A Next Step in Collaborative Policy innovation research: Analysing Interactions using Exponential Random Graph Modelling.

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ABSTRACT

Collaborative policy innovation is a relatively new research niche in the public innovation literature. Collaborative policy innovation can be interpreted as processes in which a multitude of actors intentionally work together to develop, realize and propagate enriched policy solutions that are radically different from their predecessors in terms of policy understanding, program theory, objectives, and strategies in order to tame unmet societal challenges. The articles of Carstensen and Bason (2012) and Sørensen and Waldorff (2014), which were published here in The Innovation Journal, were amongst the first to use the concept in their studies. Ever since, various other scholars have explored the value of collaborations as vehicles for the promotion of policy innovations. In this discussion paper, we concisely summarize the contemporary state of the literature of the research niche, we propose a possible future venue, and we discuss a useful research methodology, Exponential Random Graph Modelling, which adds a new possibility to our methodological toolbox to study the interactive dynamics in collaborative policy innovations.

Key words: collaboration; innovation; Exponential Random Graph Modelling; governance; wicked issues.

Introduction

Many OECD governments are challenged by increasingly complex and seemingly untamable policy problems (OECD, 2014). Wicked issues like global warming, ageing society and immigration can no longer be solved by traditional policy responses solely, as these daunting problems typically transcend conventional organizational and governmental boundaries in the public sector (Ney, 2009). Hence, academics have, under the slogan of collaborative policy innovation, proposed a new form of organizing innovation in policy processes as the cure for the alleged policy-making problem of the public sector (Carstensen and Bason, 2012; Agger and Sørensen, 2014; Sørensen and Waldorff, 2014).

We interpret collaborative policy innovations as processes in which a multitude of actors intentionally work together to develop, realize and propagate enriched policy solutions that are radically different from their predecessors in terms of policy understanding, program theory, objectives, and strategies in order to tame unmet societal challenges. Such a kind of collaborative processes are expected to boost innovation, as more stakeholders and thus more knowledge, information, resources and experiences are included in the decision making (Nambisan, 2008: 11; Ansell and Torfing, 2014: 10).

Collaborative policy innovation is a relatively new strand of research, and an emerging theme, in the public innovation literature (Sørensen and Waldorff, 2014). As a result, the research foci and thereby the findings of scholars have been rather diffuse. For that reason, this paper aims to cluster and (concisely) summarize the contemporary state of the art of the research niche, and identify possible venues for future research. With regard to the latter, we will make two specific claims. First of all, we will contend that the research niche of collaborative policy innovation is in need of more research on the interactive dynamics among actors in collaborative policy innovation processes; particularly, concerning practices of resource-sharing, commitment building and learning. Second, we will argue that the statistical network method of Exponential Random Graph Modelling (ERGM) is a useful tool to analyze and make inferences about these interactive dynamics between actors in collaborations that are used as vehicles for the promotion of policy innovations. Yet, before we do so, we elaborate on the definition of the concept of collaborative policy innovation.

The Concept of Collaborative Policy Innovation

So far, various scholars have worked with the concept of collaborative policy innovation. Nonetheless, not many of them have actually defined the concept. In fact, we could only retrieve one definition from the literature, which is the definition of Agger and Sørensen (2014: 189). They write:

> …collaborative policy innovation can be understood as the formulation, implementation and diffusion of new contested normative visions of goals and strategies for realizing a good society through collaborative processes involving relevant stakeholders.

More researchers have, in contrast, indicated what they understand with the term policy innovation, and how collaboration can contribute to the development, realization and propagation of policy innovations. Sørensen and Waldorff (2014: 3-4), for example, state:

> …policy innovation is the formulation, realization and diffusion of new policy understandings, new political visions and strategies for solving problems… collaboration can enhance policy innovation in three ways: by creating new and more nuanced understandings of a policy problem; by formulating new political visions for society, and problem-solving strategies; and by enabling and mobilizing relevant audiences to adapt, realize and diffuse these problem definitions and policy ideas.

