A scenario discovery study of the impact of uncertainties in the global container transport system on European ports

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The global container transport system is changing quickly. Ports can be severely affected by these changes; therefore ports need insight into how the system might change and what the impact of this will be on their competitive position. Given the intrinsic complexity of the container transport system and the presence of a wide range of deeply uncertain factors affecting the system, we use an exploratory modeling approach to study future scenarios for the global container network. Using scenario discovery and worst-case discovery, we assess the implications of various uncertain factors on the competitive position of the port of Rotterdam. It is found that overall the competitive position of Rotterdam is quite robust with respect to the various uncertain factors. The main vulnerability is the quality of the hinterland connections. A modest deterioration of the quality of the hinterland connections, resulting in increased travel time, will result in a loss of throughput for Rotterdam.

Keywords: scenario discovery, deep uncertainty, container shipping, global freight logistics

1 Introduction

In the past couple of decades, changes in the global container transport system have happened very rapidly. These changes have affected virtually all actors in the system, but the biggest impact has been on maritime ports. Ports have to be adaptive and resilient in responding to the changes in the global container shipping system. In today's globalized economy, ports need to ensure that they can function robustly, both as a transshipment node and as a gateway node for global trade flows. A failure to respond to changes in a timely manner often results in negative consequences for the port itself, as well as the economy of the region or country to which the port belongs. For example, the recent congestion at ports on the west coast of the US resulted in estimated damages for the economy of roughly 7 billion US dollar [1].

Preparing a port for a wide range of possible future developments is a profound challenge. The global container shipping system is composed of many elements, with strong interdependencies. Often, small changes cascade quickly through the system, potentially resulting in substantial changes somewhere quite far removed from the initial small change. For example, recently Ultra Large Carrier Vessels have entered the market. Liner shipping companies have started to form alliances to pursue economies of scale. This in turn affects the frequency of port calls, the port rotation schedule, and the container volumes loaded and unloaded at each port. Changes not only take place on the seaside. Developments in the hinterland, such as the construction of new infrastructures such as road, railways, and intermodal facilities affect transport cost.

The ongoing changes on both the seaside and the land size of seaports change the spatial flow of containers globally. The operation of the Trans-Siberian railways is an example of the importance of hinterland infrastructure on global container flows through ports [2]. A similar chained effect also takes place when global policies are imposed on ports. An example of this is the recent International Maritime Organization regulation that limits the use of sulfur in a ship's fuel in many ports in the world [3]. All of these components in the system, both physical and institutional, and the potential linked changes therein demonstrate that ports are part of a complex system. In such systems, observation on the components, and their interaction mechanisms can only be done partially, leading to a limited predictability of the behavior of the system when certain changes occur.

A second reason why preparing a port for possible future developments is important, is that the future is deeply uncertain [4, 5]. Since there are many actors with different objectives involved in the global logistic system, it is virtually impossible to predict how changes in any given component of the system will affect the system as a whole. An example of a disruptive change is the labor strike case on the western coast of the US in early 2015. As a result of the strike, the port of Long Beach was shut down for several days, causing a loss to the GDP of the Unites States of America of roughly 150 M dollar [6]. Another example is the recent drop in the global oil price, which has reduced transport cost significantly. When this low oil price is sustained for a long period (>5 years), it will likely influence trade flows between countries positively. Consequently, this would result in an increase in the volume of containers flows transported globally. Predicting when the oil price will return to its 2013 level is a highly challenging task. Other changes might include the opening and closing of certain maritime routes such as the Suez Canal and the Northern passage (i.e. the arctic route), changes in competition strategies of other ports, emergence of political tensions that hamper trade agreements between countries, etc. In short, there is a massive number of scenarios that can be generated to account for the uncertainties within the global logistic system.

Because of the intrinsic complexity of the global container shipping system, many port authorities and government institutions make use of models to help them in designing appropriate policies and strategies for ports and related infrastructure. Given the many changes taking place within the global container system, however, it is highly implausible that all these changes can be quantitatively explored using a single model. In fact, there are different modeling formalisms that can be used to model changes in the whole system and its sub-systems. Examples of those modeling approaches include discrete choice models [7], computable general equilibrium models [8], discrete even simulation models [9] and optimization models [10]. Experts in each of these areas might argue that their modeling approach is best suited to represent the system. To complicate matters, different plausible scenarios can be specified using these models. Consequently, different alternative outcomes might emerge from these different modeling exercises. In short, information from models to perform predictions on such a complex system with many uncertainties might be seriously misleading [11]. Specifically, this can happen when the irreducible uncertainties, which exist in the factors that drive change, are not properly taken into account when calculating the plausible outcomes. Therefore, there is a need for a systematic approach to deal with the uncertainties in the complex container shipping system.

The objective of this paper is to apply scenario discovery [12] in order to provide insight into the main vulnerabilities for the port of Rotterdam. The main question that we address in this paper is 'what are the key vulnerabilities for the competitive position of Rotterdam in the Bremen – Le Havre range?' Scenario discovery is an innovative model-based approach to scenario development. It is inspired by the scenario logic approach to scenario development. Scenario discovery uses series of computational experiments to explore the consequences of various unresolved uncertainties. These series of computational experiments are subsequently analyzed using statistical machine learning algorithms in order to identify the combinations of uncertain developments that produce characteristic results.

Scenario discovery relies on the exploratory use of one or mode models. In this paper, we use a world container-shipping model [7]. This is a strategic network choice model. The model can be used to estimate the flows of containers between countries given assumptions pertaining network structure, port attractiveness, and origin destination data. Time is not explicitly presented in the model, for the model is static. This implies that the vulnerabilities identified through scenario discovery are not associated directly with a particular point in time. The main uncertain factors that we will be analyzing have been derived from both literatures as well as from discussions with various experts at the Port of Rotterdam. A key criterion in the selection of uncertain factors was their potential to affect the throughput of ports in the Hamburg – Le Havre range. Methodologically, we apply both scenario discovery as well as an innovative worst-case discovery technique.

This paper is structured as follows. Section 2 elaborates on the scenario discovery approach proposed in this paper. In section 3, we present a case study illustrating the application of scenario discovery approach to deal with uncertainties faced by European ports. Furthermore, this section also provides the specification of the worldwide container transport model used together with this approach. Section 4 discusses the results of the case study together with the analysis done using scenario discovery approach. Section 5 provides the conclusions of the study.

2 Scenario discovery: a model based approach to scenario development

Scenario discovery is a relatively novel approach for addressing the challenges of characterizing and communicating deep uncertainty associated with simulation models [13]. The basic idea is that the consequences of the various deep uncertainties associated with a simulation model are systematically explored through conducting series of computational experiments [14] and that the resulting data set is analyzed to identify regions in the uncertainty space that are of interest [12, 15]. These identified regions can subsequently be communicated through e.g. narratives to the decision-makers and other actors involved. In this paper, we complement this basic idea of scenario discovery with a more directed search technique that is useful for worst-case discovery.

