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Robustness – a Challenge also for the 21st Century

A Review of Robustness Phenomena in Technical, Biological and Social Systems as well as Robust Approaches in Engineering, Computer Science, Operations Research and Decision Aiding

An internship report by

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SUMMARY

Notions on robustness exist in many facets. They come from different disciplines and reflect different worldviews. Consequently, they contradict each other very often, which makes the term less applicable in a general context. Robustness approaches are often limited to specific problems for which they have been developed. This means, notions and definitions might reveal to be wrong if put into another domain of validity, i.e. context. A definition might be correct in a specific context but need not hold in another. Therefore, in order to be able to speak of robustness we need to specify the domain of validity, i.e. system, property and uncertainty of interest. As proofed by Ho *et al.* in an optimization context with finite and discrete domains, without prior knowledge about the problem there exists no solution what so ever which is more robust than any other. Similar to the results of the No Free Lunch Theorems of Optimization (NLFTs) we have to exploit the problem structure in order to make a solution more robust. This optimization problem is directly linked to a robustness/fragility tradeoff which has been observed in many contexts, e.g. “robust, yet fragile” property of HOT (Highly Optimized Tolerance) systems. Another issue is that robustness is tightly bounded to other phenomena like complexity for which themselves exist no clear definition or theoretical framework. Consequently, this review rather tries to find common aspects within many different approaches and phenomena than to build a general theorem for robustness, which anyhow might not exist because complex phenomena often need to be described from a pluralistic view to address as many aspects of a phenomenon as possible. First, many different robustness problems have been reviewed from many different disciplines. Second, different common aspects will be discussed, in particular the relationship of functional and structural properties. This paper argues that robustness phenomena are also a challenge for the 21st century. It is a useful quality of a model or system in terms of “the maintenance of some desired system characteristics despite fluctuations in the behaviour of its component parts or its environment” (s. [Carlson and Doyle, 2002], p. 2). We define robustness phenomena as solution with balanced tradeoffs and robust design principles and robustness measures as means to balance tradeoffs.

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CONTENTS

1. Introduction

Notions and definitions on robustness exist in abundance. It is an important linguistic element to describe desirable properties of an object. Today almost every scientific discipline deals with robustness problems, e.g. engineering, physics, mathematics, computer science, decision aiding, operations research, management, social science, biology, etc. In scientific literature often we face expressions like “robust result”, “robust method”, “robust behaviour”, “robust outcome”, “robust decision” and many more. This indicates that the term robustness is abstract and broad in nature and can be adapted and broken down from very general to very case specific problems. Synonyms for robustness which describe structural properties of entities are for example “physically strong”, “strength”, “hardiness” or “resistance”. Of course this notion is rather intuitive and not very sophisticated and indeed it is a much more general concept. Definitions on robustness exist in many different fashions and refer to many different contexts, moreover for confusion, they are sometimes vague or contradictory.

The general problem we face is a problem of complexity which undermines our aim to arrive at a holistic concept and theoretical framework for robustness. It is a rather impossible task to describe ideally every aspect of a complex phenomenon. It is quite easy to make precise and significant statements in simple systems, but the more complex a phenomenon is the harder it is to make statements which are not only precise but also significant. Moreover, at a certain level of complexity these two properties become exclusive. Then, one can only make precise statements for small subsystems but not significant statements for the system at a whole, or one can make significant statements on a rather coarse level but these are doomed to be vague in nature. Furthermore, if we don’t specify the domain of validity of a statement, i.e. the context, statements can be contradictory. Therefore, a proper specification of the context, i.e. system, system level, system properties, interactions, perturbations of interest, is crucial if one wants to address robustness.

In the theory of dynamic systems, for example, structural stability is also referred as to robustness and addresses in this case the persistence of system properties, i.e. the conservation of qualitative system behaviour despite perturbations on the structural level. Sensitivity analysis describes robustness in terms of insensitive model parameters that means the output variability is rather neglectable in relation to the variations in input factors. These two examples illustrate in case of robust external behaviour the perturbation of some structural properties does not or only slidely affect the functional properties of interest. Both concepts emphasis parameter as well as structural uncertainty of mathematical models. Sensitivity analysis is most frequently used to test parameter uncertainty but with knowledge about insensitive parameters we can modify and reduce, respectively, the model structure to the one which is most crucial for the analysis.

The fundamental human desire for robustness is also a desire for security and control in everyday life. Although technical progress comes up with ever more complex systems, their behaviour should be easy to understand, reliable and controllable for the user. As we will see later on, there exist a tradeoff between robustness and complexity which makes this goal in general impossible to achieve. In particular, complexity as well as chaos theory showed limitations to our understanding and the ability to predict or control complex natural systems. This paved the path for a new kind of science which focuses on robustness of complex adaptive systems such as ecosystems, social systems or economic systems. Contrasting features like fragility and robustness and their interactions are at the core of this research field. Instead of just focusing solely on the dynamics of a system as in stability theory of dynamic systems, it also deals with the internal structure of a system as well as its “design”. As a result, one can define “robust design principles” which do not guarantee robustness but many robust systems will most probably encounter a whole bundle of these design principles. Moreover, it is often this abundance of principles and not a sole one from which robustness emerges. It might be of special significance for further research to analyse the interactions of such bundles of principles. Design will be a principle with ongoing evolution, which leads to simple, robust and reliable external behaviour of a system with complex internal structure.

The general notion on robustness which is put forth in this article is the system’s ability to deal with uncertain, intransparent and heterogeneous environments and internal components, while the environment and the system itself are subject to more or less rapid changes in composition and topology as well as function. This is achieved by the system through balancing tradeoffs in the system, which also means current adaptation should not compromising the system’s ability to adapt to changes in the future.

More general questions are “Which underlying principles lead to robust behaviour in the presence of uncertainty?”, “How is it possible that complex systems are robust, yet adaptable, i.e. able to respond to changing circumstances?”, “Why show systems extreme, sometimes catastrophic or cascading, fragility after long-term success?” “What are the major differences between robustness and sensitivity and stability, respectively?” Therefore, we are interested in fundamental processes leading to robustness.

This article has two parts, the first part provides a comprehensive overview of existing research directions and several definitions on robustness, but it is not a complete literature review and does not give an overall overview. It is an attempt to illuminate and cross-link robustness approaches from different disciplines, whereby literature was selectively chosen from many different disciplines. The second part is based on the first one and ventures a first integration step of several important aspects and tries to give a holistic as well as pluralistic view from different point of views.

2. Robust Design in Engineering and Computer Science

2.1 Introduction

Robustness, reliability are two fundamental design principles for engineering products to increase production and product quality and thereby increase user or customer satisfactory. Furthermore, these principles are powerful to improve engineering productivity, i.e. reduce costs, improve quality and simultaneously reduce development interval in production processes. This indicates that optimization of the processes is most important and mostly used approach to reach these goals. In particular, it is quite accepted that the most advantage and benefit can be expected if these principles are integrate into the production process as early as possible to get the highest standard right from the beginning. Quality measures are introduces from different points of view, first, from the engineering perspective, and second, from the user or customer perspective.

2.2 Robust Design

Robust Design or Taguchi Method, (s. [Phadke, 1989], [Taguchi *et al.*, 2000]) is one example of an application of these principles. Taguchi et al. state "[r]obustness is the state where the technology, product, or process performance is minimally sensitive to factors causing variability (either in the manufacturing or user environment), and aging at the lowest manufacturing cost." (s. [Taguchi *et al.*, 2000], p. 4) This definition is manifested in a Robust Engineering concept and is related to engineering quality, whereby expressed by Taguchi two main types of product quality are important:

1. Engineered quality:
   It reflects the quality measure from the engineering perspective, e.g. criteria like serviceability, reliability, performance, etc., and is related to robust engineering. It ensures that the product will produce acceptable performance throughout the intended lifespan of the product that means without unwanted defects or drawbacks in performance.
2. Customer quality:
   It reflects the quality measure from the user or customer point of view, e.g. criteria like "look and feel", ergonomics, functionality, etc., and reflects customer satisfaction.

He claims to arrive at optimized engineering productivity and maximized customer satisfaction, therefore it is important to implement Taguchi Method in the earliest stage of production process, or in other words, to design to highest standards early in the process to eliminate all random errors. This means to integrate a priori robustness measures into the process instead of making simply ex post analysis.

In this context a robustness strategy is one that prevents problems through optimizing product design and manufacturing process designs that means it aims at variation and error reduction to improve reliability and productivity. It “provides the crucial methodology to systematically arriving at solutions that makes designs less sensitive to various causes of variation.” (s. [Phadke-Taguchi], p. 2) Phadke (s. [Phadke-Taguchi], p. 2) summarizes that Robustness Strategy uses five primary tools:

1. P-Diagram:
   P-Diagram is used to classify the variables associated with the product into noise, control, signal (input), and response (output) factors.
2. Ideal Function:
   Ideal Function is used to mathematically specify the ideal form of the signal response relationship as embodied by the design concept for making the higher-level system work perfectly.
3. Quantitative Loss Function:
   Quadratic Loss Function (also known as Quality Loss Function) is used to quantify the loss incurred by the user due to deviation from target performance.
4. Signal-To-Noise Ratio:
   Signal-to-Noise Ratio is used for predicting the field quality through laboratory experiments.
5. Orthogonal Arrays:
   Orthogonal Arrays are used for gathering dependable information about control factors (design parameters) with a small number of experiments.

2.3 Robustness Diagram

Important design and quality criteria for software design are correctness, robustness and reliability whereas robustness means, be tolerant on inputs, but strict on output. That means, despite of uncertain, variable and incorrect input by users remain reliable and secure on the output. The main idea behind the concept is also to increase engineering productivity and customer satisfaction.

In the context of Unified Modelling Language several types of diagrams exist to simplify and structure the development and design process of software. One particular diagram is the so called robustness diagram or robustness analysis (s. [Rosenberg *et al*., 1999], [Jacobson *et al*., 1997]). On the background of Use Case Diagrams which means to illustrate and identify possible interactions of the user with the software system and possible functionality of the software system to incorporate these interactions, the robustness diagram can be created. This means to create a diagram containing on the one hand the needed interfaces between user and software system and on the other hand the placeholders for the functionality which has to be integrated into the system. It is an intermediate stage in the design process and fills the gap between Uses Cases and Domain Classes. The related idea behind this concept is the “Model-View-Controller” Design Pattern (indicated in brackets below). Within this methodology there are four main objects:

1. Actor: User of the software product.
2. Interface Object / Boundary Object (View): Object at the system interface.
3. Entity Object (Model): Object representing stored data.
4. Control Object (Controller): Object representing transfer of information.

Design to distributed responsibilities as in the object-oriented programming paradigm is the main approach to deal with complex systems to increase the quality of the engineering products. If robust software is defined to create "reasonable" behaviour in unforeseen circumstances, with the robustness diagram the software developer is able to identify as many as possible, ideally all, interactions between user and software and the controlling unit and database which should tackle these interactions. If done carefully and reasonable it ensures to have no possible type of interactions left out that means at best all sources for incorrect and erroneous input and system failures are taken into account and can be handled. The same principle seems to underlie what is called "Component-based Software Architecture", whereas components are related to interfaces or entities and connectors to controller.

Further examples for design principles to increase for example robustness are modularity, an organizing structure in which different components of a software system are divided into separated functional units with protocols involved which organize communication, functionality and allowed interactions between modules; abstraction, to emphasize the important aspect and deemphasize immaterial aspects; encapsulation, packaging code and data that belongs together. Especially, although complex distributed or network systems like the internet have complex internal structure containing many modules varying in type, they show simple, robust and reliable external behaviour, because much of the complexity is hidden in standardised protocols which organize the communication of the modules.

2.4 Redundancy

Beside these approaches a rather traditional approach in engineering is to create redundant structure which could replace faulty components. Especially in spaceships, components are duplicated as safety installations and units. Despite the fact that redundancy could largely reduce software quality and robustness recent research aims at adding redundancy into complex software systems via agents (s. [Huhns, 2002], [Huhns, 2003]). It is argued that agents by design are able to detect and correct errors in complex software systems, hence increase robustness, whereas to add redundancy means to add components, here agents, with equivalent functionality into the system in order to create reliable behaviour and output in presents of uncertainty and errors. It is important to mention that these software modules can not be identical, or else they could not correct each others errors. Systems which have to provide n functionalities robustly, should have $m \times n$ agents, so that there will be m ways of producing each functionality. For example, "based on a notion of Hamming distance of error-correcting codes, $4 \times m$ agents can detect $m-1$ errors in their behaviour and can correct $(m-1)/2$ errors" (s. [Huhns, 2003], p. 2). The appropriate granularity to add redundancy and the appropriate amount of redundancy is very important since every new module increases complexity and new sources of uncertainty in the system.

