Automatic Pattern Detection in Stakeholder Networks

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Abstract

The values and opinions of the stakeholders involved in a decision making process are the key to its outcome. Reflection on how stakeholders perceive a situation, and on the consequences of these perceptions for the decision outcome is a intellectually demanding exercise. To support analysts, we have developed a conceptual modeling tool called DANA (Dynamic Actor Network Analysis). The modeling language is based on the policy network paradigm and embodies concepts from cognitive mapping and linguistic approaches to approximate reasoning. In this paper, we investigate how certain interesting properties of stakeholder networks modeled with DANA can be determined algorithmically. Automatic detection of the factors most relevant to a policy situation, and of disagreement and conflict among stakeholders may help the analyst in focussing her[1] *analysis.*

1. Introduction

There are people who believe that policy problems are an objective condition whose existence may be established simply by determining the 'facts' in a given case: What are the newest unemployment figures? How many people are homeless? What is the number of people killed in a car accident? This naive view of the nature of policy problems fails to recognize that the same facts – for example, government statistics which show that crime, pollution, and inflation are on the upswing – can and will often be interpreted in markedly different ways by the different actors involved in a policy making process. The same policy-relevant information can (and will most often) result in conflicting definitions and explanations of a 'problem'. This is not so much because the facts of the matter are inconsistent (though often they are), but because policy makers, policy analysts, and other stakeholders (actors) involved hold competing assumptions about problems and solutions, means and ends, cause and effect.

There is no single correct view; problem definitions depend on the actors' specific characteristics, loyalties, past experience, and even accidental circumstances of involvement. For an important part, policy problems are in the eye of the beholder ([12] p. 97). This applies to crime prevention or education, but also to health care, environmental planning, etcetera. Although there is a sense in which the policy problems we are dealing with in these sectors are objective, the same data with respect to these policy problems are typically framed from very different perspectives. The external conditions that give rise to a policy problem are selectively classified and evaluated. And what is more: depending on which explanation one chooses, the solution takes a different form. Every formulation of the policy problem corresponds to a statement of solution and vice versa. As a result, the actors involved in a policy process may disagree on the definition and explanation of a policy problem, and even when there is consensus about this, they may yet disagree about its scope, severity, and importance.

To sum up, policy problems are products of subjective judgement. Policy problems exist only because the actors involved make judgements about the desirability of altering some problematic situation. Policy problems are therefore socially constructed, maintained and changed.

Although policy making is often thought of as a process for solving problems, that is often not what happens. Problems are worked upon in the context of some choice, but choices are made only when the shifting combination of problems, solutions, and participating actors happen to make action possible. Quite commonly this is after some problems have left a given arena or before they have discovered it ([6] p. 16). From this point of view, the policy process is a garbage can in which issues and feelings looking for decision situations in which they might be aired, solutions looking for issues to

[1] This is not a gender bias, but a didactic choice. The distinction between 'policy analyst' and 'actor' is so important in our argumentation, that we shall consistently refer to a policy analyst as 'she' and to an actor as 'he'.

which they might be the answer, and decision makers and policy analysts are looking for work ([6] p. 2).

In addition to all this we can say that the policy analyst has to work in an environment which also exhibits the following characteristics: the information available to the policy analyst is incomplete; the actors have multiple and conflicting objectives; there are conflicts or interest; and there is always more than one participant with power to influence the outcome may be involved [22].

In such messy contexts, how can a policy analyst do her job? We argue that she should stay away from ‘hard’, solution-oriented models for the risk of a false fixation of the problem formulation. Instead, she should acquire knowledge by making a whole range of ‘soft’, perception-oriented models, trying to improve her understanding of how actors think. We introduce Dynamic Actor Network Analysis (DANA) as an approach that facilitates this mode of policy analysis.

In this paper, we focus on interesting patterns that may be detected algorithmically within actor networks, once they have been represented in a DANA model. In section 2 we introduce the conceptual base of actor network analysis. In section 3 we outline how actor network models are constructed in DANA. Since this work has been presented at last year’s HICSS [3], we limit this to the minimum that is required for a proper understanding of section 4, where we discuss a range of properties of actor networks that can be computed on the basis of a DANA model. In the last section of this paper, we address the issue of model validity, make an assessment of the costs and potential benefits of actor network analysis, and take an outlook on even more sophisticated queries that allow investigation of dynamic actor behavior and learning.

2. Actors in networks

2.1. Arenas, actors and factors

The key to ensuring a more complete understanding of the policy problem at hand lies in finding out which actors are involved. An actor could be defined as an acting unit. This unit can be an individual person or a collective, like an organization or an institute [19]. Actors can be public or private, or semi public. One reason to gather information on actors is to get an indication of whose objectives and interests are at stake in a certain situation. Information on the actors involved is also needed to determine if and how they will act in a certain situation.