A motivation for the use of scenario discovery is that the available literature on evaluating scenario studies has found that scenario development is difficult if the involved actors have diverging interests and world views [12, 16]. Another shortcoming identified in this literature is that scenario development processes have a tendency to overlook surprising developments and discontinuities [17-19]. A third problem is that any scenario development approach that relies on the mental models of the analyst will struggle when faced with complex systems. Since mental models are typically event based, have an open loop view of causality, ignore feedback, fail to account for time delays, and are insensitive to non-linearity [20], essential elements of dynamics in complex systems, namely feedback, time delays and non-linearity, cannot be appropriately dealt with. Consequently, mental simulations of complex systems are highly defective, something that has also been demonstrated empirically [21-27].

Scenario discovery is a model-based approach that offers support for decision-making under deep uncertainty. 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 [4], or when decisions are adapted over time [28]. 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 [5].

When using models to support decision making under uncertainty, models have to be used in an exploratory manner rather than in a predictive manner [14, 29, 30]). In predictive modeling, models are used to predict system behavior and developed by consolidating known facts into a single package [29]. When experimentally validated, this single model can be used for analysis as a surrogate for the actual system. In the presence of deep uncertainty and complex systems, the construction of a model that may be validly used as a surrogate is simply not possible. The complexity of, and deep uncertainty pertaining the system together imply non linearity of system behavior, dynamic complexity, and rival representations of the system which are underdetermined given the available data [31-33]. Exploratory modeling starts from this fact of not knowing enough to make predictions, while acknowledging that there is still a wealth of information and knowledge available that could be used to support decision making [29].

When developing and using models for exploratory purposes, the available information is insufficient to specify a single model that accurately describes system behavior. Instead, the information can be used to construct a variety of models, which, taken together, are consistent with the available information. This ensemble of models typically captures more of the available information than any of the individual models [30]. Each of these individual models will have different implications for potential decisions. A single model drawn from this potentially infinite set of plausible models is not a prediction. Rather, this model is a computational experiment that reveals how the world would behave if the various hypotheses encapsulated in this single model about the various unresolvable uncertainties were correct.

A key challenge is to develop effective strategies for searching through the implications of the ensemble of plausible models for the decision problem at hand. Two families of search strategies can be identified: open exploration and directed search. Open exploration can be used to systematically explore the set of plausible models. That is, open exploration aims at generating a set of computational experiments that covers the space of plausible models, or uncertainty space for short. This exploration relies on the careful design of experiments and can use techniques such as Monte Carlo sampling, Latin Hypercube sampling, or factorial methods. An open exploration can be used to answer questions such as "under what circumstances would this policy do well?", "under what circumstances would it likely fail?", and "what kinds of dynamics can this system exhibit?". An open exploration provides insight into the full richness of behaviors of the ensemble of models.

Open exploration uses series of computational experiments. In order to reason on this ensemble, the results from these computational experiments have to be analyzed. The main algorithm that is used for this is the Patient Rule Induction Method (PRIM) [34]. PRIM tries to find combinations of values for input variables that result in similar characteristic values for one or more outcome variables. Specifically, the algorithm seeks a set of hyper rectangular subspaces of the uncertainty space within which the values of a single output variable are considerably different from its average values over the entire uncertainty space. PRIM describes these subspaces in the form of boxes of the uncertainty space. This results in a very concise representation, for typically only a limited set of dimensions of the uncertainty space is restricted. That is, a subspace is characterized by upper and/or lower limits on only a few input dimensions.

In contrast to open exploration, directed search is a search strategy for finding particular cases that are of interest. Directed search can be used to answer questions such as "what is the worst that could happen?" "What is the best that could happen?" "How big is the difference in performance between rival policies?" A directed search provides detailed insights into the dynamics of specific locations in the full space of plausible models. Directed search relies on the use of optimization techniques, such as genetic algorithms and conjugant gradient methods. Open exploration and directed search can complement each other. For example, if the open exploration reveals that there are distinct regions of model behavior, directed search can be employed to identify more precisely where the boundary is located between these distinct regions.

Although scenario discovery can be applied on its own [15, 35, 36], it is also the analytical core of Robust Decision Making [13, 37-39]. Robust decision-making is a model-based decision support approach for the development of robust policies. That is, policies that perform satisfactorily across a very large ensemble of future worlds. In this context, scenario discovery is used to identify the combination of uncertainties under which a candidate policy performs poorly, the vulnerabilities of a candidate policy, allowing for the iterative improvement of this policy. The use of scenario discovery for Robust Decision Making suggests that it could also be used in other planning approaches that design plans based on an analysis of the conditions under which a plan fails to meet its goals [40]

3 A global container shipping model

In this section, we introduce the global container model which is the basis for the exploratory modeling, including the associated uncertain factors that will be explored.

3.1 A strategic global container network choice model

The World Container Model is a strategic network choice model for global container flows [7]. The model considers more than 400 major ports, 237 countries, and more than 800 shipping lines. Given a country-to-country origin destination demand matrix, the model calculates how container flows are distributed over the global network of shipping lines and through the various ports. Transport costs in the model are based on transport time, distance, toll, value of time of the goods transported, and cost of handling the containers at the ports. The formal definition of the cost model is delineated below:

$$C_r = \sum_{p \in r} A_p + \sum_{l \in r} c_l + \alpha\left(\sum_{p \in r} T_p + \sum_{l \in r} t_l\right) \tag{1}$$

where:

- C_r costs of route r
- p ports used by the route
- l links used by the route
- A_p total cost of transshipment at port p
- c_l total cost of transportation over link l
- T_p time spent during transshipment at port p
- t_l time spent during transportation over link l
- α value of transport time (USD/day/ton)

The mode of transport (sea or land modes) is embedded in the network attributes and does not appear in the cost formula. This mode-abstract formulation enables the use of a more detailed underlying multimodal network; the aggregate result is a level of service expressed in time and cost. The value of the attractiveness parameter A_p and the scaling parameter α are unknown and need to be estimated. The scaling parameter l captures the phenomenon that, although individual shippers and carriers may decide to use one port or another, their aggregate behavior results in the use of more than one alternative route and that their joint response to policies is a smooth one.

The model enumerates the majority of plausible route alternatives for major countries in the world using the publicly available service tables of shipping lines worldwide and a shortest path algorithm. A route from port of origin to port of destination is determined by first looking at the port-call order of container shipping lines worldwide and then, based on this order, using a shortest path algorithm to identify the sub-segments of the complete shortest route for each port-to-port segment of a shipping line. Hence choice sets are generated for every country O/D pair using both the physical network and the network of service lines defined on top of this physical network.