3. Robustness in Technical, Biological and Social Systems

3.1 Introduction

Complexity is a common system characteristic in many research directions. Natural systems, in particular ecosystems, are good examples for their complex internal structure and complex interactions as well as regulatory and feedback mechanisms. On the organism level, their are many processes, which on the one hand produce continuously new raw material or variants based on existing organisms and on an immense environmental heterogeneity, and on the other hand select those variants which have at least sufficient potential for survival and fit into existing conditions at least well enough. These are mutual interrelated processes and necessary to create complex natural systems. This issue also addresses the complexity of genetic material. Evolution seems to put forth organisms with ever more complex RNA sequences. For very simple organisms it can be shown that this complexity is necessary to ensure some degree of robustness. This means only a small proportion of genes is responsible to maintain basic functionality and the overwhelming majority exist to ensure the organism's robustness against environmental change, cyclic processes, and stress. Hence, it seems to be necessary to provide robustness before organisms can handle increased environmental complexity. On the other hand, increased complexity demand organisms to improve their robustness and again to increase their internal complexity. As a result living systems seem to produce more complexity as it would be necessary in order to have a buffer against sudden environmental change. In other words, most of the time organisms try to get a competetive edge to environmental challenges. Moreover, structural properties like modularity, degeneracy and redundancy have been reviewed in this article as examples for this incredible adaptability of living systems.

3.2 Highly Optimized Tolerance (HOT)

Many of the mentioned research directions refer to what J. Doyle and J. Carlson call "HOT – Highly Optimized Tolerance" (s. [Carlson and Doyle, 1999], [Carlson and Doyle, 2000], [Reynolds *et al.*, 2001], [Carlson and Doyle, 2002]). That is, tolerance to uncertainties which biological systems were able to evolve to or for which engineering systems were designed. Here the design principle of complex engineering systems recur and is compared to biological systems where similar phenomena are observed due to evolutionary processes. This community in particular shaped the phrase "robust, yet fragile" to ascribe HOT states to complex systems. That means, despite the obvious robustness of these systems, they are also fragile against unanticipated cascading failure events. "HOT systems arise where design and evolution create complex systems sharing common features, including (1) high efficiency, performance, and robustness to designed-for uncertainties, (2) hypersensitivity to design flaws and unanticipated perturbations, (3) nongeneric, specialized, structured configurations, and (4) power laws." (s. [Carlson and Doyle, 1999], p. 1414) In this sense "systems [are] designed for high performance in an uncertain environment and operated at densities well above a standard critical point." (s. [Carlson and Doyle, 2000], p. 2529) Through design and evolution, HOT systems, in biology and engineering, achieve rare structured states, which are robust to perturbations they were designed to handle, yet fragile to unexpected perturbations and design flaws. In other words, HOT systems show "(1) highly structured, nongeneric, self-dissimilar internal configurations and (2) robust, yet fragile external behaviour" (s. [Carlson and Doyle, 2002], p. 2538). "HOT emphasizes the role of robustness to uncertainties in the environment as a driving force towards increasing complexity in biological evolution and engineering design" (s. [Reynolds *et al*., 2001], p. 1).

Carlson *et al*. associate robustness with "the maintenance of some desired system characteristics despite fluctuations in the behaviour of its component parts or its environment" (s. [Carlson and Doyle, 2002], p. 2). However, they stress that one can only speak of robustness, if one references to particular system characteristics or particular component or environmental uncertainties. Thus, a robustness framework is only feasible if context and question as well as type of uncertainty has been specified first. Lattice Percolation Forest Fire Models are at the core of HOT research which simulate the impact of sparks to forest yield in varying forest systems. Reynolds *et al*. (s. [Reynolds *et al*., 2001]) study these "systems as a function of the number of DDOF's [(Design Degrees of Freedom)] [to provide] a concrete, quantitative measure of the structured sensitivity, which is a central feature of the robust, yet fragile HOT states" (s. [Reynolds *et al*., 2001], p. 2). The DDOF's represent the tunable parameters and allow the comparison of minimal to highly designed systems. As the number of DDOF's increases, the system becomes increasingly robust to common perturbations with highly optimized yield well above the critical density, but also becomes increasingly fragile to rare events, i.e. changes in the distribution of sparks and flaws in the design. The internal structure becomes increasingly ordered as the level of design increases, i.e. the connected clusters become increasingly regular in shape and separated by well defined barriers. Thereby, barriers separate acceptable from unacceptable system behaviour, in particular from cascading failure events. Such internal complexity seems to minimize external complexity and creates simple, reliable, robust external behaviour, despite uncertainty in component parts and in the environment.

A characteristic feature of these systems is that the additive fragility is almost hidden to the observer, that means, only becomes apparent if rare failure events occur. This seems to be a drawback of this exhaustive optimization, the interconnected and interdependent structure and the operation at high densities, which results in an increased risk of cascading failure events and chain reactions. An insight into the internal dynamics of complex, interconnected systems gives the statistics of events whereas the distributions of event sizes follow power laws. Thereby, the HOT states of "robust, yet fragile" systems become visible as heavy tails in appropriate $\log(P)$ vs. $\log(l)$ plots where P is the cumulative probability of events and l the size of events.

This research community claims that robustness to uncertainty in the environment is a driving force towards increasing complexity in biological evolution and engineering design. They examine tradeoffs between robustness and internal simplicity and claim that simpler systems do not lose their basic functionality, but their robustness. Therefore, most of the complex internal structure was not developed to deliver or improve basic functionalities but to ensure the robustness of these basic functionalities in uncertain environments.

3.3 Constrained Optimization with Limited Deviations (COLD)

A variation on HOT is done by Newman *et al*. (s. [Newman *et al*., 2002]). Their framework is called “COLD - Constrained Optimization with Limited Deviations” and makes up an expansion to the HOT concept. The authors give an analytical solution for the lattice model and claim to explain the origin of the power laws. In order to do so, they used a continuum forest fire model instead of lattice model which make the mathematical treatment more tractable. Moreover, they generalized the model to incorporate risk aversion by introducing an utility function. As a result, less risk aversion limits the large deviations in the event size distribution which becomes visible in truncation of the tails of power laws. Similar to the classical gambler’s ruin problem which states that optimizing total return leads to ruin with probability one, but can be avoided if one accepts suboptimal return. They state if, for example, a risk-averse engineer accepts some loss in average system performance, disasters become rare and the system more robust, i.e. less fragile to unanticipated failure events, in this context more robust against design flaws and changes to the distribution of sparks.

3.4 Modular Architectures in Biological and Technical Systems

Csete *et al*. define robustness as “the preservation of particular characteristics despite uncertainty in components or the environment” (s. [Csete and Doyle, 2002], p. 1664) and try to cross-link design principles and system-level characteristics of advanced technologies to complex biological systems. Convergent evolution describes the biological phenomenon that, in many instances, animals which live in similar habitats resemble each other in outward appearance, i.e. similar morphological, physiological and ethological features, although these similar looking animals may, however, have quite different evolutionary origins, i.e. different phylogeny. According to this, Csete *et al*. point out that convergent evolution “produces modular architectures that are composed of elaborate hierarchies of protocols and layers of feedback regulation” (s. [Csete and Doyle, 2002], p. 1664), due to the demand for robustness to uncertain environments and imprecise components.

In this context, modules are ingredients, parts, components, subsystems, and players, and protocols describe the corresponding recipes, architectures, rules, interfaces, etiquettes, and codes of conduct. Moreover, protocols are rules that prescribe allowed interfaces between modules and therefore are important for complexity and robustness respectively of biological and engineering systems. They enable modularity and supply both robustness and evolvability, that means facilitate evolution and are difficult to change, but also add complexity and create new and often extreme fragility, which is largely hidden from the observer except by large failure events, in particular if they are “fine-tuned” to robustness.

3.5 The Origin of Modules

Regarding modularity Wagner *et al*. (s. [Wagner *et al*., 2001]) review recent research about models and ideas for the evolutionary origin of modules and identify open question in explaining the expected robust and unitary mechanisms behind its origin. They stress that only a combination of mechanisms will be able to explain the origin of evolutionary modules. For them there is a connection between a selective advantage and modularity, in other words, natural selection put forth modularity because the most important effect of modularity seems to be its potential to increase evolvability. Hence, "[m]odularity evolves as a result of selection for evolvability." (s. [Wagner *et al*., 2001], p. 4) In particular, modular organisms like plants are very adaptive to changing environmental conditions. Here, recombination of its parts offers an incredible high number of new forms, while natural selection will discard all variants with low fitness. As a consequence, the more modular an organism is, the better it is able to evolve over time.

3.6 Degeneracy and Redundancy

Tononi *et al*. (s. [Tononi *et al*., 1999]) work on degeneracy and redundancy in biological networks. By using information theoretical concepts they develop functional measures of redundancy and degeneracy in a system with respect to a set of outputs. With these measures they are able to distinguish between degeneracy and redundancy within a unified framework and to make them operable to characterize and understand the functional robustness and adaptability of biological networks. They differentiate between degeneracy and redundancy as follows: Degeneracy is "the ability of elements that are structurally different to perform the same function [or yield the same output, but also] may produce different outputs in different contexts". In contrast, redundancy is apparent if the "same function is performed by identical elements" (s. [Tononi *et al*., 1999], p. 3257). In other words, a degenerate system appears to be functionally redundant with respect to particular outputs in a particular context, but it may perform different in different contexts, whereas a structurally redundant system, i.e. with identical elements, cannot do so. Therefore, they differentiate redundancy on the structural level, which means identical elements and thus same functionality, from redundancy on the functional level, i.e. the ability of structural different elements to perform similar functionality. As a consequence, degenerate systems, unlike completely redundant systems, are extremely adaptable to unpredictable changes in circumstances and output requirements. However, they acknowledge that "no element can functionally substitute for any other element and the system is extremely brittle" (s. [Tononi *et al*., 1999], p. 3261). This notion of fragility is comparable to the "robust, yet fragile" behaviour of complex systems which has been introduced above in the context of HOT systems. The system seems to be robust against changes but thereby incorporate new fragility. "In a fully redundant system, [...] [a]ll elements [...] perform the same function. Although that function may be extremely robust, there is no flexibility to accommodate different functions when circumstances change. [In contrast, a degenerate system] is [...] functionally redundant and fault-tolerant [...] [as well as] highly adaptive" (s. [Tononi *et al*., 1999], p. 3261).

As a result they emphasize the relationship between degeneracy and redundancy by stating that on the one hand a system must have a certain degree of functional redundancy to be degenerate, otherwise it would not be able to perform similar functionality. On the other hand, a fully redundant system will not be degenerate, because the functional differences between distinct elements and thus their ability to contribute independently to a set of outputs will be lost. “The ability of natural selection to give rise to a large number of non-identical structures capable of producing similar functions appears to increase both the robustness of biological networks and their adaptability to unforeseen environments by providing them with a large repertoire of alternative functional interactions.” (s. [Tononi et al., 1999], p. 3261)

Edelman *et al.* (s. [Edelman and Gally, 2001]) expand these considerations and stated that degeneracy is a feature of complexity, a ubiquitous property of biological systems at all levels of organization and a necessary accompaniment of natural selection. Furthermore, the term redundancy seems to be somewhat misleading, because it suggests to be a property selected exclusively during evolution, either for excess capacity or for fail-safe security. The authors take the contrary position and refer to degeneracy. According to them, degeneracy is not a property simply selected by evolution, but rather is a prerequisite for and an inescapable product of the process of natural selection itself. To support their argumentation and sharpen the difference at the structural level examples are given to compare design and selection in engineering and evolution, respectively. Their point of view goes further than the HOT theory and the interpretations stated above, because in this context there are fundamental differences between biological phenomena and complex engineering system. “In general, an engineer assumes that interacting components should be as simple as possible, that there are no ’unnecessary’ or unplanned interactions, that there is an explicit assignment of function or causal efficacy to each part of a working mechanism, and that error correction is met by feedback, modeling, or other paradigms of control theory. Protection can be achieved by planned redundancy, but adventitious compensation for error is neither expected nor usual. Irrelevancy is avoided from the outset. By contrast, in evolutionary systems, where there is no design, the term ’irrelevant’ has no a priori meaning. It is possible for any change in a part to contribute to overall function, mutations can prompt compensation, stochastic interactions with the environment can lead to strong selection, often there is no fixed assignment of exclusive responsibility for a given function, and, unlike the engineering case, interactions become increasingly complex [..., which] results not only from selection in rich environments [...] but also from the prevalence of degeneracy.“ (s. [Edelman and Gally, 2001], pp. 13763-13764) As a connection to complexity they state that a “[c]omplex system may be considered as one in which smaller parts are functionally segregated or differentiated across a diversity of functions but also as one that shows increasing degrees of integration when more and more of its parts interact. Put otherwise, a complex system may be viewed as one that reveals an interplay between functional specialization and functional integration. Intuitively, it is easy to see that, below a certain level of complexity, there will be very few ways in which structurally different parts can interact to yield the same output or functional result. Accordingly, at low levels of complexity, degeneracy will be low or nonexistent. In contrast to that, a defined function, however, redundancy can still exist even in relatively simple systems.” (s. [Edelman and Gally, 2001], pp. 13763-13767)