It is assumed here that actors behave in networks [1][20]. A network consists of actors and represents the relation between them. The network indicates the position and the influence of an actor in relation to the other actors involved. The term network is meant to describe the factual relation between the actors involved in a certain complex policy problem and the way in which they interact to exchange resources (for example money, authority, information, expertise) to achieve their objectives, to maximize their influence on what is going on in the network, and to avoid becoming overly dependent from other 'players in the game'.

2.2. Perceptions and positions

As might be clear from our argument so far, actors have their own perception of the world that surrounds them. A perception is an image through which the complex, ambiguous world which surrounds an actor can be made sense of and acted upon. It guides the stimuli that actor experiences and helps shaping the responses [26].

Each actor has subjective perceptions of the relevant factors with respect to the problem. Each actor also has perceptions of the action space of the problem, the linkages to other problems, the characteristics of the environment of the problem, the constraints on courses of action, and the possibility of occurrence of future natural and quasi-natural events. In addition, each has perceptions of the perceptions of the other actors concerning these factors [22]. The perceptions of the actors are therefore particular to the individuals involved and are subjective. Furthermore, inasmuch as the environment is dynamic and changing, the perceptions of the actors are likely to change as time progresses, in a manner dependent on their individual abilities to gather information about the new state of the environment [22].

The actor’s perception of the problem is based on the information available to him and depends on the nature of his motivations, spheres of competence, experience and judgement. Although the actor’s perceptions of a policy problem are always incomplete and necessarily subjective, there is a natural tendency for anyone who has studied a problem to assume that he has the facts and that what he perceives is the real situation [2][22][26]. Perceptions of an assumed ‘objectivity’, are typically put forth with the apodictic claim that they must be true, that dissent – at least in the central spheres of belief systems – is not explainable through mere ignorance of the dissenter, but that it may be due to his malevolence, hostility, or inherent incapacity to discover the ‘truth’.

Working from DANA, the perceptions of the actors in a network, in terms of relevant factors and actor-specific instruments and goals, should define the basis for evaluating relevant aspects in a specific situation. By making the perceptions explicit in a qualitative, conceptual language, the analyst can sharpen her insight by doing different types of comparative analysis.

2.3. Interdependencies

One important reason for the interaction that underlies the communication between actors is the interdependence that exists between them. Actors in networks are interdependent because they cannot attain their goals by themselves, but need the resources of the other actors to do so. Without the cooperation of other actors their ambitions cannot be realized. Interdependency is based on the distribution of various resources between actors, the goals they pursue and their perceptions of resource-dependencies. In DANA, these concepts are made explicit.

Interdependencies causes interaction between actors, which create and sustain relation patterns [1]. Continuing interactions between the actors in a network is caused by the need to exchange resources and to negotiate shared purposes. This means actors have to exchange their go alone strategies for contingent strategies: courses of action tailored to the behavior of others [16][21].

Power and perception are two factors which interfere with each other at this point. The position of power which actors hold in a network of interdependent actors influences the way in which they perceive the situation: “Where you stand depends on where you sit” [2]. And conversely, the actors’ perceptions on the situation may encompass the power of other actors, their objectives, the resources and the interests of the other parties involved, etcetera.

3. Modeling with DANA

The aim of the DANA-project is to construct a workbench to support policy analysts in their representation and analysis of information on the relevant actors in a certain policy situation. The design of the DANA workbench is largely determined by the underlying method of dynamic actor network analysis. This method leads the analyst to think in terms of actors who all have their own perception on the situation at hand.

Figure 1 shows the basic modeling concepts of DANA. Decision making situations are modeled as actor networks called ‘arenas’. Within an arena, actors each have their own perception on this situation (their ‘private thoughts’), but for strategic reasons they may present a different picture to other actors (their ‘public voice’). The perceptions of actors are modeled in terms of factors (variables of different types) and the causal relations between these factors. Factors that are particular to one actor are called ‘attributes’ of that actor.

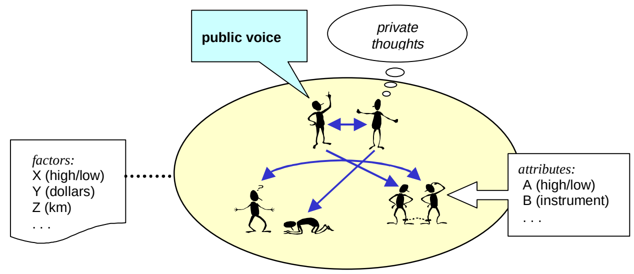

Figure 1. DANA modeling concepts

In the remainder of this section, the DANA modeling concepts are defined more formally. For a full specification of the DANA modeling language, we refer to [3]. Parentheses (…, …, …) indicate an aggregate of different modeling concepts, which are separated by commas. Braces {…} indicate a set of zero or more of the specified elements, brackets […] indicate optional parts. *Italics* indicate that the syntax of a term is not elaborated any further. Typically, they indicate where the analyst has to fill in names or specific values.

