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A collaborative expert system for group decision making in public policy

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Abstract

In the policy arena, there is high pressure to provide right and quick decisions for problems that are often poorly defined. There is thus an urgent need to support stakeholders in establishing a shared understanding of policy problems and to assist them in the design of potential solutions. Here we propose a methodology based on the construction and analysis of system maps, i.e., graphical representations of the complex interdependencies of all relevant factors that affect the problem under study. Owing to their collaborative design, system maps provide a transparent tool with broad stakeholder acceptance for analysis of ill-defined problems in a formal way. The construction of system maps involves expert elicitation to define system components, system boundaries, and interactions between system components, after which the dynamical system behavior can be approximated by means of system dynamics. Although there is great value in the construction of the system map to enhance the understanding of the problem scenario, we consider this to be an intermediate step. The final target is to assist decision-makers by constructing and analyzing system maps at each step of the decision-making process: i.e., from the understanding of the system behavior, through the definition of objectives and constraints, to the presentation of feasible solutions that are satisfactory over a range of different plausible scenarios. System maps provides us with an effective framework to collect information dispersed over experts, facilitate mediation, and analyze formally potential pathway solutions, meeting different criteria of optimality and robustness.

1 Background

Groups rather than individuals typically deal with important issues (DeSanctis and Gallupe, 1987, Conradt and List, 2009). In the context of public policy, it is frequently unlikely that any individual will have all necessary information at his or her disposal to formulate a problem. We propose in this work a group decision support system for collective decision-making that facilitates sharing of dispersed information and reconciliation of conflicting views. By pooling the biased and incomplete information of the group members, a group can create a more complete picture of the problem, which in turn can lead to better-informed decision-making. The decision support tool brings about communication within the group, and this can have a powerful effect on the decision process and the quality of the outcome.

Public policy problems often cannot be solved by traditional tools from operations research (OR). The reasons for this failure are threefold: the stringent requirements for available information and clarity of the goals (Head, 2008), the impossibility of capturing the multitude of views or value systems that prevail in social problems, and the ill-defined nature of the issues in the sense that they resist consistent problem formulation and clearly agreed solutions (Rittel and Webber, 1973). These so-called wicked problems have several recurrent characteristics, such as complex interdependencies, disagreement on the nature and the extent of the problem, high levels of uncertainty, and mathematical difficulties in describing concepts or verifying solutions. High levels of uncertainty and differing value frames contribute to opposing opinions and incompatible solution pathways. Owing to their cross-cutting nature, ill-defined problems are inevitably connected to other problems, for instance in the case of environmental preservation and economic growth, and this interconnectedness encourages the study of tradeoffs and synergies. There are many examples of ill-defined problems in international policy, in problems of global change, and in socio-economic issues in healthcare or social welfare. Since the complexity of these issues goes beyond the capacity of a single person, a collaborative approach is required for the formulation of problem solutions through the consultation of policy-makers, experts, stakeholders, and citizens. The ill-defined issues that arise in public policy do not allow for trial-and-error approaches, since there is no public tolerance for the failure of a policy. Taking into account time constraints typically encountered in policy issues, this encourages the use of simple yet formal models that allow stakeholders and policy-makers to increase their understanding of the problem scenario and the consequences of policy solutions.

Human decisions are typically based on a representation of reality consisting of the elements and relationships of the problem that seem to the decision-maker most relevant. These *mental models* differ substantially from person to person. The objective of the decision support tool that we consider here is to provide a methodology that translates the mental models of a group of experts into a single consensus model. Consensus in this context does not mean that all experts agree with the model, but that the produced framework is the best possible result that merges conflicting views. The resulting model is different from statistical models and mechanistic process-based models owing to the presence of intangible variables. The expert-based decision models considered here are not meant to represent a reality, but intend to represent the mental models of a group of experts.

All models are wrong. As Thomas Kuhn argued, the truth of a scientific model does not only depend on objective criteria, but also on the consensus within a scientific community.

Therefore, in the context of expert-based decision models, the focus is not on the veracity of the model, but rather on the usefulness of a model. The objective of models based on expert judgment is to produce results that are convincing, useful, and that inspire confidence. An expert-based model is convincing when it can reproduce simple intuitions of experts and historical facts. The model is useful if it can be applied beyond known scenarios and if it can be used to evaluate and propose new policies. Finally, it is key that expert-based models inspire confidence. Expert-based decision models have mainly been applied in the field of soft operations research (OR). Soft OR methods are participatory methods where a facilitator assists in the formulation and exploration of a problem as part of a decision-making process. The soft methods involve a group of decision-makers with conflicting views on the problem and different objectives and interests. In these ill-formulated problem scenarios, a part of the system will be difficult to quantify, for instance when social notions and subjective judgment form a critical part of the model (Munro *et al*., 2002). Soft OR methods have been developed more than thirty years ago, and to a certain extent these methods are able to address ill-defined problems. Despite that, soft OR methods have never been recognized in the OR literature and suffer from the connotation of being imprecise and non-rigorous (Mingers, 2011). As a consequence, soft OR methods do not inspire confidence, which reveals the need to develop new methods that can address the shortcomings of the prevalent soft OR methods.