Scholars related to the more generic literature of collaborative innovation, which looks at the collaborations between relevant stakeholders irrespective of the type of innovation outcome[1] in the public sector, have put more effort in formulating a definition. Within this branch of research, scholars usually ascribe three features to the concept in order to distinguish it from other analytical terms.

[1] Policy innovation is just one possible ‘innovation outcome’. De Vries et al. (2014: 13) identify other innovation outcomes, like process innovations, product innovations, service innovations, conceptual innovations, etc.

First of all, these scholars argue that collaborative innovation involves a deliberate attempt to change, or even improve, the current state of affairs. Sørensen and Torfing (2012: 849) even speak of the intentional and proactive action of governments to generate policy solutions or establish new services that are a real improvement in the light of present and future demands. According to these scholars, traditional top-down models of public governance, which mainly leave public innovation in the hands of politicians and executive managers, rarely acknowledge the full complexity of the problems they seek to solve, the limitations of existing policy actions and the potential of new and emerging policy ideas. Therefore, many governments have felt the need to include more relevant stakeholders, not only in the implementation phase but also when new policies are being developed, in order gain a better notion of the policy dynamics of many of today's complex societal challenges (Sørensen and Waldorff, 2014: 3).

Second, scholars in this research niche contend that within processes of collaborative innovation, actors aim to bring about radical change (Sørensen and Torfing, 2010: 6-7; Sørensen and Torfing, 2011: 849-850). This means that involved stakeholders do not collaborate to produce or deliver more or less the same kind of goods, services, or policy solutions (first-order change), but rather to change the form, content, and repertoire of goods, services, and organizational routines (second-order change) or even transform the underlying problem understanding, policy objectives and program theory (third-order change) (Hall, 1993; Sørensen and Torfing, 2011: 850). It is hard to determine how much change eventually is necessary to speak of radical change. This depends on the subjective interpretations of situated agents (Sørensen and Torfing, 2011: 850). However, innovation outcomes will tend to challenge conventional wisdoms and sedimented practices.

Third, advocates of collaborative innovation expect that better and more innovative solutions for societal challenges emerge, as more stakeholders and thus more (new) knowledge, information, resources and experiences are included in the policy processes. As Nambisan (2008: 11), for example, writes:

> …new knowledge will increasingly be created through repeated interactions and dialogue among the involved actors; that is, the cumulative nature of knowledge creation…which [in turn] amplifies and enhances the quality of innovation outcomes.

On the basis of these features and conceptualizations, we believe that collaborative policy innovations can best be interpreted as processes in which a multitude of actors intentionally work together to develop, realize and propagate enriched policy solutions that are radically different from their predecessors in terms of policy understanding, program theory, objectives, and strategies in order to tame unmet societal challenges.

Two generations of Studies and a Possible Future Venue

Within the contemporary literature on collaborative policy innovation, two generations of studies can be identified. The first generation primarily looked at the problems and potential of collaborative processes of policy innovation (Sørensen and Waldorff, 2014; Carstensen and Bason, 2012). In these studies, different process conditions are mentioned that hinder the innovative capacity of collaborative policy innovations. As such, scholars tried to gain a better notion of the general circumstances in which collaborative processes for the promotion of policy innovations can flourish.

A great example of a study that belongs to this first generation is the work of Agger and Sørensen (2014), who studied a collaborative policy innovation in the Danish municipality of Albertslund. In their conclusion they (idem: 204-205) inter alia write:

> …there is no guarantee that collaboration leads to innovation. Collaborative processes that aim for consensus or the least common denominator will tend to result in a marginal adaption of a policy rather than in more radical forms of policy innovation. Moreover, it is far from certain that new innovative policies developed in collaborative policy arenas will be authorized by political decision-makers. Whether the drivers for collaborative policy innovation are fully exploited and the barriers overcome depend among other things on the formal and informal institutional design in which collaborative policy innovation is to take place. The formal organizational framing conditions: what can be discussed? Who is included in the collaboration process? What is the time frame and how is the output to be communicated to relevant audiences? The formal framing influences how open or closed the collaborative innovation process will be. The informal institutional framework consists of the sedimented role perceptions and practices of involved actors. Role perceptions and practices that hamper policy collaboration are likely to reduce the innovative capacity of collaborative policy arenas.