Arena = (*arena name*, {actors}, {factors}, {relations}, analyst view) (1)

Actor = (*actor name*, {attributed factors}, perception, countenance) (2)

Factor = (*actor name*, *scale*) (3)

The scale defines the range of values that a factor may have: either a numeric scale (integer, e.g., the number of municipalities affected by the construction of a new railway, or real, e.g., the freight transport capacity of that railway in million tons per year), an ordinal scale (a range of qualitative values, e.g., noise production may be ‘low’, ‘average’, or ‘high’), a nominal scale (qualitative values with no implicit order, e.g., mode of transport may be ‘truck’, ‘train’, or ‘boat’), or an instrument (no scale; either it is applied or it is not).

From a DANA point of view it, is essential to learn how actors provide satisfactory accounts for what is happening. We define the *perception* of an actor to comprise all terms (notions, concepts) in which he – privately – thinks about a situation. More precisely, a perception includes all assumptions (regardless whether they are empirically true or false) that an actor makes about a situation. An actor acts on his perception in a rational way, i.e., his actions are consistent with his assumptions. In DANA, every actor perception is modeled in terms of factual, causal and teleological assumptions [23].

Perception = ({facts}, {links}, {goals}) (4)

The *countenance* of an actor has exactly the same structure, but models his public voice. An *analyst view* has the same structure as a perception or a countenance, offering the analyst the means to model her own, personal perspective on the problem situation.

The factual assumptions represent how an actor thinks/talks about the current state of his environment, typically by specifying the current (numeric, ordinal or nominal) value of a factor. Optionally, an actor may have/state certain expectations regarding the future. Insofar as the actor sees an expected change as autonomous, i.e., not caused by changes in other factors, it should be represented as a factual assumption as in (5), rather than a causal assumption as in (7).

Fact = (factor, *state* [, change]) (5)

where

Change = (factor, *modifier*, director) (6)

The director determines the direction of the change, e.g., that the value of the factor should increase (+), decrease (–) or reach a specific state ($\rightarrow x$), the modifier indicates the extent of the change (e.g., slight, significant, or tremendous).

The causal assumptions represent the logic that an actor (says he) attributes to chains of events, e.g., "*if* global energy consumption increases *then* CO_2 emissions will increase, and *if* more CO_2 is emitted *then* the global temperature will probably rise, and *if* global temperature rises *then* more hurricanes will occur", and so on. Formally,

Link = (cause, *certainty*, effect) (7)

where cause and effect are two different changes, and certainty is a hedge like 'possibly', 'probably' or 'definitely', typically associated with some value between 0 and 1. A link should be read as "*if* cause *then* certainty effect". The causal assumptions of an actor can be represented graphically as a causal map, one of several possible techniques (see [18] for an overview) to graphically model causal reasoning in a system.

The third type of assumptions are the teleological assumptions, which represents an actor's true/stated objectives. The insistence expresses how strongly he desires a factor to change, typically on some ordinal scale, e.g., from 'preferably' to 'definitely'. The optional negation means that a teleological assumption may also be a constraint, i.e., a change that the actor does *not* want to occur, e.g., "CO_2 emissions should definitely not increase".

Goal = ([–]*insistence*, change) (8)

All three types of assumptions are the actor's interpretations of factors. Definitions (5) through (8) show that change is the basic building block for models of actor perceptions/countenances: changes that an actor expects to occur anyhow, changes that he would (not) like to occur, and assumptions on how one change may lead to an other.

Figures 2 and 3 give an impression of what the current DANA prototype looks like. The actors and factors that have been identified by the analyst within a chosen arena can be viewed using the perspective browser on the left in figure 2. The assumptions that reflect an actor's perception are visualized in a causal map: factors as ovals, causal links as arrows. New factors can be added to a perception by dragging them from the perspective browser into the causal map. The active dialogue window in figure 2 allows the analyst to specify both facts and goals, the one in figure 3 does the same for causal links. All analyst-defined modeling concepts are stored in a dictionary, shown on the right in figure 2.

The causal mapping convention is similar to cognitive mapping as elaborated by Eden and Ackermann [13][14] [15], and supported by the *Decision Explorer* tool [8]. The main differences are:

- A standard factor coloring convention: blue indicates a desired decrease, orange a desired increase. The color intensity reflects the actor's insistence on a change. For constraints, the fill style of the oval is vertical bars, rather than solid fill.
- Factual assumptions are highlighted by showing the factor name in bold face.
- Causal links are not labeled with + or – ; instead, a solid arrow head indicates an increase, an open arrow head a decrease. Furthermore, the width of an arrow reflects the ratio of effect over cause – the modifier in (6) – and as uncertainty increases, a link takes on a lighter shade of purple.