Many relevant problems feature characteristics that are not amenable for traditional OR techniques. Specifically, the application of known methods is problematic when groups of stakeholders are involved with different interests and values, when there is disagreement over the nature of the problem, reliable data is missing, or critical factors are intangible. Moreover, the problem definition may be changing continuously, the scientific knowledge to address them insufficient, and the proposed solutions might address symptoms rather than causes. These conditions are encountered in global problems related to climate change, population, and geopolitics, but also on a smaller scale in a business environment. Traditional OR usually works with a consensual group of decision makers with clear objectives that agrees on the nature of the problem. Moreover, variables can be quantified, and uncertainty about variables can be addressed with probabilistic methods. In reality, these criteria are often not met and soft methods are a vital part of the formulation and solution of ill-defined problems. First, by bringing experts together, soft OR helps to find agreement on the nature of the problem. Stakeholders increase their understanding about the scenario by doing simulations, and this incremental process leads to enhanced insight into the model, unanticipated consequences, formulation of objectives and constraints. While this can be a final goal on itself, the output of the soft OR phase can also be integrated into a traditional OR problem setting, for which the methods are widely recognized and that inspire confidence. The participatory process of codesign strengthens the transparency of traditional OR models, which is necessary in the presence of multiple stakeholders. In conclusion, we claim that in the considered problem scenarios soft OR and traditional OR are complementary and with this paper, we aim to bridge the expert-based models in soft OR to quantifiable problems in traditional OR.

We advocate that system maps are the appropriate tool for the analysis of ill-defined problems. System maps provide a graphical representation of all factors that constitute an ill-defined problem together with their interdependencies. System maps are typically applied to get a qualitative understanding of the indirect relationships and feedback loops between the problem factors. Here, we propose a new perspective on system maps that integrates all crucial steps of the decision-making process. We do not center on issues with a perceived lack of scientific knowledge, but rather on poorly scoped problems with diverging value frameworks. When time is unavailable to develop a well-grounded model, system maps are an excellent tool to work towards a common understanding of the problem and define solutions that are collectively supported. In fact, we propose to use system maps as the main machinery for (i) cooperation, dialogue, and mediation during the construction of the map, (ii) improvement of the understanding of the system behavior through numerical simulations, (iii) inclusion of pluralistic values for the definition of objectives, and (iv) suggestion of solutions that are broadly supported.

2 Taxonomy of expert-based decision systems

The terminology to describe soft OR methods and the corresponding graphical tools applied in literature is ambiguous. Hence, we list here the main soft OR methodologies, which are also collectively called problem structuring methods (PSM), together with several graphical methods. In literature, different terminology can be found, usually with subtle differences between the different terms. We distinguish here between broad conceptual frameworks and narrowly defined methodologies.

The main conceptual frameworks that facilitate collaboration and negotiation are listed below. A recurrent feature is that these frameworks do not go beyond a qualitative analysis of the problem scenario.

- Soft systems methodology (SSM) is a sense-making framework that attempts to incorporate irrationality of agents as well as different value frames (Checkland and Holwell, 1997). Starting from a preliminary study of the problem scenario, a conceptual activity model is built that is later on used to guide a dialogue on desirable system outcomes between the involved stakeholders.

- Building on cognitive mapping, strategic options development and analysis (SODA) first tries to unite the perceptions of different people related to a particular problem scenario into a consensus group map, which is a subjective and abstract construct. This map is consequently used within the broader context of strategy design through group discussions.
- Strategic choice analysis (SCA) is a participative methodology that offers a qualitative procedure for decision analysis (Friend and Hickling, 2005). By means of discussions between participants holding different views, a feasible set of solutions is created, individual decisions are compared, and finally a solution is selected out the solution set taking into account the identified uncertainties.

There is a plethora of quantitative methods that can be classified according to different dimensions, for instance probabilistic versus deterministic models and dynamical versus static models. The most relevant methods used in literature are succinctly described below:

- Bayesian networks (BNs) provide a graphical representation of probabilistic relationships between random variables by means of a directed acyclic graph. In case of discrete random variables, for instance hypotheses, the probability of a child node as a function of each possible combination of the parent nodes is typically listed in a table. The power of Bayesian networks lies in the potential for predictive as well as diagnostic inference. The required elicitation effort for BNs increases quickly with the network size. In order to capture dynamics, dynamic BNs are used that relate the network nodes over adjacent time steps.
- Influence diagrams or decision networks are a generalization of BNs that are applied for decision-making problems under uncertainty.
- Discrete event simulation (DES) is an event-based dynamical system model that has many industrial applications, for instance in supply chain management. The usefulness of the model extends also to decision-making, and DES allows us to make statistical estimates of queue lengths and waiting times under a set of alternative policy decisions.
- System maps or causal loop diagrams are graphical models that visualize the causal relationships between different factors within a system. We prefer the term system maps, since they focus on the visual representation of a system rather than on the feedback loops that exist within the system, which can be very hard to disentangle in highly connected directed graphs. System maps provide a description of a system, its boundaries, the constituent system components, and the interactions that exist between these components. They typically consists both of hard (quantifiable) and soft (non quantifiable) variables. The soft variables or intangibles are often critical in

the system behavior. Numerical data is usually unavailable for the intangibles, but since they can significantly influence the system behavior, it is essential to include the soft variables in the system dynamics. System maps are built to enhance the understanding of the system behavior, in order to avoid unanticipated consequences and the policy resistance that can result from that. System dynamics (SD) is typically used to assist decision-makers in the design and analysis of policy options for the system described in the system map. SD is very useful for the study of complex systems, and allows the decision-maker to assess the system behavior under different conditions and strategic policies.