3.7 Biological Robustness

Krakauer *et al*. (s. [Krakauer and Plotkin, 2002], [Krakauer, 2003]) group biological mechanisms into principles of robust organization and describe case studies to illustrate these robustness principles. These include: canalization, neutrality, redundancy, purging, feedback, modularity, spatial compartmentalization, distributed processing and the extended phenotype. Krakauer *et al*. summarize several robustness concepts from different disciplines (s. [Krakauer, 2003], pp. 2-3):

- "In ecology, stability or robustness is a measure of the preservation of species diversity upon species removal or, the permanence of a configuration when perturbing some variable of ecological interest."
- "In medicine, robustness is associated with healing and compensation, neither of which imply a return to the original phenotype but rather a restoration of wildtype function."
- "In linguistics, robustness relates to competence and comprehensibility despite incomplete information and ambiguity. Thus structural transformation is acceptable subject to information remaining decodable."
- "In paleontology, robustness relates to the continuity of lineages across geological eras, and the persistence of lineages during mass extinction events."
- "In metabolism, robustness relates to limited phenotypic variation across large changes in kinetic parameters."
- "In cell biology, robustness can describe how cell fate decisions remain constant when transcription regulation is stochastic, or how conserved RNA secondary structures can remain resistant to point mutation."

Moreover, he states that in "each of these cases robustness relates either: (1) non-detectable or minor modification in phenotype following a large perturbation to the genotype, (2) non-detectable or minor modification in phenotype following a large perturbation to the phenotype from the environment, (3) non-detectable or minor modification in function following a large perturbation to the genotype or phenotype with or without a correlated change in the phenotype." (s. [Krakauer, 2003], p. 3)

Thereby, he arrives at a distinction between genotypic, environmental and functional robustness and suggests robustness measures for each type:

- In the case of phenotypic robustness perturbations are inherited while coming from the genotype, and phenotypic robustness can be measured through the mutational variance (V_m) of a trait.
- In the case of environmental robustness perturbations are not inherited while coming from the environment, and environmental robustness can be measured trough the environmental variance (V_e) of a trait.
- Functional robustness can be achieved through phenotypic invariance or phenotypic plasticity. In one case the phenotype resists perturbations, and in the second case, the phenotype tracks perturbations. Functional robustness can be measured as the variance in geometric mean fitness.

As a result of his comparison and synthesis he identified glimpse intersections among principles (s. [Krakauer, 2003], p. 13):

- "[R]edundancy, modularity, spatial compartmentalization and distributed processes, share the use of a multiplicity of self-contained units discretely connected, to ensure a degree of autonomy of processing."
- "The feedback control, the developmental module and the connectionist model all exploit saturation effects to damp down the consequences of non-linearity."
- "Almost all models assume some form of special connectivity, whether it be among neurons, classes of mutation, modules, signalling molecules, or immune effectors."

3.8 Robust Design

Erica Jen's research is about a robustness phenomenon, referred to as "Robust Design", in social, biological and engineering systems (s. [Jen, 2005], [SFI_Robustness]). In particular, she discusses the differences between robust and stable phenomena (s. [Jen, 2003]). While emphasizing that robustness has "multiple, sometimes conflicting, interpretations" (s. [Jen, 2003], p. 1) she also provides a wide spectrum of different definitions (s. [SFI Definition]), which is an important prerequisite to arrive at a pluralistic view on the subject useful as a starting point for synthesis and integration. She points out that "robustness is a measure of feature persistence in systems that compels us to focus on perturbations, and often assemblages of perturbations, qualitatively different from those addressed by stability theory." (s. [Jen, 2003], p. 1) Actually, persistence had itself different meanings depending on context as in the robustness and stability context. The following definition on persistence is related to the stability and perturbation concept: Persistence is the time which a variable last after being perturbed before changing into another state. From stability theory of dynamic systems she reviews two different stability phenomena. First, "a solution (meaning equilibrium state) of a dynamic system is said to be stable if small perturbations to the solution result in a new solution that stays 'close' to the original solution for all time." (s. [Jen, 2003], p. 2) Second, a "dynamic system is said to be structural stable if small perturbations to the system itself result in a new dynamic system with qualitatively the same dynamics." (s. [Jen, 2003], p. 2)

She observed two commonalities between the robustness and stability concepts (s. [Jen, 2003], p. 2):

1. "[B]oth concepts are defined for specified features of a given system, with specified perturbations being applied to the system. It makes no sense to speak of a system being either stable or robust without first specifying both features and the perturbations of interest."
2. "[B]oth stability and robustness are concerned with the persistence, or lack thereof, of the specified features under the specified perturbations. Persistence therefore can be seen as evidence of either stability or robustness."

She also differentiates between stable and robust (s. [Jen, 2003], pp. 2-3):

1. Compared to stability "robustness addresses behavior in a more varied class of
   - systems;
   - perturbations applied to the system of interest;
   - features whose persistence under perturbations is to be studied."
2. Moreover, "robustness leads naturally to questions that lie outside the purview of stability, including
   - organizational architecture of the system of interest;
   - interplay between organization and dynamics;
   - relation to evolvability in the past and future;
   - costs and benefits of robustness;
   - ability of the system to switch among multiple functionalities;
   - anticipation of multiple perturbations in multiple dimensions;
   - notions of function, creativity, intentionality, and identity."

More in detail, she reviews the following notions on robustness (s. [Jen, 2003], pp. 4-5):

- "Robustness is a measure of feature persistence for systems, or for features of systems, that are difficult to quantify, or to parameterize (i.e. to describe the dependence on quantitative variables); and with which it is therefore difficult to associate a metric or norm."
- "Robustness is a measure of feature persistence in systems where perturbations to be considered are not fluctuations in external inputs and internal system parameters, but instead represent changes in system composition, system topology, or in the fundamental assumptions regarding the environment in which the system operates."
- "It is typical in stability theory to postulate a single perturbation; from the robustness perspective it is often ineluctably necessary to consider instead multiple perturbations in multiple dimensions."
- "Robustness moreover is especially appropriate for systems whose behavior results from the interplay of dynamics with a definite organizational architecture. Examples of organizational architectures include those based on modularity, redundancy, degeneracy, or hierarchy, among other possibilities, together with the linkages among organizational units."
- "[T]hese organizational features are in many systems spliced together into [...] 'heterarchies'; namely, interconnected, overlapping, often hierarchical networks with individual components simultaneously belonging to and acting in multiple networks, and with the overall dynamics of the system both emerging and governing the interactions of these networks."
- "[R]obustness is meaningful for heterarchical and hierarchical systems only when accompanied by specification of the 'level' of the system being so characterized. [...] [P]resence or absence of robustness at one level does not imply presence or absence at another level[.]"
- "[R]obustness [in 'complex adaptive systems'] may be interpreted as an index of the relative strengths and weaknesses - what might also be called the 'fitness' - of the set of 'strategic options' that either have been designed top-down or have emerged bottom-up for the system.

The options available to the system serve in other words as a ’strategy’ for how to respond to perturbations.”

- “Robustness is often thought of as reflecting the ability to a system to withstand perturbations in structure without change in function - in the biological context, this is sometimes called ’mutational robustness’, and [...] may be seen as measuring the fitness of a strategy that has either emerged, or has been selected, for responding to insult or uncertainty.”
- In the context of strategic options the robustness concept is useful in unifying these different interpretations: “[R]obustness may be seen as measuring the effectiveness of a system’s ability to switch among multiple strategic options. Robustness in this sense reflects the system’s ability to perform multiple functionalities as needed without change in structure - this might be called ’phenotypical plasticity’.”

As a summary she states “robustness is a concept appropriate to measuring feature persistence in certain contexts; namely, systems [(i)] where the features of interest are difficult to parameterize, [(ii)] where the perturbations represent significant changes either in system architecture or in assumptions built into the system through history or design, or [(iii)] where the system behavior is generated through adaptive dynamics coupled to strong organizational architecture. The study of robustness naturally prompts questions relating to [(i)] organization, [(ii)] the role of history, [(iii)] the implications for the future, and [(iv)] the anticipation of insults, along with other questions even more difficult to formulate relating to [(v)] creativity, intentionality, and identity.” (s. [Jen, 2003], p. 6).

Moreover, Jen introduces the weakest and the stronger form of argument to differentiate robustness from stability (s. [Jen, 2003], p. 10):

- Weakest form:
  “Robustness is an approach to feature persistence in systems for which we do not have the mathematical tools to use the approaches of stability theory. The problem could in some cases be reformulated as one of stability theory, but only in a formal sense that would bring little in the way of new insight or control methodologies.”
- Stronger form:
  “Robustness is an approach to feature persistence in systems that compels us to focus on perturbations, or assemblages of perturbations, to the system different from those considered in the design of the system, or from those encountered in its prior history. To address feature persistence under these sorts of perturbations, we are naturally led to study the coupling of dynamics with organizational architecture; implicit rather than explicit assumptions about the environment; the sense in which robustness characterizes the fitness of the set of ’strategic options’ open to the system; the intentionality P of insults directed at, and the responses generated by, the system; and the incorporation of mechanisms for learning, innovation, and creative problem-solving.”

3.9 Design Principles in Social-Ecological Systems

Anderies *et al*. (s. [Anderies *et al*., 2003]) look at the institutional configuration that affect the interactions between resource, resource users, public infrastructure providers and public infrastructure. In particular, they focus on social-ecological systems (SESs) and try to identify on the one hand potential vulnerable parts of SESs to internal disturbance and on the other hand general robust design principles for this class of systems. Their starting point are existing design principles developed for robust common-pool resource institutions. For them SESs are complex systems composed of biophysical and social components, or in other words, systems where individuals have self-consciously invested resources in some type of physical and institutional infrastructure that affect the way the system functions over time in coping with diverse external disturbance and internal problems.

A special type of SESs are irrigation systems. For Anderies *et al*. an irrigation system contains the following elements:

- A hydrological cycle, which is affected by physical capital in the form of dikes, head-works, canals, and regulatory intakes so as to increase the availability and reduce variability of water supplies to farmers when they need it most.
- Social capital as another form of infrastructure within rules that have been constituted so as to affect when and how much water flows through the system.
- The physical infrastructure, which affects when and how much water flows through the system.
- The institutional infrastructure, which affects how much water is allocated to each farmer and the resources that the farmer must invest in the operation of the system.

Hence, the physical and institutional infrastructure affects, so to speak, the likelihood that the SES will last a long time in a particular environment that is subject to external disturbances.

At the core of their research is a set of robust design principles for common-pool resource systems, e.g. irrigation systems (s. [Anderies *et al*., 2003], pp. 13-14):

1. Clearly Defined Boundaries:
   The boundaries of the resource system (e.g., irrigation system or fishery) and the individuals or households with rights to harvest resource units are clearly defined.
2. Proportional Equivalence between Benefits and Costs:
   Rules specifying the amount of resource products that a user is allocated are related to local conditions and to rules requiring labour, materials, and/or money inputs.
3. Collective-Choice Arrangements:
   Most individuals affected by harvesting and protection rules are included in the group who can modify these rules.
4. Monitoring:
   Monitors, who actively audit bio-physical conditions and user behaviour, are at least partially accountable to the users and/or are the users themselves.
5. Graduated Sanctions:
   Users who violate rules-in-use are likely to receive graduated sanctions (depending on the

seriousness and context of the offence) from other users, from officials accountable to these users, or from both.