The DANA dictionary provides the fundament for further analysis. It enforces 'strong typing' in the sense that all concepts considered relevant by the analyst fall into one of the basic categories of DANA: either arena, actor, factor (with its subcategory instrument), relation, or rule. Furthermore, it enforces name uniqueness within categories, effectively preventing the use of homonyms. New concepts may be added either directly into the dictionary, or by means of DANA's idea generation functionality: a brainstorming and organizing tool similar to e.g. the Group Outliner of Ventana's GroupSystems [9], extended with DANA's strong typing.

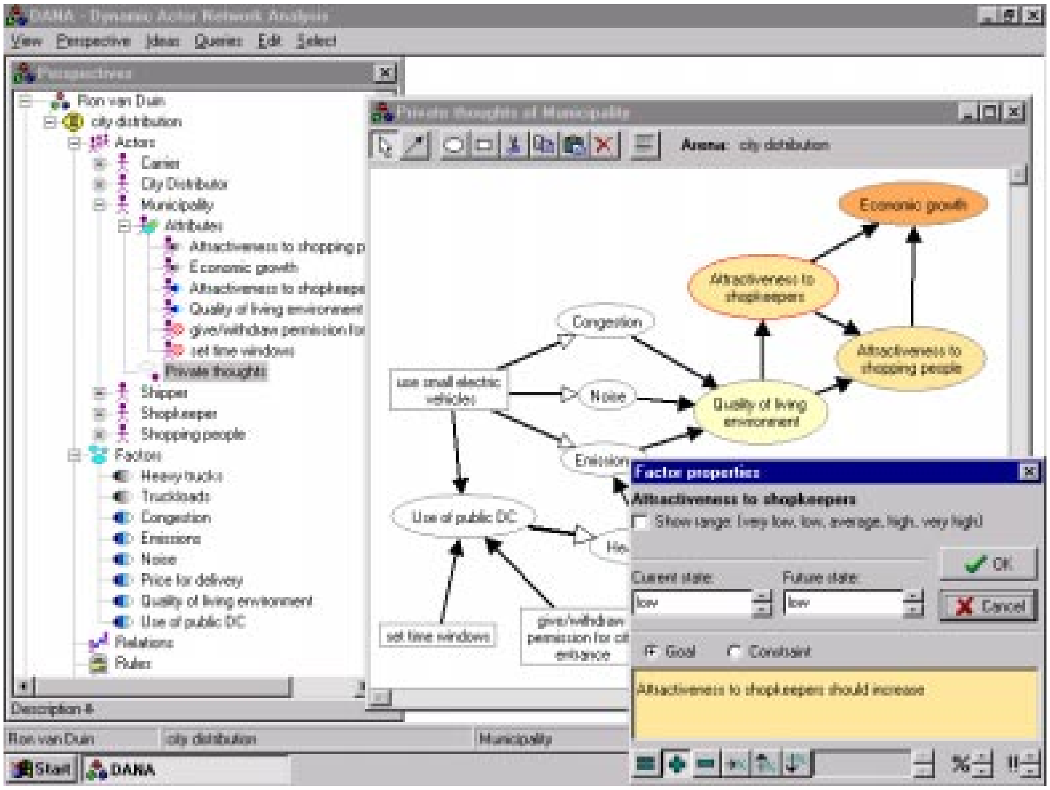

Figure 2. Specifying factual and teleological assumptions in DANA

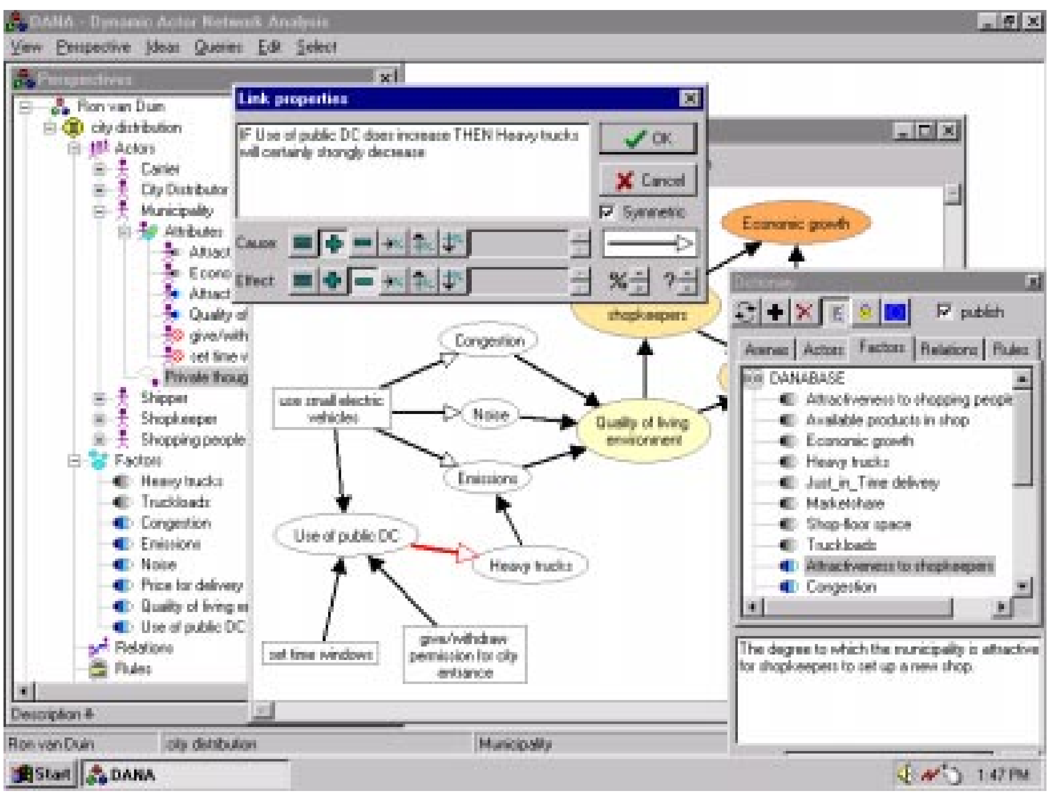

Figure 3. Specifying causal assumptions in DANA

Especially when several analysts are involved in the analysis, the use of this feature to generate and discuss concepts before entering them into the dictionary will not only mitigate the risk of synonyms, but also enhance their mutual understanding.

With the basic concepts defined in the dictionary, the actual modeling of an arena is a process of establishing relations between concepts in the DANAbase. For example, when an analyst adds an attribute to an actor by dragging a factor icon from the dictionary onto the attributes icon of some actor in her perspective browser, the software adds a record (*FactorInActorID*, FactorID, ActorID, ArenaID, AnalystID) to the FactorInActor table of the DANAbase. Note that this effectively separates arenas and analyst perspectives: if analyst *X* thinks that factor *F* is a relevant attribute for actor *A* in arena *R1*, this need not be the case in arena *R2*, and analyst *Y* might think differently as well. When she subsequently drags the newly defined attribute into the causal map that represents some actor's perception, the software adds a record (*FactorInPerceptionID*, FactorInActorID, ActorID, ArenaID, AnalystID, "**P**", X, Y) to the FactorInPerception table of the DANAbase. Again, the ID fields effectuate that different actors may have different perceptions in different arenas in the eyes of different analysts. The value "**P**" indicates perception (the actor's private thoughts) as "**C**" would have indicated countenance (his public voice). The values X and Y are the coordinates of the oval in the causal map.