As this work aims to connect conceptual frameworks with traditional OR techniques in the realm of public policy, we are mainly concerned about complex issues that deal with multiple views and intangible variables, while maintaining a formal approach that combines network dynamics with probabilistic methods. BNs mainly evolve around static inference problems and the elicitation requirements are infeasible for network sizes that usually appear in problem scenarios of public policy. DES handles in practice well-defined processes with a fairly narrow scope and has mainly been applied for industrial and production processes building on strong empirical basis. In view of the peculiarities of ill-defined problems, system dynamics over system maps is the appropriate tool that lends itself well for modeling continuous processes catered to strategic policy design. System maps allow for the integration of expert judgment and the blending of discrete and continuous processes, while incorporating the statistical details of multiple experts. Ultimately, system maps open new avenues to merge the mental models of experts and reach group consensus on the problem structure.

3 Construction of a system map

Expressing the problem scenario in a rigorous and manageable model is a challenging exercise. In view of the features of ill-defined policy problems, system maps can represent the problem formally and with some caution do not involve excessive elicitation efforts. The construction of a system map is a creative process of translating the ill-defined problem into a set of well-defined system components and interconnections (von Winterfeldt, 1980). Through this process, both objective (affected variables) and subjective (values and perspectives) factors are combined, and the resulting system map will subsequently facilitate the modeling and numerical analysis in the inference engine.

System maps were originally designed as a qualitative model, and the description of the model itself was deemed to be useful to gain insight into the system behavior (Coyle, 2000).

Considering the quantification of qualitative models, it was argued that quantification could introduce so many uncertainties that the policy conclusions drawn from quantified models were potentially illusory. At the same time, there are many supporting arguments for a quantified analysis of system maps that claim that simulation or quantification nearly always adds value, even in face of possible uncertainties and the difficulties related to the quantification of soft variables (Homer *et al*., 2001). Interestingly, experimental studies have shown repeatedly that people perform poor mental simulations, even when they have complete knowledge of the system structure and when the structure is relatively simple. As a consequence, one cannot draw reliable conclusions from causal maps without simulation. System maps contain variables of different nature, soft variables and hard variables, and the meaningfulness of operations between these variables is often not obvious. Nonetheless, the quantification of the system behavior discloses trends and indirect effects that are not obvious by mere visual analysis of the system map.

System maps are a suitable tool able to handle soft variables, uncertainties, and missing data. Current methods for the analysis of system maps are subject to different sources of uncertainty, which can be classified as parametric, structural, and experimental uncertainty. The dynamics that take place over the system map can be described and quantified by means of dynamical systems theory. Several key references in the field of system dynamics and soft systems methods are (Sterman, 2000, 2002, Jackson, 2006, Checkland, 1985, 2000).

Although decisions in organizations or in the policy domain are predominantly made collectively, most decision support tools are still aimed at individuals. The proposed expert system based on system maps combines individual opinions, aggregates partial information, and gathers different perspectives, objectives, and preferences to reach a decision supported by the group. The resulting framework is co-owned and co-designed by the users, and the influence of a facilitator is minimized throughout the process. The proposed methodology allows users to be both co-located or at different locations.

The objective of this section is to present a step-by-step procedure for the construction of a system map and to reduce the uncertainty from which the current methods suffer. The main challenges to establish a system map can be listed as follows:

- *Expert selection*: The problems we are focusing on are too large in scope to be addressed by a single person. The aggregation of expert judgment is mandatory for informed analysis of the problem setting and the system behavior. A first important problem relates to the selection of the group of experts that will define the problem, in light of the risk of groupthink and confirmation bias.

- *Elicitation of relevant system components and system boundaries*: There are different strategies to distinguish between system and environment and define the system boundaries. In this respect, the definition of the system needs to balance the competitive requirements of complexity and tractability. The system needs to have a sufficient level of complexity to allow non-obvious insights, while the complexity in terms of number of state variables needs to be limited for reasons of feasibility (Ferrara *et al.*, 2010). Although the construction of the system map may seem problem-specific, we present a method that addresses the following questions. How can data and expert elicitation best be exploited to define the system map? How should the expert surveys be designed to get optimal results, while minimizing the influence of the workshop facilitator on the definition of the system map? What is the approach to complement expert opinions with available data?
- *Estimation of the graph structure*: The correlation between the system components translates the individual system components into a directed graph. A crucial aspect of the network construction is that only direct interactions between system components should be included.
- *Estimation of parameters with known graph structure:* The weights of the links in the graph are estimated by a group of experts. Should expert opinions by aggregated or is it advisable to keep the full range of uncertainty? With respect to aggregation methods, it is important to note that different aggregation schemes lead to qualitatively different results.
- *Complexity reduction*: The reasons to reduce the system map complexity are mainly related to the expert elicitation effort and the human cognitive limitations to work with large networks. A first aspect of complexity relates to network size and structure. Are there methods to reduce the number of system components and links? A second aspect of complexity relates to node interactions. The relationships between the system components can be of different nature, and the question is if a single class of relations can be defined for all links between the system components. Are linear relations sufficient to define all links, or is there a need to define several classes of interactions?