For instance, a route between an origin country O and destination country D, starting at an origin port S and a destination port E is defined by one or more maritime services between S and E, with intermediate transshipment at ports where a change of service can be carried out. For each (outgoing) port S to the (incoming) port E the shortest path is added to the choice set of this combination O–S–E–D (see Figure 1).

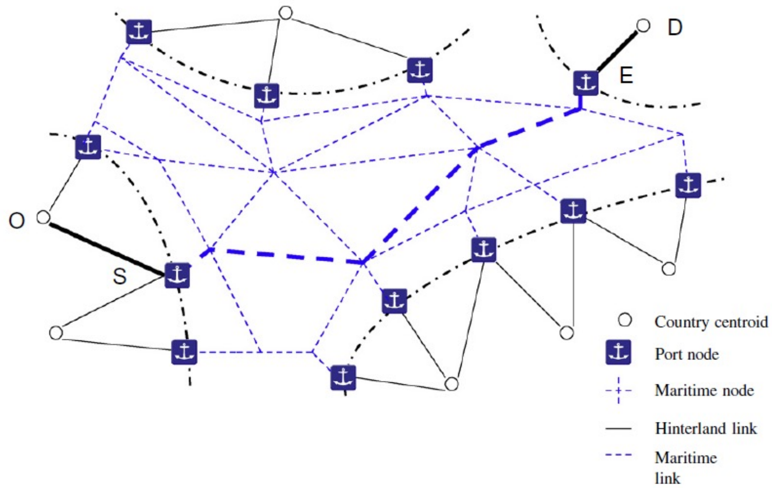

Figure 1 Example of a route between OD-country pair [adapted from 7].

The model accounts for both maritime connections between two countries as well as overland connections between these countries. The route and port choice algorithms uses a path-sized logit model which takes overlaps between the alternative routes into account and describes the transport costs associated with these alternatives correctly [41]. The following is the formal definition of the route choice model. The route probabilities are given by:

$$\mathrm{P_r} = \frac{e^{-\mu(C_r + \ln S_r)}}{\sum_{h \in CS} e^{-\mu(C_h + \ln S_h)}} \tag{2}$$

With the path size overlap variable S defined as

$$\mathrm{S_r} = \sum_{\mathrm{a} \in \Gamma_r} \left(\frac{\mathrm{z_a}}{\mathrm{z_r}} \right) \frac{1}{N_{ah}} \tag{3}$$

where:

P_r the choice probability of route r

C generalized costs

CS the choice set

h path indicator

μ logit scale parameter

a link in route r

$\mathrm{S_r}$ degree of path overlap

Γ_r set of links in route r

$\mathrm{z_a}$ length of link a

$\mathrm{z_r}$ length of route r

N_{ah} number of times link a is found in alternative routes

Calibration of the model was done at an aggregate level using available port throughput and transshipment statistics. The resulting global flows of containers are shown in Figure 2. The network allows hinterland transportation routes with different modes of transport such as truck, rail, waterways or short sea but is omitted here for visual convenience. The thickness of the lines indicates the magnitude of the flows on each links. Each port is visualized as a pie chart, which shows the magnitude of throughput (in dark grey) and transshipment (in light grey).

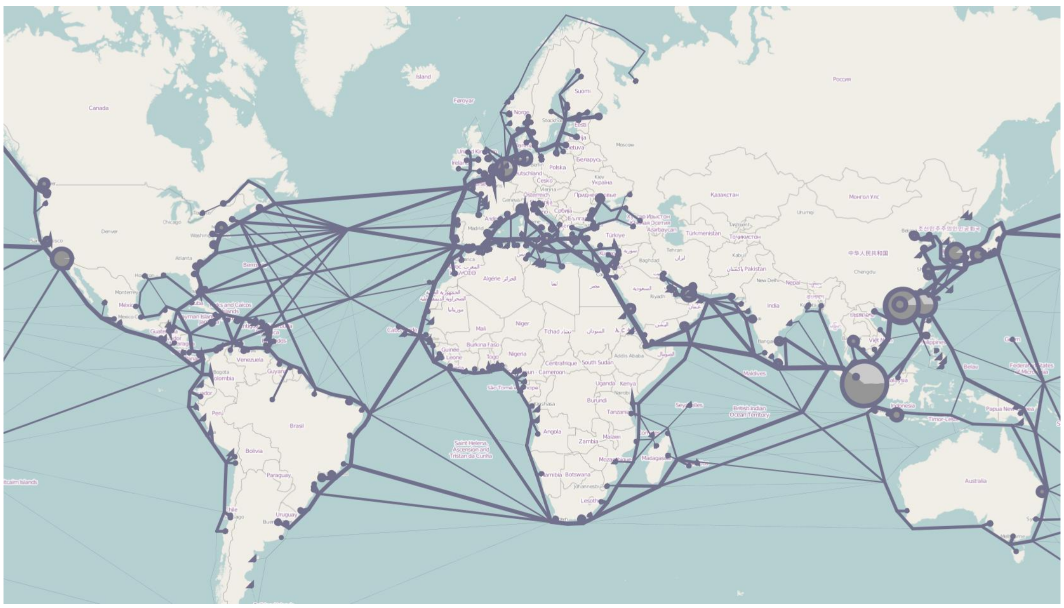

Figure 2 the global maritime shipping network in the WCM

3.2 Identification of relevant uncertainties

In this paper, we use the world container model to assess the impact of several key uncertain factors on the global flow of containers. The following key uncertainties are treated in the exploratory modeling analysis:

Table 1 Key Uncertainties that will impact the performance of ports in the Bremen- le Havre range

Name	Range
Cost of hinterland connections in Europe	0%– 25%
Hinterland cost for Rotterdam	-25% – +25%
Travel time of the hinterland connections of Rotterdam	-2 days –+2 days
Costs of the hinterland connection of Mediterranean ports	-25% – 0%
Handling costs of the Mediterranean ports	-25% – 0%
Handling costs of ports in the Bremen and le Havre range	-25% – 0%
Trade volume with Asia that is affected by availability of overland connection or shift of production to Eastern Europe	-25% – 0%

Northern passage over Arctic route	{present, absent}
Suez Canal	{present, absent}

We identified the key uncertainties above by means of brainstorming and discussions between the experts from various organizations, including the Port authority, Delft University of Technology, and the national research institute TNO. The main source of input was a group decision room session with 14 experts; 11 of which were from the Port authority, 2 were from Delft University of Technology, and 1 was from TNO. All experts in the group decision room session were male. These brainstorm sessions and in depth discussions where fed by a meta-analysis of transport scenarios and forecasts across the globe, from a heterogeneous set of actors including port authorizes, national governments, international think tanks, and other knowledge institutes. Visions on possible future developments, forecast studies, vision documents from various institutions, and historical data pertaining to each of these uncertainties have been used as input for the discussion. Since we are interested to study the impacts of uncertainties on European ports in general and Rotterdam in particular, the key uncertainties that are identified are limited to those that will potentially impact these ports.