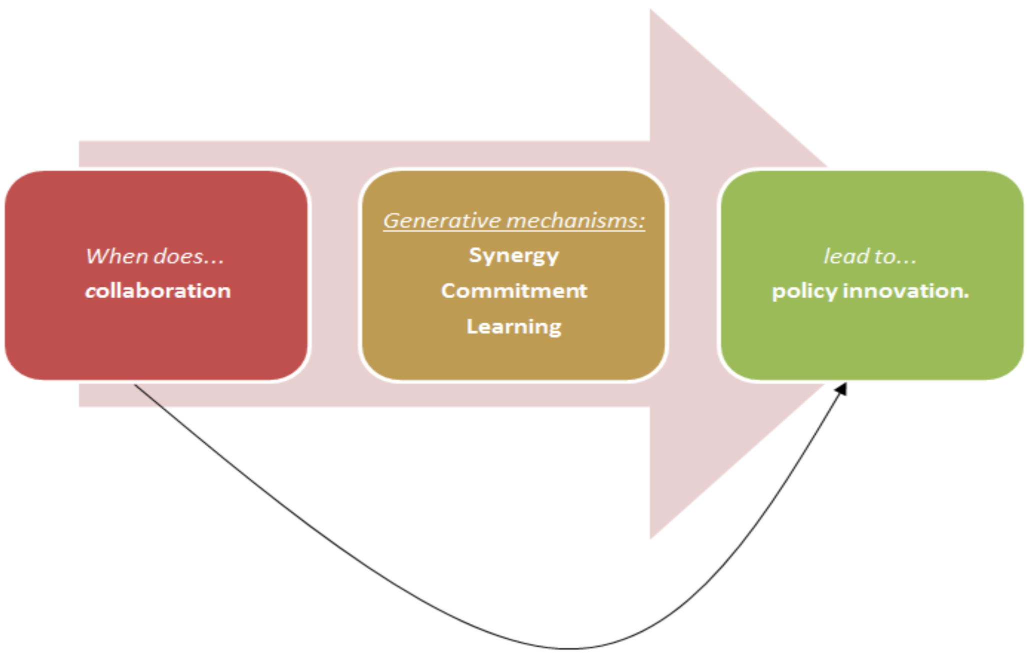
More recently, a second generation of studies has emerged that specifically looks at the generative mechanisms of collaborative policy innovation. Generative mechanisms can best be understood as the processes by which a causal relation comes about; in our case, why collaboration actually leads to policy innovation (see figure 1).

Oftentimes, three generative mechanisms are mentioned in the collaborative policy innovation literature: synergy, commitment and learning (Ansell and Torfing, 2014: 11; Gray and Ren, 2014: 127; Bressers, 2014: 103). Synergy is by Ansell and Torfing (2014: 11) defined as a social process in which stakeholders bring together complementary resources or capabilities (i.e. resource-sharing). Commitment, then, is understood as the social process through which actors in groups build consensus and support for a particular policy innovation (Ansell and Torfing, 2014: 11; Bressers, 2014: 103). Lastly, learning is considered as the social process whereby cognitive change occurs as a result of interaction between different stakeholders, which can transform or reframe the collective sense of possibility or generate new ideas (Ansell and Torfing, 2014: 11).