In the following sections, we will address step by step the main challenges listed above.

3.1 Selecting the group of experts

Expert elicitation is instrumental in the construction of a system map. Group decision-making has clearly a higher cost than individual decision-making, but as relevant knowledge in public policy scenarios is typically spread over a group of experts, the complexity of these problems demands for higher levels of participation. In contrast with individual decision-making, the challenge of group negotiation is to provide a framework that facilitates the aggregation of unshared information and the reconciliation of conflicting interests. Although groups with distributed knowledge are expected to provide higher quality decisions, this is not always empirically justified. Groups can however outperform individuals when the distribution of knowledge is asymmetric, but the processing of the information is symmetric (Brodbeck et al., 2007). The group of experts needs to be selected based on the knowledge requirements of the problem scenario. During the expert selection stage, it is difficult to avoid the involvement of facilitator, and awareness is required that group selection can affect policy outcomes.

The first fundamental question that arises in the group selection deals with the necessary number of experts in order to guarantee some pre-defined quality requirements. The wisdom of crowds is often used to elicit system components, interactions, and weights of the system map. With this technique, information is aggregated over experts, which yields good estimates when the assessment of the experts is unbiased and independent. These conditions are often not fulfilled in reality and require caution. It is not straightforward if more accurate estimates can be obtained if the number of experts is maximized. On the contrary, it is often possible to find a smaller and better-informed group that yields improved aggregated judgment. It can be shown that under certain technical conditions an optimal size of the crowd exists (Goldstein *et al*., 2014).

For policy problems, the group of experts needs to cover all crucial areas that are related to the problem scenario, and often there is little overlap between the areas of expertise of the group members. This group composition requires combining unshared information so as to improve the quality of the group decision. Often unshared information is more significant than the commonly held information in achieving a collective decision (Stasser and Titus, 1985). The effectiveness of the group builds on the transfer and integration of knowledge across experts. Through discussion, the partial and biased believes of the group members can be corrected to form a collective, unbiased representation of the system. In reality however, due to group cohesiveness individuals avoid to raising controversial issues. This desire to harmony is often referred to as groupthink and can lead to impaired decision-making. Confirmation bias is a cognitive bias that can explain the standing and lasting different opinions between groups (Tversky and Kahneman, 1973). The effects of groupthink and confirmation bias require a systematic reworking of the system map, by a systems analyst or workshop facilitator.

3.2 System components and system boundaries

Once experts are selected, the constituent elements of the problem scenario can be identified. These system components can be variables that describe the state of the system, processes, decision alternatives, or discrete events. The procedure to identify system components can be divided in the following steps:

i. The group experts collect the system components during a participative workshop. The co-location of experts is preferential during this phase of problem structuring, but experts can define the system components also individually. The scope of this exercise is primarily to find agreement on the extent of the problem scenario.
ii. The workshop facilitator or linguist pre-processes the list of system components based on linguistic vicinity to avoid duplication of factors.
iii. The experts perform a logical clustering of the pre-processed data based on semantic correlation. Specifically, system components are clustered visually based on their significance, and logical clusters are replaced by a single system component. This round of system dimension reduction needs to limit the dimension of the state space to 50 - 100 system components. This effort is necessary to ensure that the elicitation effort of the subsequent phases is manageable.
iv. The experts scale the relevance of system components visually on a diagram. This scaling is done by placing the most important components in the center and placing less important components in the periphery of the diagram. This round of system dimension reduction prunes the least relevant system components and reduces the dimension of the state space preferentially to 30 - 50 elements.
v. The experts define objectives and preferences for the problem scenario. This phase is essential to verify the extent of the problem scenario and delineate the system boundaries. Determining system boundaries is an iterative process that requires balancing the complexity-feasibility tradeoff. In essence, the group of experts verifies if the description of the system is appropriate for the purpose.

Both system components and system boundaries are now defined, but in order to allow for a quantitative analysis, a scale of measure still needs to be determined. Several approaches can be used to give meaningful values to the system components, which is particularly important for the intangible variables. The systems analyst can decide to establish specific measurement scales for all system components. The disadvantage of this approach is that operations, such as summations and products, are performed on variables with very different units, and the meaningfulness of these operations needs to be analyzed. Conversely, a common relative scale can be used with unitless variables, which solves the problem of operations with variables with different units. In this case, system components take values for instance over the range [0, 100]. This approach enables an intuitive interpretation of the variation between different system components and lends itself better to accommodate intangible variables.