6. Conflict-Resolution Mechanisms:
   Users and their officials have rapid access to low-cost, local arenas to resolve conflict among users or between users and officials.
7. Minimal Recognition of Rights to Organize:
   The rights of users to devise their own institutions are not challenged by external government authorities, and users have long-term tenure rights to the resource.
8. Nested Enterprises (for resources that are part of larger systems):
   Appropriation, provision, monitoring, enforcement, conflict resolution, and governance activities are organized in multiple layers of nested enterprises.

By robustness of a system, Anderies *et al*. refer to the definition given by Carlosn and Doyle: “the maintenance of some desired system characteristics despite fluctuations in the behavior of its component parts or its environment” (s. [Carlson and Doyle, 2002], p. 2), and define robustness as “the ability of a SES to remain in its social and/or ecological domain of attraction on a particular time scale” (s. [Carlson and Doyle, 2002], p. 5), which implicates that a system may be robust during one period of time and not in another. In particular, they discuss robustness of the entire system facing a collapse of parts of the system.

In this context they stress the difficulty of interpretation when systems are analyzed at different scales and give an example from a large-scale perspective to illustrate this scaling problem. Here, a local scale resource might collapse in order to maintain desired functions at a larger scale, or in the case of SESs, an ecological system might collapse, but the social system continues to function due to adaptability of social actors to derive resources elsewhere. Hence, they distinguish between the collapse of a resource or an undesirable transformation of the resource and the collapse or loss of robustness of the entire system. Thus, both the social and ecological system requires a collapse before they define a SES to have lost its robustness.

The maintenance of a social system through an environmental collapse brings also a time dimension into the definition of robustness. In fact, a social system that generates and rewards innovation can be robust to many external shocks, as long as it innovates quickly enough. On the other hand, they also discuss the phenomenon that such innovation can make the eventual collapse of a larger system more extreme. According to this, some internal feedback mechanisms might make the system more brittle and a collapse might occur from within the system. For example, the need to mobilize labor and maintain a huge irrigation network might induce a rigid social structure between the public infrastucture providers and resource users, which might make the system brittle and unable to deal with change. It may not be a catastrophic environmental event that causes the whole system to collapse, but the social arrangements that are driven by the society’s need to cope with the environment might make it collapse from within.

Anderies *et al*. argue that a SES is robust “if it prevents the ecological system upon which it relies from moving into a new domain of attraction that cannot support a human population, or induces a transition that causes long-term human suffering” (s. [Carlson and Doyle, 2002], p. 6). Moreover, they argue that the ability of a social system to persist in the face of an ecological collapse is a sign that the system has low adaptive capacity in relation to that ecological resource. Rather than looking for social changes to prevent the collapse of a resource base, the social system maintains itself and looks for another resource to exploit. They call this process a sequential destruction of natural resource and state that unless society can manage to organize around principles other than “replacement technologies”, it is likely they will all eventually collapse, at latest if the finite set of replacement technologies and hence resources have been exploited.

3.10 Heterarchy: Distributed Authority and Organizing Diversity

Stark (s. [Stark, 1999]) studies processes of organizational change with regard to transformation taking place in the societies of East Europe and the former Soviet Union. This transition process, in particular, is characterized by a surprising rapidity of the collapse of communism throughout the Soviet bloc, the election of democratic governments who face an entirely new array of political challenges, and the sweeping embrace of market mechanisms and private property. Robustness of these transition processes can be viewed as the system’s ability to adapt to external disturbances and environmental change in a way not to arrive at suboptimal outcomes in the long run and to preserve its adaptability for future change. This robustness occurs due to specific emergent organizational forms termed “heterarchies”.

He views postsocialist economies as complex adaptive systems (CAS) in which people are actively experimenting with new organizational forms. In and with these new forms, they are testing competing worldviews and beliefs. They are making do with what is available, but if they use the existing institutional materials that are close at hand, they are not for that reason condemned to mimic the old, because one way to innovate is to combine old building blocks (innovation through recombination). “Lock-in” effects, the processes whereby early successes can pave the path for further investment of new resources that eventually lock in to suboptimal outcomes, are a core problem of the postsocialist transformation. In this respect, current adaptation can pose obstacles to future adaptability. Moreover, Stark argues that mainstream notion of the postsocialist transition, the replacement of one set of economic institutions by another set of institutions of proven efficiency, cause problems due to their short-term rationality. According to this notion, economic efficiency will be maximized only through the rapid and all-encompassing implementation of privatization and marketization. Such institutional homogenization might foster adaptation in the short run, but the consequent loss of institutional diversity will impede adaptability in the long run. In particular, organizations that learn too quickly exploit at the expense of exploration, thereby locking into suboptimal routines and strategies, which means that there are possible trade-offs between exploiting old certainties and exploring new possibilities.

Because of these learned lessons from the postsocialist transition Stark turns from a concern about adaptation to a concern about adaptability. This means, he shifts from the problem of how to improve the immediate fit with a new economic environment to the problem of how to reshape the organizational structure to enhance its ability to respond to unpredictable future changes in the environment. At the level of the economic system: a greater variety of organizational forms (a more diverse organizational "gene pool") has a higher probability of having in hand some solution that is satisfactory under changed environmental conditions. The challenge of the organization of diversity is to find solutions that promote the ability to redefine and recombine resources. Stark refers to these emergent organizational forms as to "heterarchies".

Heterarchies are relations of interdependence and characterized by minimal hierarchy and by organizational heterogeneity (i.e. capacity of self-redefinition). With respect to CAS thinking, heterarchies are organizations with multiple worldviews and belief systems competing with each other. Heterarchical features are a response to the increasing complexity of the organization's strategy horizons, or "fitness landscapes". In relentless changing organizations the strategy horizon is unpredictable and its fitness landscape is rugged. To cope with these uncertainties, instead of concentrating its resources on strategic planning, organizations may undergo radical decentralization in which virtually every unit becomes engaged in innovation. The functions of exploration are generalized throughout the organization. These developments of increasingly rugged fitness landscapes increase interdependencies. But because of greater complexity of feedback loops, coordination can not be engineered, controlled, or managed hierarchically. The result of interdependence is to increase the autonomy of work units. Yet at the same time, more complex interdependence heightens the need for fine-grained coordination between the increasingly autonomous units. This means, where search is no longer centralized but is instead generalized and distributed throughout the organization, the solution is distributed authority.

3.11 Fundamental Matrix

Ho *et al.* (s. [Ho and Pepyne, 2002], [Ho *et al.*, 2003]) develop the Fundamental matrix (F-matrix) as a framework for analyzing the "global" qualitative nature of decision making. Thereby they are able to explain in a qualitative and descriptive way many theorems and known results about optimization, complexity, security as well as tradeoffs like performance/sensitivity tradeoff, performance/robustness tradeoff and complexity/fragility tradeoff. Their approach explains also the No Free Lunch Theorems (NFLTs) of Optimization, which are impossibility theorems telling us that a general-purpose universal optimization strategy is impossible, and robust yet fragile nature of highly optimized tolerance (HOT) designs. Another formulation of the NFLTs is the following: "there is no universal optimization procedure of any kind that produces better solutions than all others on all problems or even on all instances of a particular problem" (s. [Ho *et al.*, 2003], p. 783). This means, if we can not make any prior assumptions about the optimization problem we are trying to solve, no strategy can be expected to perform better than any other. The only way one can outperform another is to be specialized to the particular problem under consideration, which means to explicitly exploit its "structure", but conversely, if anything is possible, then nothing can be expected.

However, Ho *et al.* also state that even solutions able to exploit problem structure seem to face fundamental limits. With regard to the theory of highly optimized tolerance (HOT), a theory of complex systems, they are able to explain these limitations. According to this, highly optimized designs, which are robust toward one set of assumed problem instances, can be very fragile and may fail catastrophically when faced with problem instances that are outside the original design assumptions.

Optimization problems are core tasks in decision making. In any case, we make a choice from a population of alternatives so as to optimize a certain objective. With this in mind, the starting point in developing the fundamental matrix is an input space $X = \{x_1, x_2, \ldots, x_{|X|}\}$ (population of alternatives. e.g. decisions, solutions, designs) with $|X| =$ size of input space, an output space $Y = \{y_1, y_2, \ldots, y_{|Y|}\}$ (their performances relative to an objective) with $|Y| =$ size of output space and problem space $F = \{f_1, f_2, \ldots, f_{|F|}\}$ (problem instances, scenarios, situations, objectives, which are unique mappings of the form $F : X \to Y$) with $|F| = |Y|^{|X|} =$ size of problem space. Then we can construct a $|X| \times |F|$-matrix with given discrete, finite sets X, Y and F as follows: The rows of the matrix are labeled with instances of X, the columns with instances of F and the entries are the performances (mappings of the form $f_j(x_i) \in Y$) of all decisions applied to all problems, i.e. the i, j-th entry represents the performance of the input x_i (i-th row) on mapping f_j (j-th column). While the indexing of X and F is entirely arbitrary, they assume the elements of Y as ordered and indexed as $y_0 < y_1 < \ldots < y_{|Y|-1}$ and use the performance rank $Y \equiv \{0, 1, \ldots, |Y| - 1\}$ with 0 the worst and $|Y| - 1$ the best performance. Furthermore, there are three basic assumptions concerning this matrix (s. [Ho *et al.*, 2003], pp. 784-785):

1. Finite World Assumption (FWA):
   All variables come from discrete, finite domains.
2. Uncertain World Assumption (UWA):
   There are always things we can not measure, model, or control, i.e., we are never entirely certain what performance an input will yield. This leads to a distribution over the columns of the F-matrix. Let z be a random column index with mass function $0 \le p(z) \le 1$ for all $z = \{1, 2, \ldots, |F|\}$ and $\sum_{z=1}^{|F|} p(z) = 1$. Then, for a given $x \in X$, they define $y \equiv f_z(x)$. That is, the performance of input x is a random variable whose distribution is determined by the likelihood of the various mappings. According to this, the task of an optimization problem is the following maximization: $\max_{x \in X} E[y] = \max_{x \in X} \left[\sum_{z=1}^{|F|} f_z(x) * p(z) \right]$. They take the decision task as one to select the F-matrix row (decision, solution, design) that maximizes the expected performance, with the expectation taken according to the likelihood of the various

columns as determined by the distribution $p(z)$.

3. Intractability Assumption (IA):
   The notion of intractability is based on considerations about computational complexity. That means, problems whose time to solve grows polynomially as the problem grows are considered "tractable" (P-Problems), while those whose time grows exponentially are considered "intractable" (NP-Problems). Furthermore, the columns (mappings) one can optimize over are referred to as "planned for" columns ($P \subseteq F$), and the remaining columns are the "unplanned for" columns. Here, the number of "planned for" columns $|P|$ grows as a polynomial function of $|X|$, but according to $|F|-|P|=|Y|^{|X|}-|P|$, the number of unplanned for columns grows exponentially in $|X|$, which are therefore intractable problems.

The fundamental matrices have some special structures, many of which come from the following fundamental "Counting Lemma": Consider the fundamental matrix F. In this matrix, each $y \in Y$ appears $|Y|^{|X|-1}$ times in each row. One consequence is that the row sum (hence row averages) are all equal. Others are that of conservation of performance telling that average performance is always conserved, and that of conservation of robustness telling that no strategy is universally more robust than any other, if a strategy is robust if it guarantees a certain level of performance over a range of problems.

With these assumptions and results in mind, Ho *et al.* are able to explain the NFLTs of optimization. According to this, averaged over all possible performance functions (columns of F), the performance is choice (row of F) independent (since all row averages of F, i.e. expected performances, are equal). In other words, no choice is universally better than any other, which means there is no strategy, decision, search algorithm, etc. of any kind that outperforms all others on all problems. This emphasizes the value of knowledge and the limits we face when we lack knowledge or refuse to make any assumptions. In particular, the NFLTs take $p(z)$ to be uniform over the columns of the F-matrix, meaning NFLTs do not hold when $p(z)$ is not uniform over the columns. In that case, some solutions are better than others. These solutions are said to be aligned to the distribution $p(z)$ in the sense that they are able to exploit the structural properties of the f 's that $p(z)$ weights most heavily. Moreover, the problems encountered in practice are usually restricted (e.g. by laws of physics) to subsets of the columns of F. Over subsets of the columns, the row sums are not generally equal, in which case some row choices (strategies) will give better performance than others. Thus, if something is known about which column f comes from, the choice of row can be specialized to this knowledge. In practice, our knowledge is usually a distribution that lies somewhere between the extreme that we know nothing about the problem $f \in F$ we are working on (uniform distribution over the columns of F, which makes all $f \in F$ equally likely) and the extreme that we know exactly which column f we are working on.