4. Queries on actor networks

Because of the formal description of these perceptions in a database that maintains semantic integrity, a wide range of queries can be executed. For instance, questions like "Which factors are considered relevant by both actor A and actor B?" and "Which actors have conflicting goals on factor X?" could be brought to our special attention. In this section, we explore a number of properties of actor networks that can be automatically derived from a DANA model, and discuss what insight they may provide to an analyst.

4.1. Relevance

In the context of actor perceptions, 'relevance' denotes whether an actor does or does not perceive a factor as being relevant to the problem. In terms of a DANA model, see definition (1), factor *f* is *relevant* to actor *a* if *f* is an element of the set of factors in *a*'s perception *Pa*. To assess the overall relevance of a specific factor in a problem situation, an analyst may count the number of actors in arena *A* that perceive this factor as relevant:

$$relevance(f) = \sum_{a \in A} \beta(f \in Pa) \tag{9}$$

where $\beta(x)$ is an indicator function that yields 1 if x is true and 0 if x is false.

A list of factors, sorted on the relevance measure defined by (9), gives the analyst an idea not only of the subset of most relevant factors, but also of the variety in problem definition amongst actors: If the relevance score of the top 10 or so factors in the list is low (say less than half of the number of actors in arena *A*), the problem definitions are must diverge widely.

Simply counting occurrence of a factor in a perception ignores that some factors may be more central to an actor's reasoning than others. A more sophisticated measure for relevance would also take into account how strongly a factor is related to other factors, e.g.,

$$relevance(f) = \sum_{a \in A} 1 + \frac{\delta_{Pa}(f)}{|F_{Pa}|} \tag{10}$$

where $\delta_{Pa}(f)$ is the number of links that enter or depart from factor *f* in perception *Pa*. The division by $|F_{Pa}|$, the number of factors in *a*'s perception, neutralizes the effect that perceptions with many factors would systematically score higher than perceptions with but a few factors. Thus, measure (10) can be used in the same way as measure (9) to assess the variety in problem definitions.

