2002) 7309–7313.
[39] Y. Ben Haim, Information-Gap Decision Theory: Decision under Severe Uncertainty, second ed., Academic Press, London, UK, 2006.
[40] J.W. Hall, R.J. Lempert, A. Keller, A. Hackbarth, C. Mijere, D. McInerney, Robust climate policies under uncertainty: a comparison of robust decision making and info-gap methods, Risk Anal. 32 (2012). 16527-11672.
[41] B.P. Bryant, R.J. Lempert, Thinking inside the box: a participatory computer-assisted approach to scenario discovery, Technol. Forecast. Soc. Chang. 77 (2010) 34–49.
[42] H. Pierreval, J.L. Paris, From 'simulation optimization' to 'simulation configuration' of systems, Simul. Model. Pract. Theory 11 (2003) 5–19.
[43] S. Andradóttir, Simulation optimization, in: Handbook of Simulation, John Wiley & Sons Inc., 2007, pp. 307–333.
[44] R.J. Lempert, D.G. Groves, S. Popper, S. Bankes, A general analytic method for generating robust strategies and narrative scenarios, Manage. Sci. 52 (2006). 541-528.
[45] J.R. Kasprzyk, S. Nataraj, P.M. Reed, R.J. Lempert, Many objective robust decision making for complex environmental systems undergoing change, Environ. Modell. Softw. (2013) 1–17.
[46] J.H. Friedman, N.I. Fisher, Bump hunting in high-dimensional data, Stat. Comput. 9 (1999) 123–143.
[47] J.H. Kwakkel, W.L. Auping, E. Pruyt, Dynamic scenario discovery under deep uncertainty: the future of copper, Technol. Forecast. Soc. Chang. 80 (2013) 789–800.
[48] D.G. Groves, R.J. Lempert, A new analytic method for finding policy-relevant scenarios, Global Environ. Change 17 (2007) 73–85.
[49] S. Dalal, B. Han, R. Lempert, A. Jaycocks, A. Hackbarth, Improving scenario discovery using orthogonal rotations, Environ. Modell. Softw. 48 (2013) 49–64.
[50] T. McDaniels, T. Mills, R. Gregory, D. Ohlson, Using expert judgments to explore robust alternatives for forest management under climate change, Risk Anal. 32 (2012) 2098–2112.
[51] S.C. Bankes, The use of complexity for policy exploration, in: P. Allen, S. Maguire, B. McKelvey (Eds.), The SAGE Handbook of Complexity and Management, SAGE Publications Ltd., London, UK, 2011.
[52] J. Rosenhead, M. Elton, S.K. Gupta, Robustness and optimality as criteria for strategic decisions, Oper. Res. Q. 23 (1973) 413–431.
[53] D. Bertsimas, D.B. Brown, C. Caramanis, Theory and applications of robust optimization, SIAM Rev. 53 (2011) 464–501.
[54] A. Ben-Tal, A. Nemirovski, Robust solutions of linear programming problems contaminated with uncertain data, Math. Program. 88 (2000) 411–424.
[55] D. Bertsimas, M. Sim, The price of robustness, Oper. Res. 52 (2004) 35–53.
[56] G. Dellino, J.P.C. Kleijnen, C. Meloni, Robust optimization in simulation: Taguchi and response surface methodology, Int. J. Prod. Econ. 125 (2010) 52–59.
[57] V. Gabrel, C. Murat, A. Thiele, Recent advances in robust optimization: an overview, in: Optimization, Online, 2013.
[58] H. Pierreval, Rule-based simulation metamodels, Eur. J. Oper. Res. 61 (1992) 6–17.
[59] S. Andradóttir, A review of simulation optimization techniques, in: Winter Simulation Conference, Washington, DC, 1998.
[60] M.C. Fu, Feature article: optimization for simulation: theory vs. practice, INFORMS J. Comput. 14 (2002) 192–215.
[61] M.C. Fu, C.-H. Chen, L. Shi, Some topics for simulation optimization, in: Proceedings of the 40th Conference on Winter Simulation, Winter Simulation Conference, Miami, Florida, 2008, pp. 27–38.