However, even with good knowledge and assumptions, there are still unavoidable limitations to our decision-making and optimization capabilities and our ability to solve problems of ever growing "complexity". Here, the complexity of an optimization problem is measured by the number of alternatives $|X|$. Ho *et al.* formulate a lemma called "Fundamental Complexity Limit" (s. [Ho *et al.*, 2003], p. 788): "[A]s the number of alternatives $|X|$ increases without bounds, the ratio of planned for columns to unplanned for columns decreases to zero. Conversely, the ratio of unplanned for columns to planned for columns increases to one." This implicates that with increasing complexity comes an increase in the chance that the system will face an unplanned for situation. Moreover, if such an unplanned for column occurs the theorem "Fragility of Complex Systems" holds (s. [Ho *et al.*, 2003], p. 788): "Suppose the output space $Y = \{0,1\}$ with $0 =$ 'bad' and $1 =$ 'good'. As $|X|$ increases without bounds, the fraction of bad outcomes in the unplanned for columns approaches 50%. In other words, should an unplanned for situation occur, there is a 50-50 chance the outcome will be bad, independent of how good the solution is for the planned for columns." Before Ho *et al.* explain the phenomenon of highly optimized tolerance (HOT) designs and of the robust yet fragile nature of complex systems, they introduce the following definition on "P-Optimality" (s. [Ho *et al.*, 2003], p. 789): "Assume $Y = \{0,1\}$ with $0 =$ bad and $1 =$ good and that the number of planned for columns $|P| \le |F|/2$. A P-optimal solution (short for polynomial-optimal) is any row $x \in X$ that gives good outcomes for all of the $|P|$ planned for columns." Consequently, the theorem about "Robust Yet Fragile" phenomena can be stated as follows (s. [Ho *et al.*, 2003], p. 789): "Suppose $Y = \{0,1\}$ with $0 =$ bad and $1 =$ good and let x be any P-optimal solution. For any given $|X|$, the outcome for a randomly chosen unplanned for column is more likely to be bad than it is to be good." According to Ho *et al.*, this notion of P-optimality is consistent with highly optimized tolerant (HOT) designs. Both give good performance over all of the planned for columns, i.e. both are highly optimized with respect to the planned for columns and tolerant to uncertainty within them. On the other hand, like a HOT design, a P-optimal solution is also fragile in the sense that its performance on an unplanned for column is more likely bad than good. This explains that when HOT designs fail, the failure size distribution tends to be heavy tailed. In other words, when "random" failures (unplanned for situations) occur, large ones happen more frequently than one might otherwise expect based on the usual normality assumptions.

Furthermore, Ho *et al.* identify general tradeoffs encountered in optimization problems. First, they describe a performance/sensitivity tradeoff, which tells us, if our knowledge/ assumptions about the distribution over the columns is ever wrong, then the performance of our optimal solution can be arbitrarily poor. That means, highly optimized designs can be very sensitive to the assumed distribution over the columns of F.

The second tradeoff, the performance/robustness tradeoff, is a way to overcome this sensitivity. Here, if we are unsure about our prior assumptions, instead of selecting the strategy with best performance, we should be conservative and select a strategy that gives good performance over a larger subset of the columns. Consequently, the probability that the outcome will be catastrophic is reduced. In other words, the tradeoff is that “a robust solution must generally give up some performance in return for reduced sensitivity to errors in the prior knowledge/assumptions” (s. [Ho and Pepyne, 2002], p. 564).

Finally, Ho et al. analyze the consequence of increased design complexity (i.e. increase in the number of design choices $|X|$). On the one hand, this increase can result in improved performance, on the other hand, the system become increasingly fragile and sensitive to failure (poor performance). In the former case, the increase in design complexity results in an exponential increase (according to $|Y|^{|X|-1}$) in the number of times the best performance value $y \in Y$ appears in each row. As a result, the possibility that there exists a solution $x \in X$ that gives the best performance for all of the planned for columns rapidly increases. Thus, assuming that the number of columns that we have to optimize against grows slowly with increasing design complexity (slower than $|Y|^{|X|-1}$), then up to a certain point, increasing design complexity can result in improved performance. In the latter case, there appears to be a fundamental tradeoff between the complexity of a design and its fragility (i.e. its sensitivity to catastrophic failure). The probability that a design will face an unplanned for column increases rapidly as the design complexity increases. Moreover, since our design will try to concentrate bad performances under the unplanned for columns, the occurrence of any unplanned for column will tend to give bad performance. That means, the probability of catastrophic bad outcomes increases with increased design complexity.

4. Robustness in Operations Research and Decision Aiding

4.1 Introduction

In Operations Research (OR) and Decision Aiding (DA) many notions about robustness exist. Due to the fact that OR-DA problems are often concerned with the optimization of some objectives, most robustness concepts incorporate these notions of optimality. In particular, robustness aims at acting against the optimality drawback of over-sensitivity towards uncertainty and changing conditions, loss of generality and suboptimal outcome. In the past real world applications of OR-DA problems often led to significant failure, i.e. wrong decisions, and paved the path of new research directions. Today, instead of providing solely an mathematical optimal solution to decision makers, analysts have to take into account on the one hand the needs of decision makers, i.e. their risk aversion and mental model of the problem, and on the other hand the inherent uncertainty and the general nature of the problem. This means, the decision maker has to be integrated a priori into the decision process. Hence, the result of an OR-DA application is not a fixed optimal solution given by the output of a model, but by consultation a bundle of recommendations with acceptable performance and feasibility. Thereby, proactive robustness measures provide means to control sensitivity and to assure solution quality in the presence of uncertainty. The decision maker's perception on the problem and involved uncertainty is valuable knowledge to be exploited in order to arrive in combination with a suitable bundle of robustness measures at robust outcomes. Although its justification is clear, the robustness measures introduced below are quite case specific and far from being general approaches. Much more work is necessary to arrive at a fundamental robustness framework useful for OR-DA.

4.2 Robust Optimization

Mulvey *et al.* (s. [Mulvey *et al.*, 1995]) criticizes traditional Operations Research approaches who incorporate "mean-value" or "worst-case" problems, because in the first case large error bounds easily arise and the second case tend to produce very conservative and potentially expensive solutions. Also inappropriate seems to be the reactive approach of sensitivity analysis (SA) which just "measures the sensitivity of a solution to changes in the input data [...][, but] provides no mechanism by which this sensitivity can be controlled" (s. [Mulvey *et al.*, 1995], p. 269). It aims at discovering the impact of data perturbations or data uncertainties on the model's recommendations. He claims for
proactive approaches which "by design, yield solutions that are less sensitive to the model data" (s. [Mulvey *et al.*, 1995], p. 264) despite the presence of noisy, incomplete, or erroneous data, and hence handle noisy data directly rather than ex post.

One approach to do so is called stochastic linear programming (SLP) which introduces probabilistic information about the data, but it does not take into account higher moments of the distribution of the objective which constitutes the optimization problem and the decision maker's preferences towards risk. The former demand is important in cases of asymmetric distributions and the latter important for risk aversive decision makers while having important decisions on stake.

An alternative approach developed by Mulvey *et al*. which takes these features into account is called Robust Optimization (RO) which integrates goal programming formulations with scenario-based description of problem data, or in other words, it integrates the methods of multi-objective programming with stochastic programming. It embodies as special cases several other approaches which handle noisy and incomplete data, and also extends SLP with the introduction of higher moments of the objective function, and with the notion of model robustness. It is claimed to be a proactive approach which generates a series of solutions that are progressively less sensitive to realizations of the model data from a scenario set and which also hedges against poor system performance which means to incorporate risk aversion, but as a drawback it is also more complex and computationally expensive. Moreover, they stress two basic limitations of RO models. On the one hand the RO models are parametric programs and have no a priori mechanism for specifying a "correct" choice of the parameters, and on the other hand the scenarios are only one possible set of realizations of the data and RO does not provide means to specify scenarios.

Within this framework they introduce two notions on robustness. First, "[a] solution to an optimization problem is defined as: solution robust if it remains 'close' to optimal for all scenarios of the input data," and second, "model robust if it remains 'almost' feasible for all data scenarios" (s. [Mulvey *et al*., 1995], p. 264). The terms "close" and "feasible" are thereby dependent on the choice of norms. They also distinct two components of the model:

1. A structural component, i.e. a vector of decision variables also called design variables, which is fixed and free of any noise in its input data, and whose optimal value is therefore not conditioned on the realization of the uncertain parameters; and
2. A control component, i.e. a vector of control variables also called control variables, which is subjected to noisy input data and to adjustment once the uncertain parameters are observed. The optimal value of this component depends both on the realization of uncertain parameters, and on the optimal value of the design variables.

In order to define the robust optimization problem with its structural and control constraints it is necessary to introduce a set of scenarios $\Omega = \{1, 2, \ldots, S\}$, a set $\{d_s, B_s, C_s, e_s\}$ of realizations for the coefficients of the control constraints associated with each scenario $s \in \Omega$, the probability of the scenario p_s, a set $\{y_1, y_2, \ldots, y_s\}$ of control variables for each scenario $s \in \Omega$, and a set $\{z_1, z_2, \ldots, z_s\}$ of error vectors that will measure the infeasibility allowed in the control constraints under scenario s. With this notation the formulation of the robust optimization problem is as follows (s. [Mulvey *et al*., 1995], p. 265):

Model ROBUST

Minimize $\sigma(x, y_1, \ldots, y_s) + \omega * \rho(z_1, \ldots, z_s)$
(optimization or objective function)

subject to constraints

1. $Ax = b$ (structural constraints whose coefficients are fixed and free of noise)
2. $B_s x + C_s y_s + z_s = e_s$ for all $s \in \Omega$
   (control constraints whose coefficients are subject to noise and adjustment)
3. $x, y_s \geq 0$ for all $s \in \Omega$

They introduce an objective function $\xi = c^T x + d^T y$ which becomes together with multiple scenarios a random variable taking the value $\xi_s = c^T x + d_s^T y_s$ with probability p_s. Here, it consists of an aggregate function $\sigma(\cdot)$ which measures the optimality robustness, whereby different choices are possible, e.g. mean value, "worst-case" measure, or higher moments; a feasibility penalty function which measures model robustness, whereby the choice of the specific form is problem dependent; and a parameter ω, i.e. goal programming weight, which is used to derive a spectrum of answers that trade-off solution robustness and model robustness. In this context it is possible to specify solution and model robustness as follows (s. [Mulvey *et al.*, 1995], p. 265):

1. Solution robust:
   "The optimal solution of the mathematical program [...] will be robust with respect to optimality if it remains 'close' to optimal for any realization of the scenario $s \in \Omega$."
2. Model robust:
   "The solution is also robust with respect to feasibility if it remains 'almost' feasible for any realization of s."

Therefore, the model takes a multi-criteria objective form and thereby measures the conflicting objectives of solution and model robustness. They state that solution robustness is easier accepted in the optimization context and in terms of feasibility rather overemphasized compared to model robustness which is novel in the optimization context regarding the fact that it may not always be possible to get a feasible solution to a problem under all scenarios. It is unlikely that any solution to an optimization problem will remain both feasible and optimal for all scenarios, except in the case in which the system being modelled has substantial redundancies build in, because optimality and feasibility are two sides of one coin and infeasibility will inevitably arise. According to this the feasibility penalty function is used to penalize violations of the control constraints under some of the scenarios. It is important to recognize that the RO model does not aim at dealing with this infeasibility inside the optimization model, but rather will generate solutions with the least amount of infeasibility to be dealt with outside the model.