3.3 Graph structure estimation

The next step is to identify relationships between system components during individual sessions. In case data is available for all system components, the graph structure can be estimated based on the conditional independence between the system components through partial covariances (Hastie et al., 2009). A prudent approach is required in designing a procedure to construct a directed graph, because the number of connections is directly related to the elicitation effort for parameter estimation. The maximum number of connections increases with the square of the number of system components. Often it is difficult to distinguish between direct and indirect relationships between system components, and therefore it is sensible to impose a limit on the number of connections to a given budget, typically 10 percent of the maximum number of interconnections. To produce the interconnections map, the following procedure can be followed:

i. A list of definitions of system components is provided, together with the budget of interconnections.
ii. Select the most strongly connected pairs of system components, up to the limit of the interconnections budget.
iii. A tally is made for all pairs and numbers are normalized by the maximum cited pair. The most selected interconnections are kept up the maximum available budget.
iv. The system map can now be finalized by depicting system components together with the links.

A similar approach has been followed in a recent report of the World Economic Forum (WEF), where an interconnections map of risks is provided, as well as a risk-trend interconnections map (WEF, 2016). The main shortcoming of their approach is that the respondents were provided with a list of system components and could not decide which risks were taken into consideration. We argue that the group of experts should determine both system components and graph structure.

The resulting graph structure can be used to re-evaluate the system boundaries. In view of the verification, it is useful to classify the system components into endogenous, exogenous, and external state variables. The exogenous state variables represent constants and policy decisions, while endogenous variables are those system components that represent the system state. Endogenous variables change over time by interacting with each other and by the influence of exogenous variables. External variables are uncoupled from the connected part of the system map. These factors are considered insignificant for the purpose of the system and can therefore be cancelled from the system map. Inspecting the link defined by the experts, it is necessary to reflect on the feedback loops and verify if some of the exogenous variables should be endogenous. A system component that is treated as exogenous is not subjective to any feedback from the system. It is important to stress that this is often the case for policy decisions. Although the policy decisions are influenced by the state of the system, they are taken at a certain point in time and remain constant afterwards. If extra system components and links are identified with potential policy implications, key participants of the workshop need to be consulted to judge the validity of the assumptions.

The complexity resulting from the number of connections is the main hurdle to keep the expert elicitation manageable. The system map, consisting of system components, connections, and the results from the tally, can be represented by a weighted adjacency matrix, which allows to exploit techniques from network science to understand which nodes behave in a very similar way, which nodes are important, and sequentially, which nodes can be excluded from the analysis. The methods that can be used are principal component analysis, feature selection, community detection, and the relevance estimation of nodes by different centrality metrics.

3.4 Parameter estimation with known graph structure

The system map is now defined by its components and the relationships that exist between them, and expert opinion is now required to turn the graph into a weighted graph. This quantification step allows us to use the system map for dynamical analysis of the system behavior (cfr. Section 4). However, the cost-accuracy tradeoff is increasingly important with network size, and therefore some assumptions need to be adopted to ensure that the elicitation efforts remain achievable. Although relationships between system components can be highly non-linear, all graph links can be approximated by linear relationships in case we aim to capture local system behavior. Since the uncertainty in the description of the system behavior is vast, this approximation reaffirms that the system model should only be used over a relatively small time-horizon. In Section 4, it will be explained in greater detail that for each link a single weight needs to be estimated that expresses the strength of the correlation between the considered system components.

Depending on the size of the network and the total number of connections, there are different strategies to estimate the link weights. In case the number of network links is reasonably small, experts can be requested to estimate all link weights individually, or all links for which they are able to make an informed guess. In this case, experts do not need to be co-located, and the elicitation can be performed by means of a survey, customized software tool, etc. This approach provides the best results and allows us to include the opinion distribution in the analysis of the system behavior. Instead of using the consensus value that follows from social choice theory, largely varying parameter values that correspond to opposing opinions can disclose potentially very different behavior. However, if the complexity reduction efforts in the former steps of the system map construction were not sufficient, it can be impractical to request the experts to estimate all link weights. In this case, the group can be subdivided according to thematic area, and link weights can be estimated in group by means of different well-known aggregation methods. In this case, sub-groups need to be co-located or a group needs to be formed in a distributed way making use of technologies commonly used today. When the link weight assessment is performed in group, the elicitation process requires also the presence of a moderator. Depending on the areas of expertise of the group members, different social decision scheme can be used, such as delegation, unanimity, majority, or plurality. There is a large body of literature on voting-based methods, and it has been shown that range voting, which selects the vote with the highest average, results in the smallest Bayesian regret.

Ill-defined problems have to cope with so-called deep uncertainty, which refers to uncertainty that follows from disagreement between experts on the model structure, the type and weight of interactions, and the extent of the problem scenario. It is essential that any opportunity to reduce the inherent uncertainty of ill-defined problems be harnessed. It is therefore highly recommended to capitalize on available data to estimate the link strength for those interactions that can be quantified.

3.5 Test cases on education and refugee crisis

To illustrate the procedure, we show the system maps of two test cases that were developed in collaboration with the Finnish Prime Minister's Office (PMO). The first policy problem on education was motivated by the deterioration of the PISA (programme for international student assessment) results in Finland. The second policy problem concerns the recent refugee crisis in Finland and the potential repercussions on employment, safety, education level, etc. The system map that has been produced during different workshop sessions is shown in Fig. 1.