[62] F. Azadivar, Simulation optimization methodologies, in: Proceedings of the 31st Conference on Winter Simulation: Simulation – A Bridge to the Future, vol. 1, ACM, 1999, pp. 93–100.
[63] H.-G. Beyer, B. Sendhoff, Robust optimization – a comprehensive survey, Comput. Methods Appl. Mech. Eng. 196 (2007) 3190–3218.
[64] G. Dellino, J.P.C. Kleijnen, C. Meloni, Simulation-optimization under uncertainty through metamodeling and bootstrapping, Proc. – Soc. Behav. Sci. 2 (2010) 7640–7641.
[65] J.P.C. Kleijnen, H. Pierreval, J. Zhang, Methodology for determining the acceptability of system designs in uncertain environments, Eur. J. Oper. Res. 209 (2011) 176–183.
[66] G.I. Schuëller, H.A. Jensen, Computational methods in optimization considering uncertainties – an overview, Comput. Methods Appl. Mech. Eng. (2008) 2–13.
[67] M. Nejlaoui, A. Houidi, Z. Affi, L. Romdhane, Multiobjective robust design optimization of rail vehicle moving in short radius curved tracks based on the safety and comfort criteria, Simul. Model. Pract. Theory 30 (2013) 21–34.
[68] G. Dellino, P. Lino, C. Meloni, A. Rizzo, Kriging metamodel management in the design optimization of a CNG injection system, Math. Comput. Simul. 79 (2009) 2345–2360.
[69] R. Al-Aomar, Incorporating robustness into genetic algorithm search of stochastic simulation outputs, Simul. Model. Pract. Theory 14 (2006) 201–223.
[70] A. Wald, Statistical decision functions which minimize the maximum risk, Ann. Math. 46 (1945) 265–280.
[71] L.T. Savage, The theory of statistical decisions, J. Am. Stat. Assoc. 46 (1951) 55–67.
[72] H.A. Simon, Theories of decision-making in economics and behavioral science, Am. Econ. Rev. 49 (1955) 253–283.
[73] D. McInerney, R. Lempert, K. Keller, What are robust strategies in the face of uncertain climate threshold responses, Clim. Change 112 (2012) 547–568.
[74] R.J. Lempert, M. Collins, Managing the risk of uncertain threshold response: comparison of robust, optimum, and precautionary approaches, Risk Anal. 24 (2007) 1009–1026.
[75] J.H. Kwakkel, W.E. Walker, V.A.W.J. Marchau, Assessing the efficacy of adaptive airport strategic planning: results from computational experiments, Environ. Plan. B: Plan. Des. 39 (2012) 533–550.
[76] J. Bérubé, C. Wu, Signal-to-noise ratio and related measures in parameter design optimization: an overview, Sankhyā: Indian J. Stat., Series B (2000) 417–432.
[77] I.E. Madu, C.N. Madu, Design optimization using signal-to-noise ratio, Simul. Pract. Theory 7 (1999) 349–372.
[78] E. Tekin, I. Sabuncuoglu, Simulation optimization: a comprehensive review on theory and applications, IEEE Trans. 36 (2004).
[79] R.-C. Lin, M.Y. Sir, K.S. Pasupathy, Multi-objective simulation optimization using data envelopment analysis and genetic algorithm: specific application to determining optimal resource levels in surgical services, Omega 41 (2013) 881–892.
[80] M.H. Alrefaei, A.H. Diabat, A simulated annealing technique for multi-objective simulation optimization, Appl. Math. Comput. 215 (2009) 3029–3035.
[81] P.M. Reed, D. Hadka, J.D. Herman, J.R. Kasprzyk, J.B. Kollat, Evolutionary multiobjective optimization in water resources: the past, present, and future, Adv. Water Resour. 51 (2013) 438–456.
[82] D. Mueller-Gritschneder, H. Graeb, U. Schlichtmann, A successive approach to compute the bounded pareto front of practical multiobjective optimization problems, SIAM J. Optim. 20 (2009) 915–934.