4.3 Robust Discrete Optimization

Kouvelis *et al*. (s. [Kouvelis and Yu, 1997]) introduces a robustness approach to decision making embedded in a comprehensive mathematical programming framework which is called Robust Discrete Optimization, which encompasses three robustness criteria: Absolute Robustness, Robust Deviation, and Relative Robustness. The result of their methodology is referred as robust decision. The authors also compared their framework with other robustness approaches and state that on the one hand the term robustness is consistent with the use of the term in the strategic decision making literature (s. [Rosenhead *et al*., 1972], [Rosenhead and Mingers, 2001], [Rosenhead Complexity]). Here, the robustness of a decision is related to its flexibility and the amount of strategic options still open to the decision maker in the future, which means after the decision had been made. This implicates the assumption that decision making is an irreversible process and might obstruct future adaptability. Hence, a decision is robust or flexible if it provides a landscape of strategic options which is as large as possible. On the other hand, in the context of robustness terminology of Mulvey *et al*. (s. [Mulvey *et al*., 1995] the Robust Discrete Optimization approach refers to the solution robustness concept. To set the stage the authors summarize the main motivating factors to use their framework:

- the decision environment is fraught with uncertainty and the unpredictability of future states is at the core of decision problems
- decisions of unique, non-repetitive nature are common in most fast and dynamically changing decision environments
- decision makers are risk averse, because he/she has to live with the consequences of the decision
- decisions that are based on uncertain information are evaluated ex post with the realized data as if the actual scenario realization has been known in advance of the decision

Traditional optimization approaches, like deterministic or stochastic optimization approaches, have all their weaknesses, in particular the inappropriate treatment of uncertainties, with which they are bound to fail if applied to real world decision problems. First, they evaluate decisions using only one data scenario whose result is called the “optimal solution” and therefore they are unable to recognize that associated with every decision is a whole distribution of outcomes depending on what data scenario is actually realized. Second, uncertainty is represented by probability distributions, whereby the decision maker is forced to assign probability values to various uncertain data instances with which these instances might be realized, albeit the fact that this task is far from being trivial if the decision environment have multiple interdependent uncertainty factors, hence subjective. “To insert notional probabilities may make the decision maker more comfortable, but that is not necessarily the objective in tackling a decision problem.” (s. [Kouvelis and Yu, 1997], p. 2) Third, decision makers have to trust the mathematical and computational procedure while being confronted with the “optimal” result, because they are separated from the actual decision process and have no possibilities to intervene or to participate. Fourth, these approaches do not take into account that decision maker know that they have to live with the consequences of the decision made, hence are risk averse.

In return the authors suggest an approach:

- which is based on multiple scenarios to represent a wide range of possible future states, which means to represent uncertainty without attaching probabilities to the various outcomes,
- which structures data uncertainty via scenario planning,
- which enables the decision maker to participate in the problem structuring process, that means in the generation as well as in the evaluation process, and
- which take into account the risk aversion of decision makers.

All in all it is claimed to better serve the decision maker's needs. The aim of the robustness approach is to "produce decisions that will have a reasonable objective value under any likely input data scenario to [the] decision model over a prespecified planning horizon." (s. [Kouvelis and Yu, 1997], p. 6) Obviously, the scenario planning approach is an important part of the robustness approach to generate scenarios by using the decision maker's mental model about decision environment. "It is the decision maker's mental image of the current system's decision situation and the future that will generate the scenarios, and subsequently the robust decision that can cope satisfactorily with all of them." (s. [Kouvelis and Yu, 1997], p. 13) Thereby, the main task the robustness approach is to identify potentially realizable input data instances for the decision model appropriate for the situation and to find the decision that performs well even in the worst case of the identified input data instances.

The mapping of risk aversion is done by minimax and minimax regret criteria. The minimax criterion, denoted as absolute robust criterion, tend to lead to conservative decisions based on the anticipation that the worst might happen. "The robust decision is that for which the lowest (highest) level of benefit (cost) taken across all possible future input data scenarios is as high (low) as possible." (s. [Kouvelis and Yu, 1997], p. 6) Decisions tend to be less conservative if minimax regret criteria are applied. They take into account the magnitude of missed opportunities of a decision by benchmarking its performance with the performance of the optimal ex post decision. In algorithmic terminology the task consists of computing the regret associated with each combination of the decision and input data scenario at first and then application of the minimax criterion to the regret values to choose the decision with the least maximum regret. Hence, the minimax regret criterion depends on the definition of "regret". The authors introduced two definitions on "regret". First, denoted as the robust deviation criterion, it is the difference between two values, or more in detail, the difference between the resulting benefit (cost) to the decision maker and the benefit (cost) from the optimal decision, which is the decision taken if they would have known which particular input data scenario would occur. Second, denoted as relative robust criterion, it is the ratio of two values, in particular the ratio of the previous mentioned quantities (i.e., the benefit (cost) of a specific decision and the corresponding benefit (cost) of the optimal decision for a specific input data scenario). It serves as a surrogate measure of the percentage deviation of the robust decision from the optimal decision for any given input data scenario. The robust deviation and relative robustness criteria attempt to exploit opportunities for improvement and look at uncertainty as an opportunity to be exploited rather than just as a risk to be hedged against. The supported definition of the robustness approach via robustness criteria is as follows (s. [Kouvelis and Yu, 1997], p. 15):

1. Absolute Robustness:
   "the performance measure (appropriate for the single scenario decision) is applied for evaluating the decision across all scenarios, and then the worst case performance is recorded as the robustness indicator of the decision";
2. Robust Deviation:
   "the performance of the decision (with the use of the agreed upon single scenario performance measure) for that scenario, and the deviation of the decision performance in that scenario from the best possible performance in the scenario is recorded for all scenarios. Then, the robustness indicator of the decision is the worst observed deviation"; and
3. Relative Robustness:
   "again the performance of the decision against the best possible performance in each scenario is performed, but what is recorded is not the deviation but the percentage from the optimal performance in a scenario. Then, the robustness indicator of the decision is the worst observed percentage deviation from optimality for the evaluated decision across all scenarios."

The formal definition on the criteria requires the introduction of some notations (s. [Kouvelis and Yu, 1997], p. 9): Let S be the set of all potentially realizable input data scenarios over a specified planning horizon. Let X be the set of decision variables and D be the set of input data. They use the notation D_s to denote an instance of input data that corresponds to scenario s. Let F_s denote the set of all feasible decisions when scenario s is realized, and suppose the quality of the decision $X \in F_s$ is evaluated using the function $f\left(X, D_s\right)$. Then, the optimal single scenario decision X_S^* for the input data instance D_s is the solution to a deterministic optimization problem and it satisfies $z_s = f\left(X_s^*, D_s\right) = \min_{X \in F_s} f\left(X, D_s\right)$. Based on the definitions given above Kouvelis *et al*. introduce three optimization problems (s. [Kouvelis and Yu, 1997], p. 9):

- "The absolute robust decision X_A is defined as the one that minimizes the maximum total cost, among all feasible decisions over all realizable input data scenarios, i.e.,
  $z_A = \max_{s \in S} f\left(X_A, D_s\right) = \min_{X \in \bigcap_{s \in S} F_s} \max_{s \in S} f\left(X, D_s\right)$"
- "The robust deviation decision X_D is defined as the one that exhibits the best worst case deviation from optimality, among all feasible decisions over all realizable input data scenarios, i.e., $z_D = \max_{s \in S}\left(f\left(X_D, D_s\right) - f\left(X_s^*, D_s\right)\right) = \min_{X \in \bigcap_{s \in S} F_s} \max_{s \in S}\left(f\left(X, D_s\right) - f\left(X_s^*, D_s\right)\right)$"
- "The relative robust decision X_R is defined as the one that exhibits the best worst case percentage deviation from optimality, among all feasible decisions over all realizable input data scenarios, i.e.,
  $$z_R = \max_{s \in S} \frac{f\left(X_R, D_s\right) - f\left(X_s^*, D_s\right)}{f\left(X_s^*, D_s\right)} = \min_{X \in \bigcap_{s \in S} F_s} \max_{s \in S} \frac{f\left(X, D_s\right) - f\left(X_s^*, D_s\right)}{f\left(X_s^*, D_s\right)}$$"

In mathematical notation the mathematical programs are:

(PA) $z_A = \min \left\{ y \middle| f\left(X, D_s\right) \le y, s \in S; X \in \bigcap_{s \in S} F_s \right\}$

(PD) $z_D = \min \left\{ y \middle| f\left(X, D_s\right) \le y + z^s, s \in S; X \in \bigcap_{s \in S} F_s \right\}$

(PR) $z_R = \min \left\{ y \middle| f\left(X, D_s\right) \le \left(y+1\right) * z^s, s \in S; X \in \bigcap_{s \in S} F_s \right\}$

with the constraint $\bigcap_{s \in S} F_s \neq \varnothing$, which means the intersection of the constraint set, over all feasible scenarios is non-empty. The notation for the general program is:

$\left(P\right) = \min \left\{ y \middle| g\left(X\right) \le y, s \in S; X \in \bigcap_{s \in S} F_s \right\}$ where

$$g\left(X\right) = \begin{cases} f\left(X, D_s\right) & \text{for program } (\mathrm{P_A}) \\ f\left(X, D_s\right) - z^s & \text{for program } (\mathrm{P_D}) \\ \frac{f\left(X, D_s\right) - z^s}{z^s} & \text{for program } (\mathrm{P_R}) \end{cases}$$

Here, the "quality" of the decision is evaluated ex post, whereby the decision quality measure is the deviation of the implemented decision from the performance of the optimal decision for the realized data scenarios. By comparing the "content" of the decision set resulting from minimax and minimax regret criteria it seems to be obvious that in the latter case the content is much "richer", if the decision maker is willing to accept some risk and average system performance to get a broader set of robust decisions.

4.4 Robustness Analysis

Roy (s. [Roy, 1998]) starts with his implications on robustness with a general notion of uncertainty by stating that it is impossible to compute, calculate or measure "true values" of parameters characterizing a natural phenomenon. The "true value" of a parameter may either be unknown or in some cases non-existent. Uncertainty is therefore an obstacle which is not conquerable by computational procedures in the last sense. Obviously, this is also true for analysts who base their work on algorithms or heuristics and are therefore forced to assign numerical values to various parameters in order to obtain results. In the operations research (OR) and decision aiding (DA) context, he makes the remark that finding the "right" solution to problems confronting decision-makers or the attempt to approach the "true" solution for a problem, hence the underestimation or ignorance of uncertainty and imprecision in parameter values as well as lack of determination led to failure in cases where results derived from OR-DA approaches were applied to real world problems in the past. This discrepancy between OR-DA results and reality seems to be the main obstacle to increase usability for decision aiding problems.

Today, Roy sees the objective of OR-DA in providing partial answers to questions asked by decisionmakers. In particular the supported robust conclusion concept combined with robustness analysis approach aims to elaborate partial solutions by taking into account the aspects of lack of knowledge, imprecise values and uncertain future. Robust conclusions which result from robustness analysis are in general used to establish recommendations for decision-maker, but recommendations are not deducible in a logical or objective way from the robust conclusions. Creative and elaborate work has to be done to bridge this discrepancy to infer a recommendation from a robust conclusion. This also reflects the discrepancy between results derived from modelling process and reality, where in the context of OR-DA the analyst have to provide partial answers. Or in other words, "[t]he recommendations that should emerge from the analyst's decision-aiding work concern decisions whose effects will be localized in a universe more or less correctly represented by the model considered" (s. [Roy, 1998], p. 148). Therefore concepts, like robust decision and robustness analysis, which aim at strengthening the robustness of the decision aiding, have to be developed.

According to Roy robustness analysis stays in contrast to sensitivity analysis and turns the perspective upside down. Sensitivity analysis studies the impact of certain variation in the input factors to the output of a procedure or model, whereas robustness analysis starts with an assertion referring to an output going towards a set of input factors which allows the analyst to validate this assertion. This procedure should aim at what happens to feasibility and performances (absolute or relative) of actions directly concerned with a result or output of a model if the actions are put into operation in the "universes" of possible futures or possible true values corresponding to diverse input factors. Or in other words, in order to analyse the robustness of an action we are interested in the performance or payoff of a fixed action if it is confronted with varying assumptions. That means, we fix the output with assertions and look at the performance by varying the input. Thereby, it is possible to assess the range of variation of the input without changing the output significantly and the performance is measured by comparing the losses of the actions regarding variations in the input.

In this context the author suggest some conventions on notation and terminology. First, he distinguished data from parameters. Data are variables for which one and only one value can be used, whereas parameters are variables whose field of values can not be reduced to a single value. Moreover, he defines the set of data as D and the set of parameters as Π. J represents an instance of Π and can be interpreted as a scenario for the model. In particular, the problem at hand is that instance of Π are based on a more or less rigor and subjective assignment of values to the set of p parameters. The chosen values are called $h_i \left(i = 1,\ldots, p\right)$ and constitute J as a set of specific values. $R(J)$ is the result R of the procedure which is depending on a specific scenario J. In order to carry out a global analysis, ranges of each parameter had to be evaluated which are called $E\left(h_i\right)$. All possible instantiations of Π are denoted as $\hat{\Phi}$, whereas, Φ is any subset of $\hat{\Phi}$. Finally, A is the set of potential actions (set of alternative, set of feasible solutions).