4.2. Interest

In the context of actor perceptions, 'interest' denotes whether an actor desires that the value of some factor should decrease (goal) or not increase (constraint). In terms of a DANA model, see definition (1), actor *a* takes *interest* in factor *f* if his perception contains a goal g = (<u>i</u>nsistence, *f*, <u>m</u>odifier, <u>d</u>irector). To assess the overall interest in a specific factor *f* in a problem situation, an analyst may take the sum of the insistences *i* for all actors *a* in arena *A* that take interest in this factor:

$$interest(f) = \sum_{a \in A} \sum_{(i,f,m,d) \in G_{Pa}} |i| \tag{11}$$

By taking the absolute value of the insistence *i*, goals and constraints add up, rather than compensate each other. The interest measure could be extended by multiplying *i* with the modifier *m* to distinguish between larger and smaller desired changes. Note that this does not hold for the director *d*, since the direction of the change is not related to interest in a factor *per se*.

Change directors *do* matter when the analyst wishes to take into account implicit goals as well. If an actor wishes factor f_1 to increase and thinks that a decrease in factor f_2

causes an increase in factor f_1, such a decrease can be seen as an implicit goal. According to this reasoning, an actor will take interest in any factor that through some sequence of causal links in his link set L_{Pa} affects a factor that occurs in his goal set G_{Pa}. The *direct* causal influence of one factor on another as perceived by actor a can be computed as a matrix:

$$\forall f_1, f_2 \in F_{Pa} : impact[a, f_1, f_2] = \begin{cases} \varphi(d_1, c, m, d_2) & \text{if } (f_1, d_1, c, f_2, m, d_2) \in L_{Pa} \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

where φ is a function that converts any combination of two directors d_1 and d_2, certainty c and modifier m into a numeric value, where $\varphi > 0$ indicates an increase, and $\varphi < 0$ a decrease, of f_2 as a result of an increase in f_1. We shall return to the definition of φ in the next subsection.

Assuming that the causal map has no cycles, the *indirect* causal influence as perceived by actor a can be computed by a graph traversal algorithm such as described in [11]. Like φ, the addition and multiplication of influences in the algorithm must be defined to properly propagate the modifiers and certainties. Assuming that this can be achieved, the interest measure in (11) can be extended with implicit goals:

$$interest(f) = \sum_{a \in A} \sum_{(i,f,m,d) \in G_{Pa}} \sum_{k=1}^{|F_{Pa}|} |influence[a,k,f] \cdot i| \tag{13}$$

A list of factors, sorted on the interest measure defined by (11) or (13), gives the analyst an idea which factors are at the core of the issue at stake. Like relevance, the interest measure may also reveal variety in problem definition amongst actors. By clustering actors on the basis of their interest vector, particular sub-problems within an arena may be identified.

4.3. Computing uncertain effects

Firstly, we have assumed that a function φ can be defined that converts any combination of two directors d_1 and d_2, certainty c and modifier m into a (numeric) value that is consistent with the intuitive semantics of a change. Secondly, we have assumed that an additive operator and a multiplicative operator can be defined that preserves these intuitive semantics while propagating changes through a causal network using matrix multiplication. In this subsection, we review some possible candidates for φ, and the operators ⊗, and ⊕.

Reduced to its simplest form, a causal map like the ones used in DANA can be represented with only directors + and – (and 0 indicating no causal relation), and binary certainty (+ indicating certainty, ? indicating uncertainty). All relations have equal impact, i.e., all modifiers have a multiplicative value of 1. Using the definitions of ⊗ and ⊕ as given in [11], function φ can then be defined as:

$$\varphi(d_1, c, m, d_2) = d_1 \otimes c \otimes d_2 \tag{14}$$

⊗	+	–	0	?
+	+	–	0	?
–	–	+	0	?
0	0	0	0	0
?	?	?	0	?

⊕	+	–	0	?
+	+	?	+	?
–	?	–	–	?
0	+	–	0	?
?	?	?	?	?

Figure 4. Multiplication and addition of directors [28]

To accommodate for modifiers, the tables in figure 4 can be extended by adding rows and columns labeled with, e.g., + + +, + +, – –, and – – –, and filling the new cells with appropriate results (see [10] for an example).

Certainties may be implemented in several ways [10][11][28], e.g., as ranges (upper and lower bounds for the factor value), as value distributions, or as fuzzy sets. For DANA, with its aim of qualitative insight of actor perceptions and positions, rather than quantitative prediction of system behavior and outputs, a single, qualitative value for φ is preferred. Presently, certainty propagation is implemented with $c_1 \oplus c_2$ defined as MAX(c_1, c_2) and $c_1 \otimes c_2$ defined as MIN(c_1, c_2) [5] and modifier and certainty are maintained as separate values. This is, however, a pragmatic choice that requires careful reconsideration when have analyzed in more depth such properties as the robustness of the actor network measures we propose here (future research, see section 5).