Within this second generation of studies, scholars mainly indicated whether or not these generative mechanisms were present in the analyzed cases; and if so, in what ways these were important for the development of the collaborative policy innovation process. Waldorff et al. (2014: 85), for example, stated:

> …in the climate management case, synergy, learning and commitment played an essential role in the innovation process. All three mechanisms were important for the implementation of the local climate management initiatives. An important driver for the innovation was the synergy created when the local knowledge of the ECAN ambassadors was combined with the general knowledge of the ECAN coordinator about resources consumption, environmental behaviour and especially the administrative dimensions of the local government. Learning was crucial for the ambassadors in order to get new ideas for local initiatives. Commitment was also crucial for the success of the ECAN from the perspective of the ambassadors.

Figure 1: The expected causality and generative mechanisms in collaborative policy innovations.



Again other scholars pointed to the fact that the generative mechanisms are closely interconnected or sometimes even mutually reinforcing. Bressers (2014: 103), for example, wrote:

> …the synergy between the innovation stakeholders was reinforced by learning and openness to learning, whereas commitment of these stakeholders also improved the synergy.

In a similar vein, Ansell and Torfing (2014: 12) argued:

> …learning may help to build commitment among actors in collaborative policy innovations, which facilitates synergy, which feeds back to shape learning.

Most of these studies have, however, been rather superficial when it comes to making inferences about the dynamics in which these three generative mechanisms operate (Ansell and Torfing, 2014: 238-239). That is to say, scholars have not been very explicit about *how, when* and *why* individual actors are likely to engage with other actors in practices of learning, resource-sharing and consensus-building in collaborative policy innovations. In point of fact, the only behavioural insight that can be derived from existing (case) studies is that not all actors have the same propensity, or ability, to engage with other stakeholders in these three generative processes (Bressers, 2014: 104; Montin et al., 2014: 117; Harris, 2014: 8; Keast and Waterhouse, 2014: 156; Termeer and Nooteboom, 2014: 179).

This lack of scholarly attention to the behavioural manifestations of actors in collaborative policy innovations is striking, as it means that we (i.e. the academic community) actually have little knowledge about the interactive dynamics within collaborative processes of innovation, and thus also about the manner in which emergent interaction patterns between actors impact the quality of the generative mechanisms in terms of their contribution to the development, realization and propagation of a policy innovation. For example, how do individual agencies usually behave in processes of collaborative innovation, what possibly explains different sorts of actor behaviour, how might different sorts of actor behaviour lead to different patterns of social clustering in collaborative networks of innovation, and what impact do different sorts of social clustering, in turn, have on the innovative capacity of a collaborative group of actors?