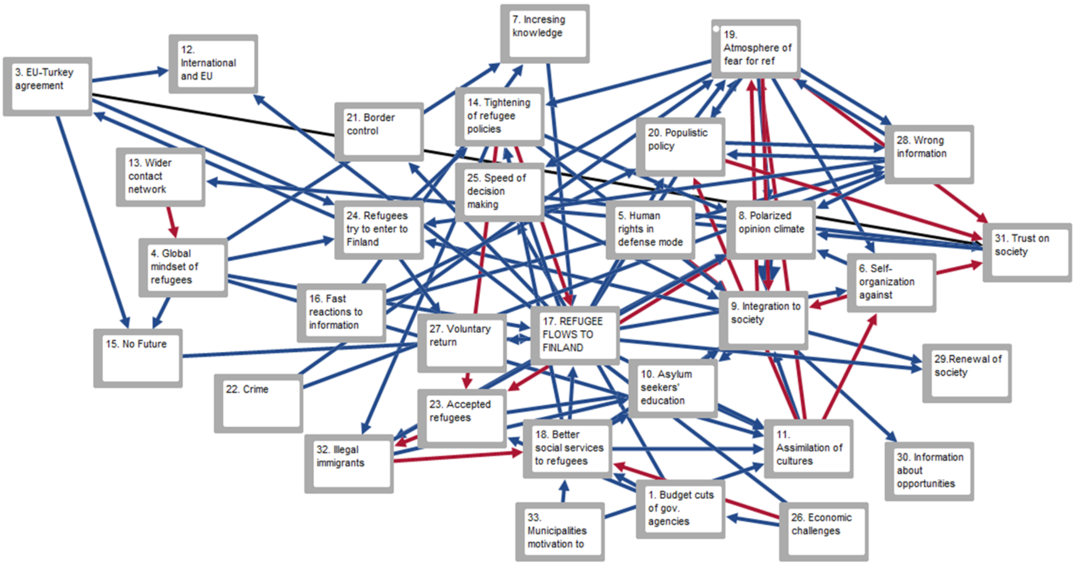

Figure 1 - System map of the refugee problem scenario created during collaborative workshop sessions.

4 Inference engine for analysis and policy design

4.1 Analysis of a system map through system dynamics

In this section, we establish an analytical model to describe the network dynamics and indicate how the uncertainty following from diverging expert opinions should be integrated in the framework. By complementing the qualitative system map with an analytical model, we allow experts and decision-makers to run simulations of the problem scenario and assess different futures according to different mental models and policy options. We call this quantitative model the inference engine, since it enables us to look at the consequences of policy options over all system components.

When data is available for some of the system components, correlation-based metrics can disclose linear interactions between the system components, but they fail to infer nonlinear relationships. Network maximum correlation (NMC) has been proposed to identify nonlinear relationships within networks without knowing the shape of the underlying nonlinearity (Feizi *et al*., 2015). In the absence of closed solutions for nonlinear systems, simulation is a necessary tool to quantify system component values and understand the system behavior (Sterman, 2000). However, in order to control the model complexity, we assume that interactions between system components are locally described by linear functions.

We consider a network consisting of n system components or nodes v_i that are marked with a value x_i. We further have a weighted adjacency matrix $A = [a_{ij}]$ that describes how changes of system component values are driven by changes of the neighboring system components. We consider here the scenario where changes *Δx(k)* at time step *k* result in changes of the system component values at time step *k + 1*, but where *Δx(k)* does not have a persistent effect further in the future. Let $u_j(k)$ denote an identified policy option that directly affects node *j* at time *k*, and let us assume that the relation between changes in node *i* and the changes of its neighborhood happen in a linear fashion; then we can write

$$\Delta x_j(k+1) = \sum_i \quad a_{ij}\Delta x_i(k) + u_j(k),$$

which can be formulated in matrix form as

$$\Delta\mathbf{x}(k+1) = A\Delta\mathbf{x}(k) + \mathbf{u}(k).$$

By iterating the recurrence relation, we get

$$\Delta\mathbf{x}(n) = A^n\Delta\mathbf{x}(0) + \sum_{\tau=0}^{n-1} \quad A^{n-\tau-1}\mathbf{u}(\tau).$$

Considering that $\Delta\mathbf{x}(0) = 0$ and for constant input, we get

$$\Delta\mathbf{x}(n) = \sum_{\tau=0}^{n-1} \quad A^{n-\tau-1}\mathbf{u}$$

which can be reformulated differently in case $|\lambda_i(A)| < 1$ (such that A^n converges and $(I - A)$ is invertible) as

$$\Delta\mathbf{x}(n) = (I - A)^{-1}(I - A^{n+1})\mathbf{u},$$

and the long-term effects can be written as

$$\Delta\mathbf{x}(\infty) = (I - A)^{-1}\mathbf{u}.$$

In order to satisfy the condition that $|\lambda_i| < 1$, we scale the weights of the matrix *A* with $\rho(A) + 1$, where $\rho(A) = \max_i\{|\lambda_i|\}$. By rescaling the system matrix such that all eigenvalues fall within the unit circle, we make sure that the system is stable. The stability assumption is restrictive, but valid for many realistic systems. For the aggregate differences of the feature values, we normalize with respect to the total aggregated input into the system

$$\Delta\mathbf{x}_{\text{agg}} = \frac{\sum_{k+1}^{N} \quad \Delta\mathbf{x}(k)}{N \times u_i}.$$

It is relevant to note that the relation with time is weakly defined, mainly due to the scaling imposed by the stability requirement. During the workshops, the facilitator needs to clarify that a link weight with value 10 does not relate to a 10-fold increase of the destination node in a single time step.