Assuming that it can be constructed in a meaningful way, the causal influence matrix provides the basis for several other measures that are of interest to the analyst: utility of instruments, disagreement and conflict between actors, and problem solving potential. Each of these will be discussed in a separate subsection.

4.3. Utility

Utility can be defined as a property of instruments: the utility for actor a_1 of instrument i in the hands of actor a_2 is the extent to which the use of i may cause (directly or indirectly) changes that correspond with the goals in G_{Pa1}. (indirect). In formula:

$$utility\,(a, x) = \sum_{(i,f,m,d) \in G_{Pa}} i \cdot (\Phi_{\max} - |\, influence[a, x, f] - \varphi(+,1,m,d)\,|) \tag{15}$$

assuming that the function φ returns values between $-\Phi_{max}$ and Φ_{max}. Note that the perceived beneficial impacts of an instrument are balanced against its negative side effects, if any. Thus, the utility function in (15) may result in a negative value. Note also the straightforward multiplication with insistence *i*; there may well exist better ways to weigh goals to determine utility.

The utility measure is useful in finding protagonists and antagonists of a particular instrument, e.g., by sorting the list of actors on their perceived utility of that instrument. To assess overall utility of an instrument in a given arena, the utility of an instrument for an actor may be aggregated by summation over goals of groups of actors. Here, again, no absolute values should be used, since positive utility for one actor may be ruled out by negative utility for other actors.

4.4. Disagreement

Two actors may disagree about factual or causal assumptions. If actor a_1 thinks that factor f has state X, and actor a_2 thinks that it has state Y, the extent of their disagreement can be defined as |X–Y| / (|X|+|Y|), or possibly even better using an Euclidean distance measure. For causal assumptions, the same measure can be used when $influence[a_1, f_1, f_2] = X$ and $influence[a_2, f_1, f_2] = Y$. To speed up computation, the algorithm need only determine disagreement on the set of factors that two actors share in their perceptions: $F_{Pa_1} \cap F_{Pa_2}$. When aggregating agreement, care must be taken that aggregate measures remain comparable: it is wise to divide disagreement between two actors by the total number of factors involved before comparing it to the disagreement between two other actors. The analyst may cluster actors into groups with low disagreement scores within groups and high disagreement scores among groups to detect different ‘schools of thought’ within an arena.

4.5. Conflict

Conflict refers to a situation where two actors want to change a factor in opposing direction. A conflict measure should aggregate for all changes desired (indirectly) by actor a_1 the difference in utility of those changes as perceived by a_1 and as perceived by a_2. Assuming that the utility measure for instruments (15) is generalized to a utility measure for changes in any factor *f*, a conflict measure can be defined that is very similar to disagreement:

$$conflict(a_1, a_2, f, m, d) = \frac{|utility(a_1, f, m, d) - utility(a_2, f, m, d)|}{|utility(a_1, f, m, d)| + |utility(a_2, f, m, d)|} \tag{16}$$

The sum of conflict over all changes (indirectly) desired by two actors can be used by the analyst to test her own intuition about conflicting interests. Also, she may aggregate conflict over all actors on one particular factor (cf. interest in section 4.2) and sort the list of factors to find ‘the largest bone for which the dogs are fighting’. The conflict measure may also help to find the subset of actors with largest conflict in an arena. One step further is looking for arenas in which the same actors are in conflict as well. Such arenas constitute an opening for conflict resolution: loss in one arena may be compensated for by gain in some other arena.

4.6. Problem solving potential

Without elaborating this concept in depth, the problem solving potential of an actor could be defined as the extent to which the instruments of that actor contribute to the realization of goals. The ‘external’ potential of an instrument could be defined as the total utility for actors other than the owner of the instrument. This leads us to an operationalization of two concepts that are frequently used in actor network theory: ‘power’ and ‘resource dependence’. An actor’s power may be defined as the sum of his external potential. An actor’s resource dependence may be defined as the maximum utility U_{max} he thinks he will get from any instrument in his perception *minus* the utility U_{own} of his own instruments, or as a relative measure $U_{max} – U_{own} / U_{max}$.

5. Conclusion and future research

Dynamic Actor Network Analysis (DANA) is a conceptual modeling approach which intends to portray the perceptions of actors and their relationship to one to another in a form which is amenable to study, analysis and (re-)design. It is also a computerized support tool we are in the process of developing, based on the assumption that the situations by which actors are influenced and to which they adapt themselves do not stem from the ‘objective’ world of the policy analyst, but from their own subjectively perceived world. The representation of an actors’ perception in DANA is not supposed to be an objective reality in the way some influence diagrams are, but rather a representation of a part of the world as a particular person sees it. Therefore, a perception is not to be shown to be right or wrong, in an ‘objective’ sense. Conversely, the *representation* of a perception, made by an analyst using DANA, can be validated to a certain extent. Through seeing as and thinking as actors, a policy analyst using DANA produces knowledge that is 'objective', in the sense that it is refutable (in the scientific sense). She might confront actors with the DANA-models of their perceptions, and find that she misunderstood them.