[83] R.T. Marler, J.S. Arora, Survey of multi-objective optimization methods for engineering, Struct. Multidiscip. Optim. 26 (2004) 369–395.
[84] C.A. Coello Coello, Evolutionary multi-objective optimization: a historical view of the field, Comput. Intell. Mag., IEEE 1 (2006) 28–36.
[85] D.E. Goldberg, Genetic Algorithms in Search, Optimization, and Machine Learning, Addison-Wesley, 1989.

[86] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Trans. Evol. Comput. 6 (2002) 182–197.
[87] K. Deb, H. Gupta, Introducing robustness in multi-objective optimization, Evol. Comput. 14 (2006) 463–494.
[88] European Commission, Europe 2020: A European Strategy for Smart, Sustainable and Inclusive Growth, European Commission, COM (3.3. 2010), 2010.
[89] J.W. Forrester, Industrial Dynamics, MIT Press, Cambridge, 1961.
[90] J.D. Sterman, Business Dynamics: Systems Thinking and Modeling for a Complex World, McGraw-Hill, 2000.
[91] E. Pruyt, Small System Dynamics Models for Big Issues: Triple Jump towards Real-World Complexity, TU Delft Library, Delft, The Netherlands, 2013.
[92] Ventana Systems Inc., Vensim DSS Reference Supplement, Ventana Systems Inc., 2010.
[93] E. Loonen, Exploring Carbon Pathways in the EU Power Sector, Using Exploratory System Dynamics Modelling and Analysis to Assess Energy Policy Regimes under Deep Uncertainty, Master, Faculty of Technology, Policy and Management, Delft University of Technology, 2012.
[94] J.H. Kwakkel, E. Pruyt, Using system dynamics for grand challenges: the ESDMA approach, Syst. Res. Behav. Sci. (2013).
[95] G.G. Pilger, J. Costa, J.C. Koppe, Improving the efficiency of the sequential simulation algorithm using Latin Hypercube Sampling, in: O. Leuangthong, V.C. Deutsch (Eds.), Geostatistics Banff 2004, vols. 1 and 2, Springer, Dordrecht, 2005, pp. 989–998.
[96] Eric Jones, Travis Oliphant, P. Peterson, et al., Scipy: Open Source Scientific Tools for Python, 2001.
[97] K. Deb, R.B. Agrawal, Simulated binary crossover for continuous search space, Complex Syst. 9 (1995) 115–148.
[98] V. Belton, T.J. Stewart, Multiple Criteria Decision Analysis: An Integrated Approach, Springer, 2002.
[99] J. Figueira, S. Greco, M. Ehrgott, Multiple Criteria Decision Analysis: State of the Art Surveys, Springer, 2005.
[100] R. Oliva, Model calibration as a testing strategy for system dynamics models, Eur. J. Oper. Res. 151 (2003) 552–568.
[101] J.H. Miller, Active Nonlinear Tests (ANTs) of Complex Simulation Models, Manage. Sci. 44 (1998) 820–830.
[102] G. Yücel, Y. Barlas, Automated parameter specification in dynamic feedback models based on behavior pattern features, Syst. Dyn. Rev. 27 (2011) 195–215.
[103] R.G. Coyle, The use of optimization methods for policy design in a system dynamics model, Syst. Dyn. Rev. 1 (1985) 81–91.
[104] D.E. Goldberg, The Design of Innovation: Lessons from and for Competent Genetic Algorithms, Kluwer Academic Publishers, Norwell, Massachusetts, USA, 2002.
[105] J.B. Kollat, P.M. Reed, Comparing state-of-the-art evolutionary multi-objective algorithms for long-term groundwater monitoring design, Adv. Water Resour. 29 (2006) 792–807.
[106] D. Hadka, P.M. Reed, Borg: an auto-adaptive many-objective evolutionary computing framework, Evol. Comput. 21 (2013) 231–259.
[107] National Research Council, Informing Decisions in a Changing Climate, National Academy Press, 2009.