One of the most plausible uncertain factors that could make the ports in Bremen-Le Havre range to experience a decline in container flows is the increase of hinterland transport cost. This increase in cost can be caused by congestion at the terminals, environmental tax, bottlenecks in the inland waterways, etc. A related factor that is subject to change is the hinterland cost of Rotterdam. This change can be caused by congestion or improvement in efficiency of the transport networks that connect Rotterdam to the hinterland destinations. In line with the scenario discovery approach, we took a broad bandwidth into account for this factor. We assumed that the change in cost can vary from 25% increase to 25% decrease respectively. Next, the same presumption is also applied to the travel time of Rotterdam's hinterland connections. Improvement in logistics services at the terminal and throughout forwarding process can bring reduction to the total time needed to transport the containers. We specify a range of plausible change for this variable between -2 to 2 days, representing an increase and a decrease in the time efficiency respectively. For the ports in the Bremen – Le Havre range, a change of two days amounts to a significant change on virtually all hinterland connections.

Furthermore, we also identify the developments in Mediterranean ports that can potentially present threats and opportunities for Rotterdam. The Mediterranean ports are closer to the main sources of products shipped to Europe in South East Asia and China. From a logistical point of view, this makes these ports quite attractive. A plausible development is the improvement of hinterland connections of these ports. The improvements can take form of better connectivity due to availability of better infrastructure such as rail and road, and the availability of better freight forwarding services. Eventually, this development can be foreseen to reduce the cost of the hinterland connections of these ports. Furthermore, in the face of competition with ports in the Bremen-Le Havre range, Mediterranean ports might reduce their tariff so that they can increase their attractiveness for the freight forwarders, especially for containers that can be directly shipped from and to Southern Europe. The plausible range for the reduction of hinterland cost due to this development is assumed to reach a maximum of 25% of the current cost.

The ports in the Bremen – Le Havre range are quite competitive and part of their strategy can be a reduction in tariffs. This reduction in tariff would also increase their attractiveness for liner shipping alliances that use Ultra Large Container Vessels (ULCV) so that they would call hub ports in the Bremen-Le Havre range. Again, we use a range of up to 25% reduction in tariffs.

At the trade level, we also identify that there can be a reduction in overseas trade volume with Asia due to the presence of overland connections or the possible shift of production to Eastern European countries. As the plausible range of the reduction we used 25% of the current trade volume. Last but not least, we also include uncertainties in the availability of maritime routes such as those via northern passage and Suez Canal. Due to political instability in the Middle East, and the presence of pirates in the Gulf of Aden, the Suez Canal might become too dangerous to be use for shipping. Due to climate change, slowly but steadily, a new possible maritime route is emerging. This northern passage offers an alternative direct route from China and Japan, via the Arctic to Europe.

3.3 Implementation and Computation

The various uncertain factors may affect the same model parameter. In this case, we handle the effects from the different uncertain factors additively. That is, say we have a computational experiment with an increase of costs on the hinterland connections in Europe of 20%, in combination with a change of the hinterland connection costs for Rotterdam of -10%, than the final costs will be the original costs + original costs * 0.2 + original costs * -0.1.

To explore the consequences of the various uncertain factors in an open exploration, we defined 10,000 experiments using Latin Hypercube sampling across these 9 uncertainties. This means we generate 10,000 random values for each of the uncertainties within the specified ranges and combine these values in a random order into 10,000 sets of 9 input parameters for the model. So, we sample across the 9 uncertainties simultaneously. Next, the world container model is run for each of the 10,000 scenarios. The experiments where performed of a 48 logical core Xeon E5 workstation, and 192 GB of RAM. Runtime was roughly 4 hours. To support the computational experimentation, and the subsequent analysis, we used the Exploratory Modelling Workbench [42]. This is an open source python project that facilitates the entire process of scenario discovery. The World Container Model is implemented in Java and connected to the workbench using JPype, a Python-Java bridge.

4 Results

In this section we present the results of exploratory analysis using two different approaches: open exploration and directed search. By using the open exploration approach, we identify how the uncertain factors jointly impact the throughput of the ports in the Bremen- le Havre range. Subsequently, we use PRIM in order to gain a deeper insight on the meaning of the results for Port of Rotterdam. This analysis results in the identification of main factors, which jointly cause Port of Rotterdam to be both vulnerable and flourishing. They are the combination of input variables that cause the ports to experience decline and gain in their throughput respectively. Next, we also apply directed search technique to identify the worst possible scenario that could happen to the port of Rotterdam. This analysis results in the identification of the conditions under which this scenario manifests itself, and to what extent Rotterdam will be negatively impacted by plausible uncertainties.

4.1 Open exploration and scenario discovery

Figure 3 shows the change of throughput for the ports in the Bremen – Le Havre range across the 10,000 scenarios. To facilitate interpretation, we divided the throughput resulting from the model by the base flow when there is no uncertainty introduced. This implies that a score lower than 1 means a loss of flow, while a score above one means an increase in flow. In order to allow a comparison across the different ports in the Hamburg – Le Havre range, we have visualized the results across the 10,000 scenarios using a Gaussian Kernel Density Estimate (KDE). The colloquial interpretation of a KDE is that it is a continuous alternative to a histogram.

So, the figure suggests that Hamburg, Antwerp and Dunkirk are most vulnerable to losing flows. Most of the mass of the KDE of each of these ports is below 1. In contrast, Le Havre and Bremen have most of their mass above 1, suggesting that they benefit from the various uncertain factors. The ports of Rotterdam and Zeebrugge occupy a middle position. The figure also suggests that there is substantial downside risk, and a smaller percentage wise upside opportunity: ports can lose close to 50% of their flow, but only gain a max of almost 20%.