With this terminology the definitions on robust conclusion and robustness analysis are the following (s. [Roy, 1998], pp. 149-150):

- Definition 1:

  Given a set Π of parameters to which a field of possibilities $\hat{\Phi}$ relative to a set A of potential actions is associated, a preference model (mono or multi-criteria) and a computational procedure, leading to the result $R(J)$ defined $\forall J \in \hat{\Phi}$, a perfectly robust conclusion on $\Phi \subseteq \hat{\Phi}$ is a well-formulized assertion concerning all or part of R which is verified by $R(J)$ for all $J \in \Phi$.
- Definition 2:

  An approximately robust conclusion on $\Phi \subseteq \hat{\Phi}$ is a perfectly robust conclusion on a subset $\Phi' \subset \Phi$, Φ' is not necessarily clearly identified but as (in the form of $\Phi|\Phi'$) may only contain instances of negligible values, relative to $\hat{\Phi}$; J is negligible relative to Φ if it is judged to be much less suitable than other elements of Φ to instantiate models and procedures likely to best represent the universe in which the decision will become operational.
- Definition 3:

  Given a set Π of parameters to which a field of possibilities $\hat{\Phi}$ relative to a set A of potential actions is associated, a preference model (mono or multi-criteria) and a computational procedure leading to the result $R(J)$ defined, $\forall J \in \hat{\Phi}$, a pseudo-robust conclusion on $\Phi \subseteq \hat{\Phi}$ is a more or less formal statement concerning all or part of R which is judged valid for all $J \in \Phi$.
- Definition 4:

  By robustness analysis we designate any way of acting which helps in the elaboration of robust conclusions on one or several sets Φ which should be as large as possible.

Thereby he makes further remarks (s. [Roy, 1998], p. 150):

- "any perfectly robust conclusion is approximately robust, and any approximately robust conclusion is pseudo-robust;"
- "a robust conclusion (whether it is perfectly, approximately or only pseudo-robust) can be totally devoid of interest because trivial."

As a demarcation to sensitivity analysis he says: "Sensitivity analysis is oriented towards studying the impact of certain variation of J on $R(J)$. Robustness analysis directs its attention towards bringing to light the assertions which are valid for all $R(J)$s when J describes a certain Φ. In addition, but this is secondary, this set Φ brings into play concomitant variations from several or even all of the parameters used. In sensitivity analysis, it is generally the impact of a single variation from each parameter which is brought to light." (s. [Roy, 1998], p. 150) In this respect robustness analysis can be expressed as follows: "It is [...] appropriate to attempt to know [...] [the] performances when we combine any element $J \in \hat{\Phi}$ (regarded as a possible J) with a J_0 which could be any element from a subset Φ on $\hat{\Phi}$." (s. [Roy, 1998], p. 149)

4.5 Robust Method

Vincke (s. [Vincke, 1999a]) introduces a notion on robustness as well as of neutrality of methods and a mathematical framework in the context of outranking relations, which is called robust method. This concept is based on two properties of a preference aggregation problem: robustness and neutrality. By considering the fact that robustness is related to the problem that the user of decision aiding methods often has to chose parameter values to specify the problem at hand, he claims that a method will be considered as robust "if the solutions obtained for different plausible values of its parameters do not contradict each other" (s. [Vincke, 1999a], p. 405), or, "if the procedures which constitute this method do not lead to contradictory solutions when they are applied to an instance of a problem" (s. [Vincke, 1999a], p. 408), or, a "method is robust for our problem if, for every instance of the problem and for every pair of procedures of the method, the application of these two procedures to this instance does not lead to contradictory solutions." (s. [Vincke, 1999a], p. 408) Obviously, this definition strongly depends on the definition on contradictory solutions and a slight change in the concepts would certainly change the results. In this paper "two solutions R and R' are contradictory if there is a pair $\{a,b\}$ of alternatives such that aPb and $bP'a$ (where P and P' are the asymmetric parts of R and R' respectively)." (s. [Vincke, 1999a], p. 408)

This also implies that there is a tradeoff between degrees of freedom left open to the user and potential for contradictory solutions. In this sense there is no contradiction between solutions if no degrees are left open to the user and the method will be considered as robust, but on the other hand significant risk is apparent that the solution depends more on the method than on the problem, which would imply that the method is not neutral. That means that the robustness of a method not only depends on the definition on contradictory solutions, but also is related to the neutrality of the method, which in turn is based on its flexibility and generality. In other words, "robustness has to be counterbalanced by a property expressing the fact that the method does not build conclusions which are specific to the logic of the method (and not to the particular problem to be treated): this property will be called neutrality." (s. [Vincke, 1999a], p. 408) In contrast, the "non-robustness of a method means that the application of such method to the information included in an instance of the problem can lead to fragile conclusions" (s. [Vincke, 1999a], p. 405), where as fragility means that "information contained in the instance is not rich enough or not appropriate to be treated by the method" (s. [Vincke, 1999a], p. 408). Therefore, it is necessary that in such conditions a robust method lead to incompatibility, moreover a feasible and neutral method must completely respects the intrinsic information of every instance of the problem.

In decision-aiding methods are often chosen or built on the basis of common sense or usage, but without a methodology to choose the most suitable method for the problem. As a result, either they always use the same method, what ever the problem is, or they build new methods, based again on the common sense. This framework suggested by Vincke aims to assist in the question whether the method is feasible, robust and neutral for the problem and should be used as a guide in the choice of one method in the set of possible methods, by tackling the questions how to formulize the problem and which properties should be satisfied by the method.

In another context Vincke (s. [Vincke, 1999b]) discussed the robustness concept further and tried to propose an operational formalism that allows to rigorously define the concept of robustness. The problem description resembles parts of the former paper (s. [Vincke, 1999a]), i.e. he is interested in a framework to give assistance for characterizing or choosing a method, whereby a robustness property related to the definition of contradictory solution; but here a more general framework is introduced focusing on ill-determined data of a decision problem, instead of neutrality of a method.

Two distinctions are common in OR-DA for the sources of uncertainty. On the one hand, the information describing the decision situation (i.e. data for formalization of the model) contain values which are (more or less arbitrarily) built by the analyst, and on the other hand, decision-aid methods often give some freedom to the user to (more or less arbitrarily) choose the values of some parameters. As a result the sets of data for the model and sets of parameters for the method are not unique, that means several plausible sets of data and parameters exist, possibly very different from each other, and it is not possible to know which one will occur. In this context the role of the scientist is to propose solutions that are as good as possible simultaneously for different plausible sets of data and different acceptable values of these parameters and at least to give some information on the validity of the proposed solution concerning these different sets of plausible values.

In contrast to sensitivity analysis, which consists of studying how a given solution changes with perturbations of the values of the model, robustness is related to a notion of distance or dissimilarity between solutions. More in detail, "a solution, obtained for one scenario of data and one set of values for the parameters of the method is 'far or not' from another solution, obtained for another scenario of data and another set of values for the parameters of the method." (s. [Vincke, 1999b], p. 183) To introduce the robust method framework he proposes the following definitions on problem, procedure, method and robustness (s. [Vincke, 1999b], p. 184-185):

1. Definitions on "problem":
    a. "A problem Π is a quadruple $\{D, S, L, G\}$, where D is a set characterizing the data, S is a set characterizing the solutions, L is a set of complementary conditions that must be satisfied by the solutions to be considered as feasible, G is the set of pairs of contradictory solutions (solutions considered as too far from each other)."
    b. "An instance π of the problem Π is a quadruple $\{d, S, L, G\}$, where d is an element of D."
2. Definition on "procedure":
   "Given a problem Π, a procedure for this problem is an application which associates a solution to every instance of the problem."
3. Definition on "method":
   "A method is a set of procedures."
4. Definitions on "robustness":
   "Let $\{\pi_1, \pi_2, \ldots, \pi_l, \ldots\}$ be a set of instances of problem Π. Let $\{\rho_1, \rho_2, \ldots, \rho_k, \ldots\}$ be a method, i.e. a set of procedures. A couple (π_l, ρ_k) is called treatment: it corresponds, in a concrete situation, with the choice of one set of values for the data of the problem and one set

of values for the parameters of the method, and leads to one solution, denoted s_{lk}.

Definitions:

a. A solution s is robust relatively to a set T of treatments if for every treatment (π_l, ρ_k) of T, s and s_{lk} are contradictory for instance π_l.

b. A method $\{\rho_1, \rho_2, \ldots, \rho_k, \ldots\}$ is robust for an instance l if, for every pair of procedures (ρ_j, ρ_k) of this method, s_{lj} and s_{lk} are not contradictory for instance π_l.

c. A method is robust for a problem if it is robust for every instance of that problem."

4.6 Robust Solutions

Sörensen (s. [Sörensen, 2001]) investigates how a basic tabu search technique can be adapted so that it finds solutions that (1) have a good solution quality and (2) are more robust than other solutions. A tabu search is a meta-heuristic that guides a local search procedure to efficiently explore the search space of a problem. It uses both short-term and long-term memory structures to prevent the search from getting stuck in local optima.

He emphasizes that the notion of robust solutions has been neglected in the research on tabu search and meta-heuristics, but in many real-life combinatorial optimization problems robustness seems to be as important as optimality. He states that "[i]f a solution is very sensitive to small perturbations in the input data, it might not be a good solution at all." (s. [Sörensen, 2001], p. 707) Therefore, Sörensen developed a technique that modifies a tabu search heuristic so that it searches for solutions that not only are a good quality but are also robust. In his terminology the discussed robust tabu search procedure is intended to produce solutions that are quality robust. For him robustness refers to the insensitivity of a solution with respect to the input data and he distinguishes two types of robustness:

- Quality robustness:
  "A solution is called quality robust if its solution quality [with respect to optimality] remains high if changes in the input data occur [i.e. if the solution remains 'close' to optimal compared to the solution if no perturbations occur]. This type of robustness is important in problems in which frequent re-optimization of the problem is infeasible[.][...] Therefore, it is imperative that the solution initially found remains as close to optimal as possible under changing circumstances. In general, quality robustness is needed in situations where volatile input data is used to base inflexible decisions on." (s. [Sörensen, 2001], p. 707)
- Solution robustness:
  "A solution is called solution robust if the new solution changes only slightly with changes in input data." That means, "a new solution has to be found when changes in input data occur and - as a result - the original solution does not satisfy the constraints of the new problem. To this end the problem is re-optimized [...][and the new solution requires] to be as close to the original as possible." (s. [Sörensen, 2001], pp. 707-708)

The main differences between these two definitions is that "[c]ontrary to quality robustness, solution robustness is [...] not only a property of the solution, but also of the solution algorithm", and moreover "[...][in the case of quality robustness], it is the quality of the solution that is not allowed to change [...][, while in the case of solution robustness], it is the solution itself that is not allowed to change." (s. [Sörensen, 2001], p. 708)

Backing his argumentation with the notion on robustness from Mulvey *et al.* (s. [Mulvey *et al.*, 1995]) Sörensen states "[r]obustness and optimality are often conflicting objectives in that an increase in one of them will often incur a decrease in the other." (s. [Sörensen, 2001], p. 707) Also discussed by Mulvey *et al.* (s. [Mulvey *et al.*, 1995]) in the context of operations research is the fact the models are always subject to incomplete, noisy, and erroneous data, but in most cases techniques for solving such models assume deterministic data. Examples are models which are performing worst case or mean-value analysis, which have been shown to produce very conservative and sometimes very expensive solutions in the former case or to have either large error bounds in the latter case. Other work on robustness has also been cited by Sörensen with emphasis on robustness of the solution to a problem with regard to changes in input data.

The robust tabu search approach only modifies the solution evaluation function $f(x)$ of a tabu search procedure to a new one $f_r(x)$, but it does not alter any tabu-search-specific features of the procedure. Moreover, the form of the function is relative general, so that the choice of the function could be any deterministic or stochastic function. The basic principles are as follows (s. [Sörensen, 2001], pp. 708-709):

- Principle 1:
  "The new evaluation function adds some noise to the current solution before evaluating it. So, the robust tabu search procedure evaluates $x^* = x + \delta$ instead of x. We will call x^* a derived solution. Derived solutions may or may not belong to the original solution space. The noise added is dependent on the expected noise in the input data and should reflect the expected changes in input data."
- Principle 2:
  "The new evaluation function does not evaluate a single point, but evaluates several derived solution and combines these into a single function value. This new function will be called the robust evaluation function $f_r(x)$. A general form of a robust evaluation function is $f_r(x) = \frac{1}{n}\sum_{i=1}^{n} w_i * f(x+\delta_i)$."