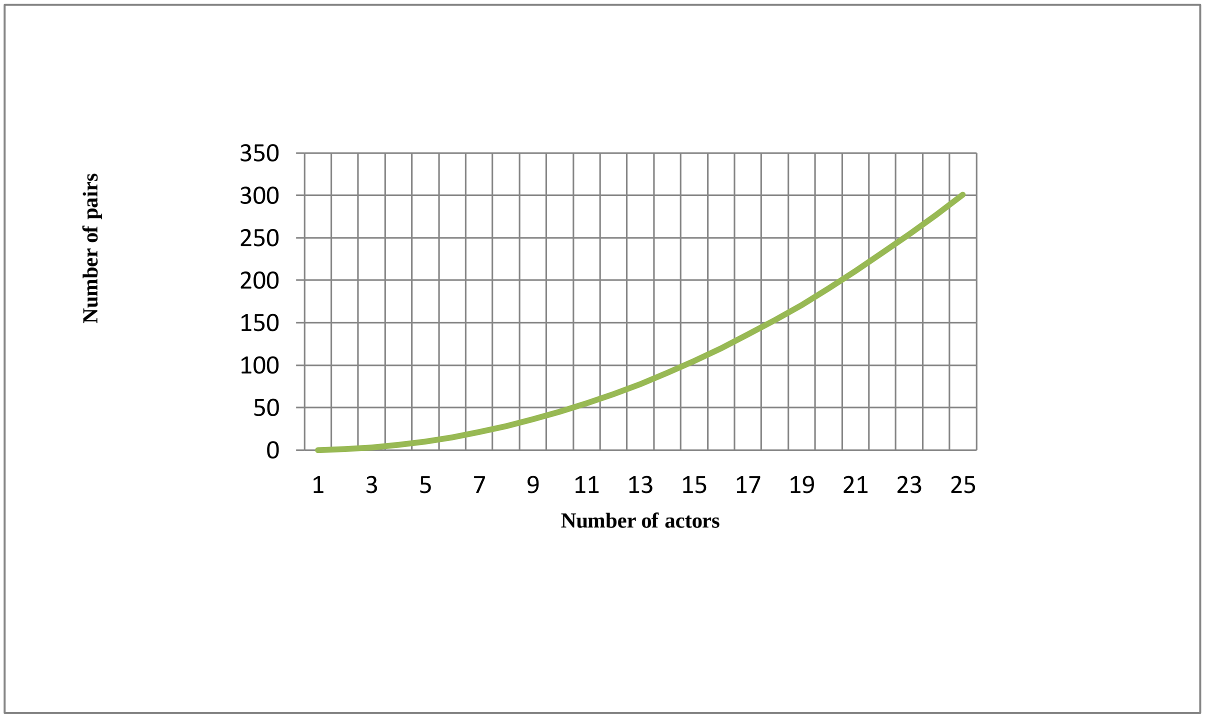
From a more critical stance, it can even be argued that on the whole scholars have only put a little effort in scrutinizing accepted truisms about the interactive dynamics and corresponding benefits that arise from collaborative processes of policy innovation (Ansell and Torfing, 2014: 238-239), like 'collaborative interaction facilitates trust-based circulation and cross-fertilization of new and creative ideas between actors' or 'collaboration ensures that public innovation draws upon and brings into play all relevant innovation assets in terms of knowledge, imagination, creativity, courage, resources, transformative capacities and political authority' (Sørensen and Torfing, 2012: 5).

Hence, we argue that for scientific purposes (in terms of scientific progress), and in order to gain a better notion of the value of collaborations as vehicles for the promotion of policy innovation, it would be wise to devote in prospective studies more attention to the determinants that explain why individual actors engage in, or refrain from, practices of learning, resource-sharing and commitment-building with some stakeholders and not with others in processes of collaborative policy innovation.

The Limitations of Traditional Methods for Studying Network Data

There are various traditional research methods and strategies that can be used to analyze and make inferences about these actor-dynamics in the generative mechanisms of collaborative policy innovations. Then again, each method and strategy also has certain limitations. Scholars can, for instance, use the case-study method or other qualitative methods, such as process-tracing. This will provide them with rich and detailed information about the interactions under study. However, using either one of these qualitative methods would be very labor-intensive and time-consuming, given the fact that the researcher has to determine for every actor that participates in the collaborative policy innovation process whether it engages in practices of learning, resource-sharing and consensus-building with all other involved stakeholders; and if not, the researcher has to explain what makes that a specific actor does connect with some stakeholders but not with others.

Graph 1: Actor-pair diagram.



In a small network comprising ten actors, for example, where connections (e.g. learning practices) between two actors are for convenience sake considered to be reciprocal, this would already imply that the researcher has to analyze the sort of relationship, and the reasons for the existence of this particular relationship, of 45 actor pairs[2]. For a network consisting of 20 actor members, this even entails that the relationships of 190 different pairs of actors have to be investigated (see graph 1). Therefore, we do not really perceive these qualitative research methods as useful tools for analyzing and making inferences about the interactive dynamics in the generative mechanisms of collaborative policy innovations, if the amount of involved stakeholders is larger than 8.

Another possibility would then be to incorporate every relationship (e.g. learning practices) an actor has with all other involved actors as a single observation in the dataset, and subsequently perform a multiple regression on this dyadic data (i.e. data that describes a particular connection of one actor with another) and a number of selected predictor variables. Yet, there are two problems with using regression for such a kind of analysis.