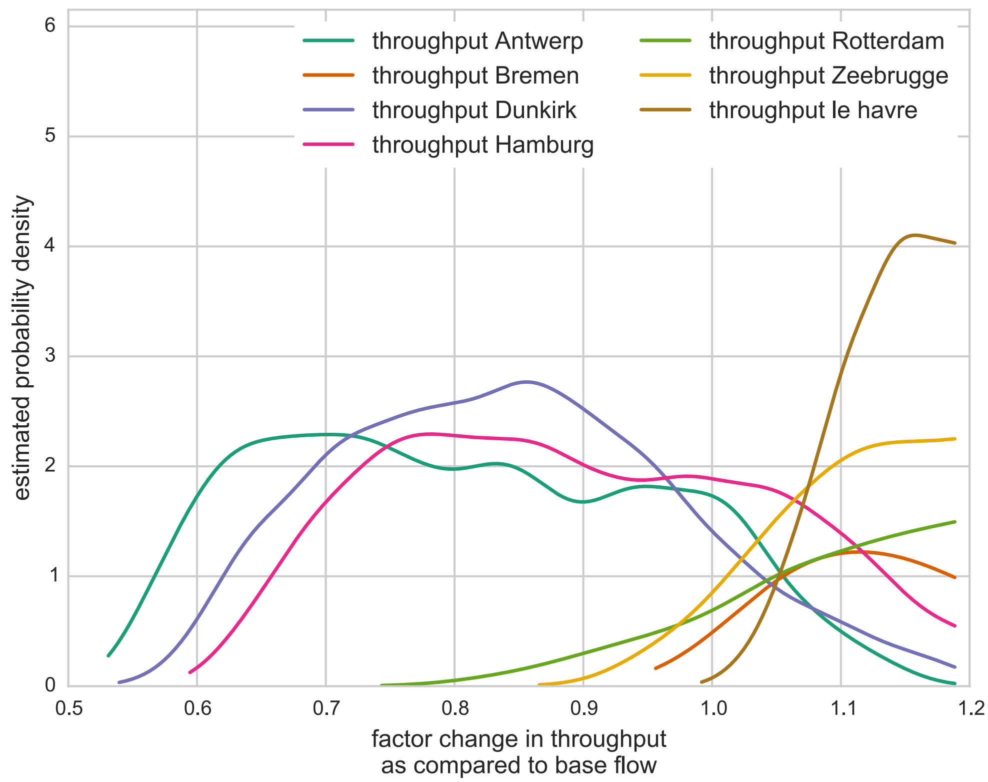

Figure 3 Impacts of key uncertainties on the throughput of ports in the Bremen-Le Havre range

Looking closer at the result for Port of Rotterdam, we observe that there is a small but substantial amount of mass below 1. This suggests that there are quite a number of scenarios where Rotterdam loses throughput as a result of the various uncertain factors. This is indicated by the relatively large area covered by the graph between roughly 0.75 and 1. This suggests that the consequence of the uncertainties can be significant, where Rotterdam suffers a 25% reduction in their throughput. Based on these findings, it is valuable to get a deeper insight into the combination of uncertain factors that jointly cause Rotterdam to be vulnerable and potentially lose their throughput.

First, we specify when a scenario is of interest or not by establishing a classification rule. To this end, we classify all cases where Rotterdam witnesses any decline in throughout compared to the reference case as being a case of interest. Specifically the following equation is used to classify all the results:

$$f(x) = \begin{cases} 1, & if\ x < 1 \\ 0, & otherwise \end{cases} \tag{4}$$

where x is the factor change in throughput as compared to the base flow for Rotterdam as also used in Figure 3. Next, we use PRIM to identify the combinations of uncertainties that jointly produce undesirable results. PRIM returns multiple explanations for the undesirable results. The analyst can select the explanation that covers most of the undesirable result - this is known as coverage in scenario discovery - while also being mainly valid for the undesirable results – this is known as density in scenario discovery [12]. To assess whether the inclusion of a given uncertain factor in a given explanation is statistically significant, one can use a one-sided binomial test - this is sometimes also called the quasi-p value in scenario discovery [12].

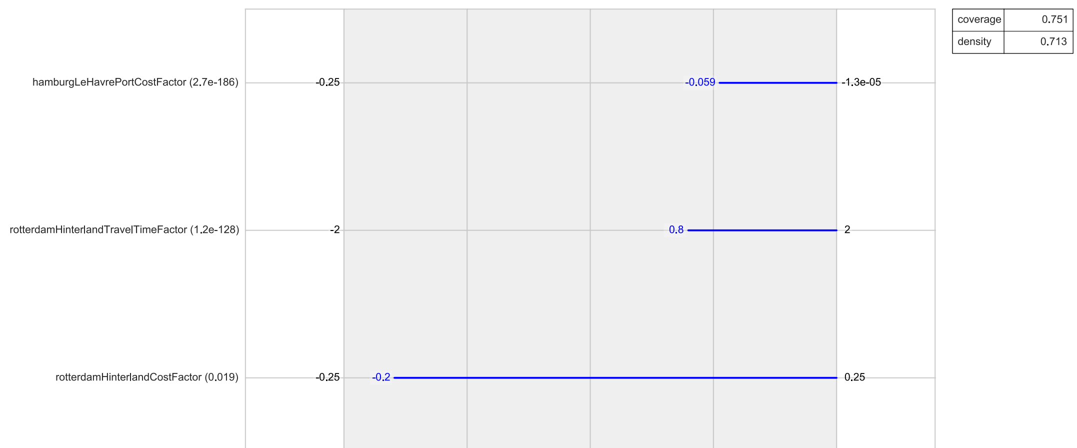

Figure 4 Key uncertainties that play a significant role in explaining major cases with negative impact for Rotterdam

Figure 4 shows the results from the PRIM analysis. This figure shows that 75% of the cases with a loss of throughput can be explained by the combination of three uncertain factors: the Hamburg – le Havre cost factor, the Rotterdam hinterland travel time factor, and the Rotterdam hinterland cost factor. The shaded light grey background specifies the full range for each of these uncertain factors, while the blue bars specify the subspace as identified by PRIM. Between brackets, behind each label, the quasi-p value is shown. As can be seen, each of the three restrictions is statistically significant. So, what does this result imply? In essence, if Rotterdam experiences an increase of travel time on the hinterland of 0.8 days or more, in combination with a small reduction in costs for the ports in the Bremen – le Havre range, and not an extreme reduction in costs on the hinterland of Rotterdam, Rotterdam will lose throughput. This suggests, that the quality of the hinterland connections of Rotterdam strongly determines the competitive position of Rotterdam in the Bremen – le Havre range.

Interestingly, an increased efficiency on the hinterland connections of the Mediterranean ports in combination with a reduction in costs for these ports does not cause a significant decline in the throughput of Rotterdam. Furthermore, it is also remarkable that the reduction in trade with Asia does not significantly affect the changes in the throughput of Rotterdam.