Ultimately, the validity of a DANA model could be tested through empirical observation of the policy process as it enfolds in the real world. The analyst might discover that the model did not satisfactory forecast change or decision making behavior. This type of policy and stakeholder network analysis would fit in the traditions of game theory [3][17] and quantitative social networks [7].

Although this interpretation of the validity of a DANA model may appeal to the policy *scientist*, it discards the usefulness of 'invalid' models to a policy *analist*. Even though the knowledge she produces is subjective, bounded by the perceptions of the actors involved and restricted by her own analyst perspective on the situation, which is marred typically by missing or ambiguous information, it may be quite useful. 'Garbage in, garbage out' applies to models in general, and it would seem to invalidate DANA models and the properties derived from them as defined in section 4. However, as long as the analist is aware of the inherent subjectivity of the model, the process of modeling and analysis itself becomes a means to better understanding in the situation. Queries on the model may lead to surprising answers, suggesting for example a conflict between two actors that the analyst was not aware of before. Rather than to accept this outcome as a fact, it triggers the professional analyst to investigate *how* DANA could generate such an insight. The structure of the DANA conceptual model, with its integrity enforced by the underlying database engine, allows the definition of all kinds of intermediary queries that can show the assumptions underlying the model output. Even though (some of) the assumptions in the model might prove false, the exercise of finding out why may sharpen the analyst's insight in the situation.

In the terminology of Donald Schön ([24], p. 163), the analyst functions as an agent/experient in the reflective conversation she has with a situation to construct her own perspective on this situation. Through her transaction with the situation, she shapes it and makes herself a part of it. Hence, the sense she makes of the situation must include her own contribution to it. Through the unintended effects of action, the situation talks back. The analyst, reflecting on this back-talk, may find new meanings in the situation which lead her to a new reframing. Thus, she judges a problem-setting by the quality and direction of the reflective conversation to which it leads. This judgement rests, at least in part, on her perspective of the potentials for coherence and congruence which she can realize through her further inquiry ([24], p. 135).

We expect that the utility of DANA to a policy analyst will be similar to that of expert systems for medical or technical diagnosis to a doctor or an inspector of power plants, where human experts are not replaced by the system, but use it as a 'sparring partner' [27]. Whether the benefits of making and using a DANA model outweigh the costs of doing so remains yet to be seen. A series of use cases may reveal at what point DANA becomes more than a training device in actor network analysis.

As a tool, DANA's primary user group consists of strategic analysts, not only in the field of policy making, but also in business, the military, or everywhere else where situations are assessed for which decision making requires understanding how the other actors (stakeholders, competitors or partners, enemies and allies, ...) think, reason, and feel. DANA may assist the analyst in her investigation of real-life situations as well as fictive contexts, such as war games and business simulations. DANA would seem to be the ideal tool to properly balance roles and plots while designing decision making games.

For all its potential applications, DANA in its current stage of development is itself an object of research. First and foremost, we must investigate the properties of the actor network measures defined in this paper by means of Monte Carlo simulation (with a focus on mathematical properties, extreme values and so on) and case studies (with a focus on information value for analyst).

An extension of the current version of DANA would be to implement actor relations. So far, we have operationalized three such relations:

1. *Authority:* if a_1 has authority over a_2, a_2 automatically inherits the goal set of a_1;
2. *Sympathy:* if a_1 is a friend of a_2, a_1 will adopt all goals of a_2 insofar as there is no conflict with his own goals;
3. *Trust:* if a_2 trusts a_2 , a_2 will have access to the private thoughts of a_2 , which may have an impact on his preferences for instruments.

When such actor relations have been specified by the analyst, she may investigate to which extent they affect the various actor network properties defined in this paper.

The next obvious step would be to incorporate game dynamics: the simulation of 'rounds' in a policy process (see e.g., [3] and [7]). Each round, actors would behave according to their perceptions, using their preferred instruments. The main impediment for this obvious seeming extension of DANA is that in DANA there is no 'true' reality, there are only perceptions of reality. Even when the effects of the use of instruments are determined (e.g., by introducing a 'true' perception that determines 'real' impacts, or by means of scenarios or expert judgement), the question remains how actors will then perceive this new situation.

A challenge that is more in line with DANA's focus on how actors think about reality would be to incorporate what might be called 'second order dynamics': the simulation of actor learning [25]. Actor perceptions are known to change over time. It should be possible to capture learning mechanisms in production rules that define how and when concepts may migrate from one perception to another. Clearly, dynamic actor network analysis will have to draw on additional disciplines than those of the authors (computer science, decision analysis, econometrics, and policy science). We hope to learn.

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7. References

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