[2] We used the following formula: The amount of actors * (the amount of actors=1)

The first problem is that regression models always work with the assumption that observations are independent of each other (Robins et al., 2012). Research has, however, shown that the very presence or absence of other connections between actors in collaborations, or in any other sort of network setting, also affects whether relationships are initiated, maintained or destroyed (Lubell et al., 2012). Within the literature this is called the tie[3]-interdependence effect.

A classic example of a tie-interdependence effect is the transitivity feature – better known as the ‘a friend of a friend is my friend principle’ – which was developed by scholars to describe the phenomenon in friendship networks that person A is more likely to become friends with person C, if person B (who is a good friend of person A) also has a close friendship with person C (Hunter et al., 2008: 5). As such, regression models are inherently biased and flawed when it comes to making inferences about the relational dimension between stakeholders in collaborations, as the method tears the individual actor from his or her social context (Ward et al., 2007).

A second problem that arises when using regression models for analyzing and interpreting dyadic data in collaborations, is the problem of data multiplication (Cranmer, et al., 2012: 283). The problem of data multiplication entails that the number of observations in these dyadic datasets is much larger than the real number of actors active in the collaboration that is being studied. In consequence, the standard errors of the multiple regressions shrink progressively, which in turn, makes it a lot harder to conclude that an effect of a given predictor variable is not statistically significant. This is a problem, because, if the number of observations in the dataset is artificially large, then it becomes quite likely that we will erroneously accept that a significant effect exists when, in fact, it does not (idem: 284).

To this end, we would like to bring another flexible methodological tool to attention which, according to us, is more suited for studying the actor-dynamics in each of the generative mechanisms of collaborative policy innovation: the statistical network method of Exponential Random Graph Modelling (ERGM).

ERGM is a relatively new methodology. In fact, only a few scholars in the political sciences have so far worked with the social network method (see Feiock et al., 2010; Henry et al., 2010; Lubell et al., 2012; Scott, 2015). In addition, the development of extra features for the statistical network tool is still ongoing (Krivitsky, 2012). The method already has, however, a huge potential.

The great merits of ERGM, in comparison to the aforementioned research methods and strategies, are that the method is capable of performing inferential tests on the interactive dynamics in both relatively small, as well as, extremely large actor networks, while accounting for the aspect of tie-interdependence in its analysis by considering so-called endogenous factors as predictor variables. In the next section, we will go into more detail on these merits plus the functioning of the ERGM methodology.

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[3] A tie is jargon for a particular sort of relationship between an actor and another actor. Within the academic literature edge is also used as a synonym for a tie.

Exponential Random Graph Modelling

Hunter, Goodreau and Handcock (2008) describe ERGM as a statistical network method that aims to explain tie-formation. In laymen's terms, this means that with the help of ERGMs a scholar is able to draw inferential conclusions about why actors have the tendency to connect (e.g. resource-sharing, learning and consensus-building) with some actors and not with others in network settings. This outcome variable (i.e. tendency to connect or not), and thereby the overall purpose of the methodological tool, thus makes the ERGM-methodology well-equipped for exploring and analyzing the actor-dynamics in the future venue that we proposed in section 3.

Documentation about the functioning and operational system behind ERGMs is well established in the literature (Scott, 2015). Handcock et al. (2015); Hunter et al. (2008); Yaveroğlu et al. (2014); Hunter, Goodreau and Handcock (2008); and Desmarais and Cranmer (2012) have written detailed accounts about: the basic principles of the statistical network model, the guidelines for performing the analysis, checking the network assumptions, diagnostics and interpreting the results, the algorithm and the formulas of ERGM-models, the jargon of these models in graph-theoretical language, and how to retrieve and use the ERGM-package[4] from the Comprehensive R Archive Network (CRAN). As such, it is not our intention to provide a step-wise description of how to utilize the ERGM methodology. Yet, we do want to give the readers a basic sense of how ERGM works, and what kind of predictor variables (and hypotheses) can be tested when scholars intend to use the methodology for making inferences about the interactive actor-dynamics in the generative mechanisms of collaborative policy innovations.