4.2 Directed search for worst case discovery

4.2.1 In search of a perfect storm

In light of the results of the open exploration, a follow-up question was formulated by the Port Authority: is there a perfect storm scenario, where a set of disconnected small changes substantially affects the throughput and transshipment of the Port? This question can be formulated as a two objective optimization problem

$$\text{maximize } F(l_p) = \left(\frac{Tp_{rotterdam}(l_p)}{Tp_{rotterdam}(l_{rc})}, \frac{Ts_{rotterdam}(l_p)}{Ts_{rotterdam}(l_{rc})}\right) \tag{5}$$

$$\text{Where } l_p = \begin{bmatrix} P_{eucosts} \\ P_{rothintercosts} \\ P_{rothintertravel} \\ p_{medportcost} \\ p_{medhintercost} \\ P_{hlehcosts} \\ p_{northern} \\ p_{suez} \\ P_{tradechange} \end{bmatrix}$$

$$p_{northern} \in \{true, false\}$$

$$p_{suez} \in \{true, false\}$$

subject to:

$$c1: 0 \leq P_{eucosts} \leq 0.05 \tag{6}$$

$$c2: -0.05 \leq P_{rothintercosts} \leq 0 \tag{7}$$

$$c3: -0.1 \leq P_{rothintertravel} \leq 0.1 \tag{8}$$

$$c4: -0.05 \leq p_{medportcost} \leq 0 \tag{9}$$

$$c5: -0.05 \leq p_{medhintercost} \leq 0 \tag{10}$$

$$c6: -0.05 \leq P_{hlehcosts} \leq 0 \tag{11}$$

$$c7: -0.05 \leq P_{tradechange} \leq 0 \tag{12}$$

where l_{rc} is the performance in the reference case without any uncertain factors, Tp is throughput, and Ts is transshipment. So, the aim is to find a scenario where the ratio compared to the reference case is minimized, subject to a max 5% change on each of the 7 continuous uncertain factors.

To solve this multi objective optimization problem, we used ε-NSGA2, a state of the art genetic algorithm for solving multi-objective optimization problems [43]. We ran the algorithm for 150 generations, and as can be seen in Figure 5, the algorithm converged over the course of this simulation. A detailed inspection of the results reveals that all solutions are at the edges specified by the constraints. That is, the maximum negative deviations that are possible specify the worst-case scenarios for Rotterdam. These worst-case scenarios all point to a little bit less than 5% reduction in throughput and transshipment for Rotterdam, given a maximum of 5% change on the uncertain factors. Follow up analyses where we change these boundaries to 10% and 15% respectively, yielded essentially the same results. The loss in transshipment and throughput is about equal to the maximum percentage change allowed on the various uncertain factors.

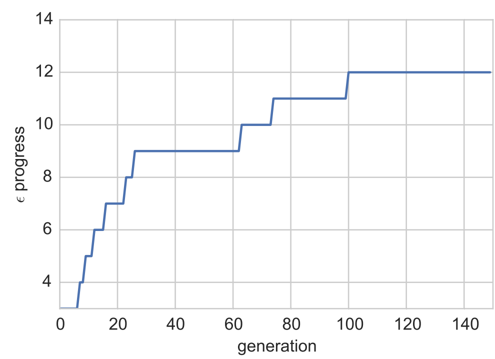

Figure 5. Cumulative ε-progress over the course of running ε-NSGA2

4.2.2 Impact of the competition from Mediterranean ports

The analyses so far aimed at investigating situations where Rotterdam experiences changes in their throughput, or where its competitiveness changes as a result of changes in ports in the Bremen-Le Havre range. Based on the previous analysis, we have discovered that a decrease in the cost factor in Mediterranean ports is not able to increase the competitiveness of these ports relative to Rotterdam. Specifically, the container flows to Rotterdam are not affected significantly when port cost factors of these ports are reduced.

Since there have not been many studies concerning competition between Rotterdam and Mediterranean ports, a more thorough investigation on how increased competitiveness of Mediterranean ports will impact container flows in Rotterdam can give a valuable insight to the port of Rotterdam. Hence, in this analysis, we address the question: under which change in the hinterland costs of the Mediterranean ports will Rotterdam be impacted negatively? Thus, instead of defining a plausible range of variable values in which uncertainties might be present and looking at the outcomes caused by one or more major variables, we look at how big the change in input variables needs to be in order to cause the system to behave in a very specific manner. Specifically we are interested to find combinations of factors, which will minimize the throughput difference between Rotterdam and each of the Mediterranean ports. This problem can be modeled as a multi-objective optimization problem where the values of input variables, which minimize the throughput differences simultaneously, are searched. The following is the formulation of the problem.

$$\text{Minimize } F(l_p) = \left(f_{genoi}, f_{barce}, f_{marsf}, f_{laspii}, f_{venii}\right) \tag{13}$$

$$\text{Where } l_p = \begin{bmatrix} p_{eucosts} \\ p_{medportcost} \\ p_{medhintercost} \\ p_{northern} \\ p_{suez} \end{bmatrix}$$

$$f_i = |T_{rotterdam} - T_i|$$

$$i \in \{Genoi, Barce, Marsf, Laspii, Venii\}$$

$$p_{northern} \in \{true, false\}$$

$$p_{suez} \in \{true, false\}$$

subject to:

$$c1: 0 \leq p_{eucosts} \leq 0.25 \tag{14}$$

$$c2: -1.0 \leq p_{medportcosts} \leq 0 \tag{15}$$

$$c3: -1.0 \leq p_{medhintercosts} \leq 0 \tag{16}$$

Again, ε-NSGA2 is used for solving this multi-objective optimization problem. As can be seen in Figure 6, the algorithm converged over the course of 150 generations.. Figure 7 shows the results found by the optimization algorithm. In the two sub figures, we use parallel coordinate plots. These plots can be used to visualize data with more than three dimensions. This is achieved by depicting each dimension as a vertical line. A multidimensional data point is depicted as a line connecting each of the different dimensions. The left hand side figure presents the values of each decision variable for each solution, while the right hand side figure present the values of the objective functions of the problem.