The uncertainty that originates from differing views on the model is typically called deep uncertainty. Under conditions of deep uncertainty, we can get a better view on the range of plausible futures through individual expert opinions. Instead, when aggregated metrics, expected values, of consensus values are used for the link weights, the resulting model does not allow exploring different potential pathways according to the mental models of the experts. A model based on aggregate metrics can yield good results when the problem scenario is not contentious, or in case accurate estimates exist of the model parameters. However, in the context of ill-defined problems it is highly recommended to account for deep uncertainty and use the diverging opinions in a robust decision-making framework. The analysis of multiple pathways facilitates dialogue between experts and decision-makers and can result in the selection of a consensual policy option. The final goal of the inference engine is to support decision-making while accounting for the multiplicity of plausible futures. By incorporating explicitly multiple views on the problem scenario, system maps can be very helpful to find a consensus on the action to be taken. In this context, notice that the analytical model is not a representation of reality, but a useful aid to link policy decisions to consequences under diverging expert opinions.

In general, the expected value of the system dynamics is different from the dynamics of the expected system, which can be expressed as

$$\mathbb{E}[f_i(\mathbf{x}(k),\mathbf{u}(k),A)] \neq f_i(\mathbf{x}(k),\mathbf{u}(k),\mathbb{E}[A]),$$

where $f_i(.)$ represents the function representing the system dynamics. For the system described here, $f_i(.)$ is a linear function such that we get an equality

$$\mathbb{E}[f_i(\mathbf{x}(k),\mathbf{u}(k),A)] = f_i(\mathbf{x}(k),\mathbf{u}(k),\mathbb{E}[A]).$$

It is however not clear if the dynamics of the expected system provide any meaningful insight. Through all methods of aggregation, the expected system provides results that exclude extreme expert judgments, even though very thoughtful. By running simulations over system models corresponding to contrasting expert views, different pathways can be distinguished and studied. Instead of focusing on optimality, ill-defined problems predominantly focus on robustness of the proposed solutions by assessing how many of the plausible pathways yield desirable outcomes under a given policy option. The policy option should be chosen that provides desirable outcomes over the largest possible subset of expert opinions. The reliability of the chosen policy can be expressed in terms of the ratio of the subspace cardinality of the parameters that yields desirable outcomes over the entire parameter-subspace cardinality.

4.2 Validation of the system map

A model is always wrong and cannot be verified nor validated (Sterman, 2000). Still, it is essential to perform a set of tests that improve the quality of the model and can make it convincing and useful. Validation in the strict sense of proving the validity and accuracy of the inference engine is not applicable in this context. The system map is built on expert knowledge, and is not verifiably wrong, meaning that there is no formal way to validate expert judgment. Instead of a proper validation process, a sensitivity analysis can be performed with respect to the system boundaries, system links, and if aggregation is performed, with respect to the aggregation rule. The validation process as defined here is a sanity test for the overall system behavior, and the system analyst can adjust the system map in order to rule out obvious errors that went unnoticed. During validation, it is advisable to compare the system behavior with historical data where possible. For problem scenarios in public policy, data can be typically be found for certain subsets of the system map and the meaningfulness of the inference engine should be verified for these subsets. The following steps can be followed for system map validation:

i. Boundary adequacy can be tested both by including and excluding system components and analyzing the sensitivity of the crucial state variables of the problem scenario. In case additional system components have significant effects on the system behavior, the system boundaries need to be re-evaluated.
ii. The structural adequacy relies heavily on the foreseen link budget. The sensitivity with respect to the number of node interactions can disclose if the increase or reduction of the link budget results in qualitatively different results. Quantitative differences and varying speed of the system response are less relevant in this context. In addition, the structural assessment requires also to verify if the system behavior is conform physical laws, such as conservation laws.
iii. The parametric adequacy of the model makes use of historical data for subsets of the system map to verify contentious opinions and outliers.
iv. The susceptibility of the model response with respect to model assumptions needs to be analyzed. Model assumptions can relate to the functional relationships between the system components, the imposed stability of the system, etc.
v. The focus of the sensitivity analysis is on tests that reveal the limitations of the model. Model limitations can apply to the time horizon over which the model can be used, the awareness of outliers in expert opinions, etc.