Thereby, the function value $f(x+\delta_i)$ of the i-th derived solution $x+\delta_i$ is weight by a factor w_i, and n is the number of derived solutions that are evaluated, which is also "an indicator of the importance that is attached to robustness, as opposed to solution quality. If n is larger, more derived solutions will be evaluated, resulting in a more robust solution." (s. [Sörensen, 2001], p. 709)

5. Robustness and Uncertainty - Relations, Tradeoffs and Dependencies

Pluralistic View and Integration

All these concepts mentioned above from technical, biological, social, optimizational and decision aiding perspectives form a pluralistic view onto the robustness phenomenon. It is likely that they are all correct in their specific context and domain of validity and thereby enlighten many different aspects of a complex phenomenon from varying points of view. Moreover, they are also likely to contradict each other if put into a different context or domain of validity, although they are descriptions of the same phenomenon. Therefore, the specification of context, system level, system properties as well as uncertainties or perturbations fixes the domain of validity and is a necessary prerequesite for an operable classification and generalized and demarcated theoretical framework on robustness. Furthermore, due to that fact that uncertainties occur in many different fashions and on many different levels, they have also to be treated on multiple levels and with multiple means simultaneously. Hence, each of the concepts treated in isolation can not be as efficient in providing robustness as a whole bundle of robustness measures.

As already emphasized in the introduction it needs a systematic integration step in order to unify all concepts and to widen knowledge base, while this work only ventures the first step in collecting some notions, concepts and definitions on robustness and some selected functional and structural properties of robust systems. In summary, we revisit some of the above concepts and try to illustrate their relations, tradeoffs and dependencies.

Sensitivity

First of all, we might ask for the relation between sensitivity and robustness since in so many cases insensitivity has been used as a synonym for robustness. In particular, we observed the tradeoff that increased optimality could lead to increased sensitivity towards basic assumptions since our knowledge used to optimize a situation, solution, decision, alternative, etc. is inevitably based on some assumptions. If the assumptions turn out to be wrong or no longer valid because the conditions changed we are likely to face a situation of high sensitivity and fragility, respectively. Now, one could conclude that robustness turns the view of sensitivity up-side-down, but it should be repeated here, that in contrast to robustness sensitivity does not address the internal structure and adaptability of a system on the on hand and gives no means to control this sensitivity on the other hand. Thus, even though statements about sensitivity give some information about how a system respond to uncertainty in input factors, it is not a surrogate measure for robustness, because the sensitivity concept is not able to give information about other and in terms of robustness more important characteristics like preservation of structure, organization, properties, function or identity.

Stability

Second, as we have already concluded from the work of Erica Jen (s. [Jen, 2003]), robustness in general is not the same phenomenon as (structural) stability in dynamic systems, although both concepts are linked to the persistence of specified properties under specified perturbations. In contrast to stability, robustness addresses systems whose features of interest are difficult to parameterize, whose perturbations represent significant changes either in system architecture or in assumptions built into the system through history or design, or whose system behaviour is generated through adaptive dynamics coupled to strong organizational architecture. This also implies that in addressing robustness we are interested in specifying the system level, e.g. structural or functional level, on which perturbations occur, while this is not important in the stability context since structure has no specific meaning for stability.

Resilience

Furthermore, as pointed out by Anderies *et al*. (s. [Anderies *et al*., 2003]) robustness and resilience are frequently used as equivalent or similar concepts. In both concepts the history of a system as well as its course of development is of particular significance. Therefore, we ask how the system took shape, i.e. the evolution or the design of the internal structure. Resilience has often been used in the context of ecosystem development and its sustainable use, while Anderies *et al*. (s. [Anderies *et al*., 2003], p. 4) suggest to use the term robustness if one focuses on “partly designed systems rather than strictly evolved systems”.

Complexity and Heterarchy

The structural and functional components in the term robustness are also inevitably linked to complexity. In particular, natural systems, i.e. biological and social systems, show an immense complexity in form of spatial and temporal heterogeneity and interacting components and feedback mechanisms. If viewed as networks they can also be described in terms of heterarchies, i.e. networks with high heterogeneity and minimal hierarchy. The structure is diverse and partially overlapping. Components show a high degree of autonomy and belong to as well as act in multiple networks simultaneous. They are characterized by a enormous adaptability, which is often explained by its modular organization. New organizational forms can therefore created through recombination of existing building blocks or modules.

Complexity, Redundancy and Degeneracy

These properties of robust networks can also be described in terms of redundancy and degeneracy. Components in a diverse and degenerated structure with some degree of structural similarity are able to switch between different functions which could also lead to synchronized behaviour in a synergetic sense on the functional level. This functional redundancy based on a degenerate structure is, for example, a prerequesite for ecosystems to adapt to changing environmental conditions. This means, not only components but also whole feedback mechanisms can be replaced by other components or mechanisms which are better fitted to the prevailing conditions. A diverse fitness landscape, thereby, does not guarantee robustness, but with respect to strategic options it is more likely that the system has already a good solution at hand or is able to find a good solution to preserve its identity.

Complexity and Indirect Effects

In complex systems we can also observe that the indirect effects become dominant and form important feedback loops which govern the system dynamics. Moreover, far-from-equilibrium system states are characterized by non-linear behaviour within the system. In order to create reliable and simple external behaviour puffer and saturation effects, as examples for indirect effects, damp down non-linearities. This complex internal but simple external behaviour is comparable with the robust yet fragile bahaviour of HOT systems. Complex internal configurations with dominant indirect effects create simple and robust external behaviour by damping down non-linearities.

Evolution and Design

The historical component in these systems stresses temporal aspects of evolution and design in these complex adaptive systems. Because adaptation to prevailing conditions like optimization and specialization is a development with a specific direction, i.e. irreversible process, and the system is not able to go back to a former state and will never meet the same external conditions again, often as a drawback this also restricts future adaptability in a way that some strategic options are no longer open to the system which narrows its fitness landscape. Therefore, the number of strategic options open to the system determines its adaptability. Hence, a system with high flexibility (i.e. with a diverse strategic landscape) can perform more robust than simpler, more restricted or specialized systems if the prevailing conditions change. In particular, we observed the tradeoff that optimization solely with respect to performance might make a system more sensitive and brittle to changing external conditions. This means, the more a solution is specialized to certain conditions, it is likely that this solution will have worse performance compared to a solution which is less specialized. This also implies that in turn suboptimal solutions and accepting some risk of suboptimal performance might make a system more robust. Therefore, robustness is not only linked to adaptability and flexibility but also to generality. The more general a system is the more situation it can deal with. In other words, a solution that solves many problems, a method that is applicable to many cases, a strategy that fits in many situations can be called general or likewise robust. Moreover, exploration and exploitation are strategies which need to be balanced in order to foster robustness. As we have seen in the example of transformation processes taken place in the societies of East Europe, early success can lead to an early lock-in which limits adaptability (often amplified by short-term rationality). This means, exploitation is done without sufficient exploration and many potentially good (long-term) strategies remain unseen and unexplored. Similar to search methods, this means, that local methods only give a narrow view onto the problem and might get stuck into local optima, while a more global view provides more flexibility and is more likely to find global optima. But this is not the only tradeoff which robustness has to balance. On the contrary, robustness itself is about balancing tradeoffs, or in other words, about balancing the costs and benefits of adaptation. In general, the more complex a system is the more tradeoffs it contains. In this respect adaptation will not only have benefits but also many drawbacks which in total might outweigh the benefits. In this case, we face a specialized situation in which benefits and costs are not balanced and therefore adaptation could reduce the system's robustness.

Robust Design Principles and Robustness Measures

All these facets mentioned above have to be consider if we want to get an idea what the nature of robustness actually is. In the end it might be possible to arrive at robust design principles which are on the one hand guidelines to more robustness in system design and on the other hand indicators for robustness, or even at robustness measures which quantify the system's robustness. But it should be emphasised that these robust design principle can not guarantee robustness, we might rather conclude that the more robust design principles are apparent the more likely it is that the system is robust. Moreover, they are likely to have far greater effect if they have been integrated into the design process right from the start.

Balance Tradeoffs

Finally, we define robustness as the ability to balance tradeoffs triggered by interactions within the system and between the system and its environment and in particular to balance the tradeoff between current adaptation and future adaptability; and the ability to deal with uncertainty in the system's components and environment and to preserve important structural or functional properties or solely its identity. In this context, sustainability can be regarded as a measure for robustness by balancing social, economical, ecological and political affairs with respect to short-term as well as long-term effects. In combination with adaptive management it can be used as a guideline through a complex, uncertain and ever changing fitness landscape.

6. Concluding Remarks and Outlook

This paper argues that robustness phenomena are also a challenge for the 21st century. It is a useful quality of a model or system in terms of “the maintenance of some desired system characteristics despite fluctuations in the behaviour of its component parts or its environment” (s. [Carlson and Doyle, 2002], p. 2). We define robustness phenomena as a solutions with balanced tradeoffs and robust design principles and robustness measures as means to balance tradeoffs. These design principles and measures serve as guidelines as well as indicators for robustness. If different components are put together in a robustness framework it can serve as a toolbox applicable to many different contexts, covering many aspects of uncertainty on multiple levels simultaneously. Here, the crucial aspect is to implement these measures right from the start of the process, be it modelling, manufacturing, computation or decision aiding. Otherwise, if done as ex post analysis there are no means to control sensitivities or uncertainties. Moreover, the system of interest no matter of which type, e.g. economical, social, technical or biological, has to be complex, i.e. many components and interactions as well as many feedback loops and regulatory mechanisms, in order to ensure some degree of diversity and hence adaptability on functional and structural level. Robustness measures and mechanisms have to be part of the system and have to be evolved with or designed for the system. The degree of complexity is an indicator for the amount of mechanisms build into the system to ensure robustness despite uncertainty in components and environment.

Despite tradeoffs and feedbacks, uncertainty and change are important factors. Assumptions we make may hold only for specific conditions which means a change in the conditions or a incorrect representation of the conditions by the assumptions due to ignorance or uncertainty could lead to poor outcomes and extreme fragility which is unexpected and would occur by surprise. In general, optimality means to optimize according to a singular measure, in contrast to that considering suboptimal outcomes is a way to move away from very context-sensitive outcomes. This may lead to more balanced and hence robust outcomes, because tradeoffs will have a minor effect, in particular if conditions are changing, and the result is more suitable in a generalized context, i.e. for more situations. Moreover, the less assumptions we have to make or the less specific the context is, the more flexible and robust, respectively, a model or system can be.

Risk aversion of actors is another important factor to be considered in the context of robustness. While an unawareness of the risk of a poor outcome is one extreme, total risk aversion is the other extreme which could also lead to a poor, i.e. very conservative, outcome. The acceptance of the risk of minor losses also means to prefer strategies which are less optimized and hence less specific. As shown above, incorporating risk aversion not only means a minor loss in average performance, but could also mean an important gain in robustness, i.e. poor outcomes are less frequent.

At the moment we are far away from having a sound basis for a theoretical robustness framework. Research on this topic is most often very discipline or problem specific, and less work is done on a general, interdisciplinary basis. Therefore, much more work needs to be done to integrate from different disciplinary points of view or from different problem domains. The analysis of structural and functional properties as well as regulatory mechanisms, feedback loops and indirect effects like puffer effects of existing systems leading to robustness, for example, can be used to establish robust design principles and robustness measures. Moreover, the interactions of the robustness components with other components in a system as well as with other robustness components need to be analysed.

In a design, manufacturing, production, management, decision making and consultation context, for example, process design is a crucial factor for its successful outcome. There is also much room to develop soft system methods which structure theses processes through an a priori implementation of robust design principles. In a decision making context of integrated water resource management, for example, more and more soft system approaches like participation, interviews, mind mapping, role playing, qualitative system diagrams, etc. are used to integrate stakeholder and decision maker into the management process in order to improve communication and information exchange, resolve conflicts and illuminate diverging interests, mental models and value systems as well as balance tradeoffs through interactive learning, hence to make the process more adaptable and robust, respectively.

Case studies are an appropriate test bed to implement and test robust design principles and robustness measures. Here, we can verify and improve in an iterative process validity and performance. Environmental resource management is a good example where such principles and measures can be embedded in case studies. These management problems are most often complex in nature, which means not only the natural system but also the stakeholder environment is complex with conflicting interests and values. Many tradeoffs have to be considered and balanced to ensure a sustainable outcome.

Finally, to outline some open question for future research and case studies we can ask for example: “How does the use of robust design principles and robustness measures affect the outcome of a environmental resource management problems?” “Which principles and measures are appropriate for which problem domain?” “How do these principles interact with each other principles and which combinations lead to more robustness?”

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