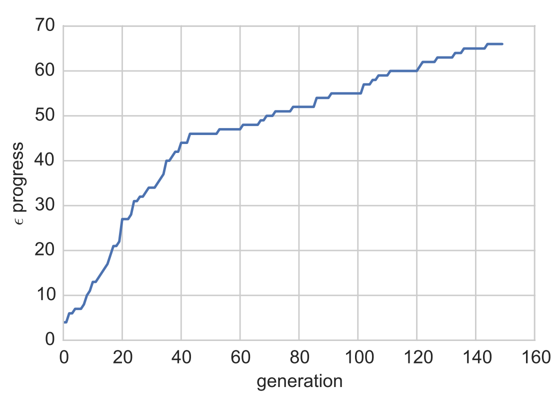

Figure 6 ε-progress

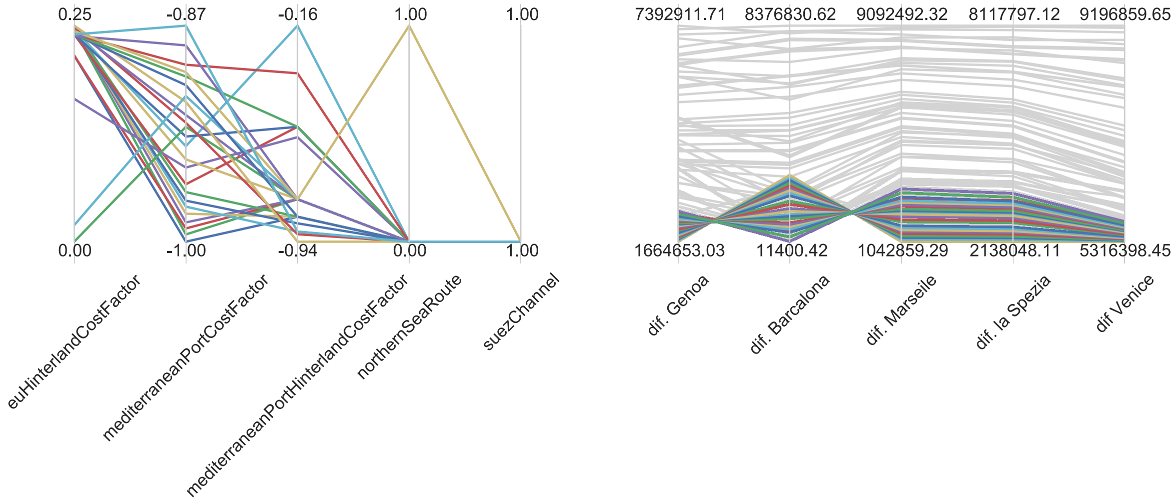

Figure 7 Optimization results

As can be seen from the right hand side figure in Figure 7, when the throughput difference between Rotterdam and each of the Mediterranean ports is minimized simultaneously, each of the solutions presents a trade-off across the objective functions. This means all of these solutions are non-dominated. That is, there is not a solution with superior performance in comparison with other solutions. For example, virtually all lines trade off the performance of Genoa and Barcelona. If one has minimized the difference between Genoa and Rotterdam, the difference between Barcelona and Rotterdam increases and vice versa.

From the result, it can be concluded that both port and hinterland costs of the Mediterranean ports need to decline significantly in order for them to be competitive against Rotterdam. Surprisingly, the closing of Suez Canal and the opening of arctic route also contribute to the increase of Mediterranean port's competitiveness. This can only happen when liner-shipping companies that call at Mediterranean ports before calling Rotterdam do not change their port rotation schedule in the event of such disruptions. In this case, the shortest path from many countries in Far East to Rotterdam is through the northern passage if this is available. As a result, transport cost from these countries to Rotterdam will increase significantly due to the increase in distance that has to be travelled by these shipping companies. If the northern passage is not available, the shortest route is via Cape Town. In a more realistic scenario, an adaptation of the shipping routing is expected to take place. We return to this point below.

5 Closing remarks

The global container transport network is constantly changing in response to a wide range of developments. It is virtually impossible to correctly anticipate the future dynamics of global flows of containers, due to the intrinsic complexity of the network and the wide range of uncertain factors affecting the network. For ports, this poses a fundamental challenge in the long term planning of their strategy and investments.

To address the combined challenge of complexity and uncertainty, we used a novel model-based approach to scenario development. Rather than predicting future container flows for a limited set of alternative assumptions, we systematically explored what the container flows could be across 10,000 scenarios, covering 9 uncertain factors. The analysis focused on the consequences of uncertainty for the competitive position of the port of Rotterdam in the Bremen – le Havre range. Uncertainties that were taken into account included changes in global trade flows, changes in the physical network available to ships, and various factors related to transportation costs of ports in Europe and costs on the hinterland connections within Europe. It was found that the critical factor affecting the competitive position of Rotterdam is the quality of their hinterland connection. A modest increase in travel time on the hinterland connections from Rotterdam will shift flows away to other ports in the Bremen – le Havre range.

In two follow up analyses, we used an optimization based search strategy in pursuit of two worst-case scenarios. First, we searched for the presence of a perfect storm scenario, where a set of small changes jointly substantially deteriorates the competitive position of the port of Rotterdam. We were not able to find such a perfect storm, which suggests that the competitive position is quite robust with respect to small changes.

In a second analysis, we tried to find a scenario where the Mediterranean ports become serious competitors of Rotterdam. We were able to find such a scenario, which includes the use of the northern passage and the closure of the Suez Canal. This counterintuitive result suggests two things. First, it points again to the robust position of Rotterdam in the current global container-shipping network. Second, the results of the second directed search point to one of the main limitations of the presented study. The uncertain factors we explored focus on different aspects of global container transport, but they were mainly focused on the ports and the hinterland connections. We have not explored the impact of changes in the shipping line network itself and how these could affect global trade flows. The analyses that have been performed assumed the global shipping service networks to remain the same across different scenarios. This is a gap that needs to be addressed, as this change in the networks presents an additional uncertainty to the ports in the Bremen- Le Havre range and makes the position of these ports more vulnerable. This is not a trivial challenge. At present, to the best of our knowledge, no model exists that represents the dynamics of all global shipping line networks over time. The available literature, instead, focuses on optimizing the routing and frequency for individual shipping lines, or occasionally for an individual shipping company.

Modeling how shipping companies change their network is not simple as there are many factors, both observable (such as cost of transport, market share coverage, and international competition policy) and unobservable (internal agreement between shipping companies to form alliances, political agendas of relevant governments, strategic behavior on part of the shipping companies, etc.), that contribute to the actual structure of their network at any given point in time. Hence, in order to systematically deal with this uncertainty, a separate model would be needed. Combining this model with exploratory modeling analysis and scenario discovery would give more valuable insights on how uncertainties in global shipping network will impact the performance of the ports.

The results of this paper demonstrate the value of using scenario discovery with simulation models to explore a wide range of plausible futures and summarize the results into concise and clear insights. Scenario discovery, both through open exploration and directed search provides a solid for answering strategic questions that come up in the long-term planning of ports.

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References

[1] CNBC, West Coast ports: Retail's $7 billion problem, in, 2015.

[2] C. Rastogi, J.-F. Arvis, The Eurasian Connection: Supply-Chain Efficiency along the Modern Silk Route through Central Asia, The World Bank, Washington, 2014.

[3] I.M.O. (IMO), Ships face lower sulphur fuel requirements in emission control areas from 1 January 2015, in, 2014.

[4] R.J. Lempert, S. Popper, S. Bankes, Shaping the Next One Hundred Years: New Methods for Quantitative, Long Term Policy Analysis, in, RAND, Santa Monica, CA, USA, 2003.

[5] J.H. Kwakkel, W.E. Walker, V.A.W.J. Marchau, Classifying and communicating uncertainties in model-based policy analysis, International Journal of Technology, Policy and Management, 10 (2010) 299-315.