4.3 Preference elicitation and problem formalization

In public policy, it is essential to have a good understanding of the public value framework. The elicitation of public values can be performed in expert groups, but also by means of public involvement in focus groups of layman (Keeney et al., 1990). The elicitation process consists of two sequential phases: (i) identification of the objectives and criteria to be met, and (ii) collection of the weights corresponding to all criteria. The first phase is performed in expert workshops during the construction of the system map, since the objectives help to elucidate the system boundaries. Usually, competitive system objectives are defined taking into account multiple perspectives within society. For the weighting of preferences, several methods are commonly used such as cardinal ranking, nominal ranking, and interval selection (Wang et al., 2009, Triantaphyllou, 2013), but the entire weight space can also be explored (Lahdelma and Salminen, 2001). The robustness of these weighting methods needs to be carefully assessed (Danielson and Ekenberg, 2016). Building on techniques from multi-objective decision analysis, the criteria and preferences are merged in an objective function. The inference engine can generate and visualize both the aggregated utility and the individual objectives, which is very helpful for decision-makers to understand the tradeoffs and synergies that result from chosen policy options.

4.4 Design of realistic policies

Some solutions that result from the optimization exercise can be unworkable. As an example, there are cases where optimal control solutions suggest bang-bang control policies, i.e., policies where the control only takes the extreme values within the set of admissible controls. Although there are methods to circumvent this particular control structure, in general we need to evaluate if the obtained adaptive control policy is practically useful and meaningful to implement.

If reliable probabilistic information is available about the different potential models, the policy option should be selected that maximizes expected utility. However, under conditions of deep uncertainty, a strategy is required that performs reasonably well across the range of plausible futures defined by experts (Lempert, 2002, Lempert et al., 2006). Stated differently, a robustness criterion is needed that allows us to make a comparative analysis of the available policy options. Robust decision-making can help decision-makers to formulate solutions in the absence of information about the likelihood of the model parameters, which is standard for system maps and the corresponding ill-defined problems. By evaluating the range of pathways, sub-optimal solutions can be identified that satisfy a minimum performance in the largest possible subset of expert opinions. This approach allows us to discover the policy options that yield acceptable performance over most of the future pathways. What distinguishes system maps described in this work from traditional robust decision-making, is that the uncertainty is not defined by a set of possible probability distributions of the system parameters, but instead by diverging expert opinions for which no likelihood information is available.

4.5 Use case and benchmark exercise

In the refugee problem scenario, we study now the preferential areas of policy action. Policy actions need to address the following objectives that have been identified by the group of experts: (i) reduce fear amongst Finnish population, (ii) control the refugee flow, (iii) manage expectations of asylum seekers, (iv) preserve Finnish economy under migration pressure, and (v) avoid collapse of Finnish society.

As a benchmark exercise, we aim to make a comparative study of the expected system dynamics versus the dynamics of different plausible systems. The sensitivity of the system outcomes as a function of the adopted aggregation rule can provide insight into the most informative aggregation methods. By taking values from the empirical distribution of link weights, plausible models are constructed and different pathways can be explored under different realistic policy options. In view of the large uncertainties present in the system maps, the emphasis is not on optimization, but rather on the selection of robust policy solutions.

5 Closing comments

We proposed a methodology to develop an expert system addressing public policy issues within a group setting. The expert system builds on a system map in combination with an inference engine. The system map is defined during participative workshops and consists of all essential factors and the interconnections between these factors that affect the problem scenario. The inference engine can simulate future pathways and allows us to select solutions that are robust over the largest possible set of expert opinions. The robust solution includes and weighs multiple priorities of the decision-makers, according to their conflicting value frameworks .

When aggregation rules are used for link weights, system maps represents the average perception of the problem scenario and its meaningfulness can be questioned in view of conflicting opinions. Other issues with aggregation rules relate to group bias and groupthink. We therefore recommend using the full set of expert opinions and include in the analysis the notion of robustness by providing policy options that yield acceptable performance over the uncertainty domain.

Although we use a quantitative model to describe the system dynamics, we need to recognize that the system map and its dynamics are fully based on expert judgment and on a set of restrictive assumptions (e.g., linearity). The trajectories of the system components very often do not have a direct physical interpretation, and therefore the quantitative model still leads only to qualitative results. This means that the interpretation of numerical values is usually done in a comparative way. Ultimately, we account for uncertainty by gathering expert opinions in a robust decision-making context, but also here a prudent approach is necessary. Group selection has a crucial impact on the quality and range of collected opinions, and there are no formal ways to determine the completeness of the collected uncertainty set. The proposed policy options are therefore only robust with respect to the set of opinions developed in the considered group of experts.

6 Lexicon of system maps

System: A system is a closed set of state variables that all together represent the behavior of a system. We call the state variables here the system components, and these system components are augmented with interrelationships between them. The system components, system links, and the interaction rules between connected system components determine the behavior of the system under study.

System component: System components are the features, factors, or state variables that determine the evolution of the system over time. System components can be classified according to endogenous and exogenous variables, where the exogenous system components can in some cases be used as policies or control variables. System components can also be classified along another dimension, more specifically we can distinguish between measurable and intangible state variables. Intangible system components frequently appear in ill-defined problems and typically can be expressed by means of a common relative measurement scale.

System links: System links represent a relationship between system components and are represented by edges in the graph structure. The system links in system maps as described in this paper are marked with a weight, where the of the link strength is informed by data or expert judgment.

System boundaries: The system boundaries separate the system from the environment, which can affect the overall system behavior by means of exogenous effects or inputs.

7 References

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