[6] T. Durden, The "Catastrophic Shutdown Of America's Supply Chain" Begins: Stunning Photos Of West Coast Port Congestion, in, 2015.

[7] L.A. Tavasszy, M. Minderhoud, J.-F. Perrin, T. Notteboom, A strategic network choice model for global container flows: specification, estimation and application, Journal of Transport Geography, 19 (2011) 1163-1172.

[8] T. Hertel, Future Directions in Global Trade Analysis, in, Center for Global Trade Analysis, Purdue University, Purdue, Indiana, 1999.

[9] P. Sinha-Ray, J. Carter, T. Field, J. Marshall, J.W. Polak, K. Schumacher, D. Songs, J. Woods, J. Zhang, Container World: Global Agent-based Modelling of the Container Transport Business, in: 4th International Workshop on Agent-Based Simulation, Montpellier, France, 2003.

[10] M.G.H. Bell, X. Liu, J. Rioult, P. Angeloudis, A cost-based maritime container assignment model, Transportation Research Part B: Methodological, 58 (2013) 58-70.

[11] J.H. Kwakkel, E. Pruyt, Exploratory Modeling and Analysis, an approach for model-based foresight under deep uncertainty, Technological Forecasting and Social Change, 80 (2013) 419-431.

[12] B.P. Bryant, R.J. Lempert, Thinking Inside the Box: a participatory computer-assisted approach to scenario discovery, Technological Forecasting and Social Change, 77 (2010) 34-49.

[13] S. Dalal, B. Han, R. Lempert, A. Jaycocks, A. Hackbarth, Improving Scenario Discovery using Orthogonal Rotations, Environmental Modelling & Software, 48 (2013) 49-64.

[14] S.C. Bankes, W.E. Walker, J.H. Kwakkel, Exploratory Modeling and Analysis, in: S. Gass, M.C. Fu (Eds.) Encyclopedia of Operations Research and Management Science, Springer, Berlin, Germany, 2013.

[15] J.H. Kwakkel, W.L. Auping, E. Pruyt, Dynamic scenario discovery under deep uncertainty: the future of copper, Technological Forecasting and Social Change, 80 (2013) 789-800.

[16] S.A. van 't Klooster, M.B.A. van Asselt, Practising the scenario-axes technique, Futures, 38 (2006) 15-30.

[17] J. Derbyshire, G. Wright, Preparing for the future: Development of an 'antifagile' methodology that complements scenario planning by omitting causation, Technological Forecasting and Social Change, (2013).

[18] P.W.F. van Notten, A.M. Sleegers, M.B.A. van Asselt, The future shocks: on discontinuity and scenario development, Technological Forecasting and Social Change, 72 (2005) 175-194.

[19] T.J.B.M. Postma, F. Liebl, How to improve scenario analysis as a strategic management tool?, Technological Forecasting and Social Change, 72 (2005) 161-173.

[20] J.D. Sterman, Learning in and about complex systems, System Dynamics Review, 10 (1994) 291-330.

[21] P.W. Atkins, R.E. Wood, P.J. Rutgers, The effects of feedback format on dynamic decision making, Organizational Behavior and Human Decision Processes, 88 (2002) 587-604.

[22] J.D. Sterman, Modeling managerial behavior: Misperceptions of feedback in a dynamic decision making experiment, Management science, 35 (1989) 321-339.

[23] L. Sastry, D.R. Boyd, Virtual environments for engineering applications, Virtual Reality, 3 (1998) 235-244.

[24] D. Dörner, The logic of failure: Recognizing and avoiding error in complex situations, Basic Books, 1996.

[25] B. Brehmer, Dynamic decision making: Human control of complex systems, Acta psychologica, 81 (1992) 211-241.

[26] B. Kleinmuntz, Computers as clinicians: An update, Computers in biology and medicine, 22 (1992) 227-237.

[27] E. Diehl, J.D. Sterman, Effects of feedback complexity on dynamic decision making, Organizational Behavior and Human Decision Processes, 62 (1995) 198-215.

[28] S. Hallegatte, A. Shah, R. Lempert, C. Brown, S. Gill, Investment Decision Making Under Deep Uncertainty: Application to Climate Change, in, The World Bank, 2012.

[29] S. Bankes, Exploratory modeling for policy analysis, Oper. Res., 41 (1993) 435-449.

[30] S.C. Bankes, Tools and techniques for developing policies for complex and uncertain systems, Proceedings of the National Academy of Sciences, 99 (2002) 7263-7266.

[31] D. Campbell, D. Farmer, J. Crutchfield, E. Jen, Experimental mathematics: the role of computation in nonlinear science, Commun. ACM, 28 (1985) 374-384.

[32] N. Oreskes, K. Shrader-Frechette, K. Belitz, Verification, Validation, and Confirmation of Numerical Models in the Earth Sciences, Science, 263 (1994) 641-646.

[33] J.D. Sterman, Business Dynamics: Systems Thinking and Modeling for a Complex World, McGraw-Hill/Irwin, Boston, MA, 2000.

[34] J.H. Friedman, N.I. Fisher, Bump hunting in high-dimensional data, Statistics and Computing, 9 (1999) 123-143.

[35] J. Rozenberg, C. Guivarch, R.J. Lempert, S. Hallegatte, Building SSPs for climate policy analysis: a scenario elicitation methodology to map the space of possible future challenges to mitigation and adaptation, Climatic Change, (2013).

[36] M.D. Gerst, P. Wang, M.E. Borsuk, Discovering plausible energy and economic futures under global change using multidimensional scenario discovery, Environmental Modelling & Software, (2013).

[37] R.J. Lempert, D.G. Groves, S.W. Popper, S.C. Bankes, A General, Analytic Method for Generating Robust Strategies and Narrative Scenarios, Management Science, 52 (2006) 514-528.

[38] R.J. Lempert, M. Collins, Managing the Risk of Uncertain Threshold Response: Comparison of Robust, Optimum, and Precautionary Approaches, Risk Analysis, 24 (2007) 1009-1026.

[39] C. Hamarat, J.H. Kwakkel, E. Pruyt, Adaptive Robust Design under Deep Uncertainty, Technological Forecasting and Social Change, 80 (2013) 408-418.

[40] 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.

[41] M. Ben-Akiva, M. Bierlaire, Discrete Choice Methods and their Applications to Short Term Travel Decisions, in: R. Hall (Ed.), Handbook of Transportation Science, Springer US, 1999, pp. 5-33.

[42] J.H. Kwakkel, E. Pruyt, Using System Dynamics for Grand Challenges: The ESDMA Approach, Systems Research and Behavioral Science, (2013).

[43] P. Reed, J.B. Kollat, V.K. Devireddy, Using interactive archives in evolutionary multiobjective optimization: A case study for long-term groundwater monitoring design, Environ. Model. Softw., 22 (2007) 683-692.