The reason for this is that we can tell from our personal experience that the available literature on ERGM is highly technical and largely inaccessible. In fact, most work on the methodology has been written by and for statisticians (but see Harris, 2014). These articles are full of complex equations that a scholar has to grasp first, before being able to get a basic understanding of ERGMs. This may cause that applied scholars – to which we also consider ourselves – feel quite some anxiety with utilizing the ERGM methodology, and in the worst case even decide to avoid working with it. This will, in turn, undermine the great potential the methodology has in terms of unravelling the black-boxes of the operative dynamics of each of the generative mechanisms of collaborative policy innovations, in comparison to more traditional methods like regression models and case study research (see section 4).

Figure 2 presents, as an example, such a complex formula that is commonly used to describe the functioning of an ERGM. Oftentimes, this equation is accompanied with a ditto complex description, like the following text of Desmarais and Cranmer (2012: 403-403):

> …the ERGM takes the form of a probability distribution that gives the probability of observing the entire network of n actors, which we present as Y, an n n-matrix with Y_{ij} if there is a tie from i to j and 0 otherwise. The Γ_j are network statistics that are specified to measure features of the network that are hypothesized to influence the likelihood of observing a particular realization of the network. The θ are parameters, similar to regression coefficients that give the

[4] See the website: https://cran.r-project.org/web/packages/ergm/index.html

effects of the respective network statistics on the likelihood of observing a particular realization of the network; the higher θ_j, the higher the likelihood of observing a network with a high value of Γ_j.

Figure 2: The Mathematical Equation of ERGMs.

$$P(Y) = \frac{\exp\left(\sum_{j=1}^{k} \theta_j \Gamma_j(Y)\right)}{\sum_{Y^* \in \mathcal{Y}} \exp\left(\sum_{j=1}^{k} \theta_j \Gamma_j(Y^*)\right)}$$

The logic behind ERGM is, however, quite straightforward. After data is collected (with the help of surveys or structured interviews) and turned into numerical values, an ERGM first calculates the probability of observing the analyzed network compared to other possible random networks with the same number of network members[5]. Subsequently, specific features (i.e. predictor variables) of the observed network are selected and included as a set of statistics computed on the network. If eventually a predictor variable is significantly different from zero, it can be interpreted that the corresponding statistic significantly affects the probability that one member forms a connection (i.e. the outcome variable) with another member in the network, while controlling for the other statistics in the analysis.

Exogenous Factors: Node Attributes and Dyadic Effects

Generally, two types of statistics are included as predictor variables in ERGMs: exogenous and endogenous variables (Scott, 2015: 11-12). Exogenous variables, also called covariate effects, are influences from outside the collaboration that impact the behaviour of involved actors. In graph-theoretical terminology, it can be stated that exogenous variables manifest themselves at both the node and dyad level. This means that some exogenous factors are specific features of single actors (i.e. node attributes), while other covariate effects (i.e. dyadic terms) specifically relate to the relational dimension between two network members.

When the ERGM methodology is used for examining the interactive actor-dynamics in the generative mechanisms of collaborative policy innovations, a scholar may experience some difficulty with defining the node-level in the analysis. The reason for this is that in some situations it is not so much the organization itself that takes part in the collaborative policy innovation process, but rather a person (e.g. minister, high-ranked policy officer or civil servant) who represents the organization. As such, a scholar may have to deal with two interrelated units of analysis at the node-level: the representative and its home organization. Hence, we argue that two sorts of node attributes can be considered as predictor variables in these kinds of ERGM analyses:

[5] Because there are many possible network configurations, it is not feasible to compare the analysed network to all other network graphs with the same amount of participants (Hunter, Handcock, Butts, Goodreau, Morris, 2008: 6). Therefore, an ERGM uses a so-called Markov chain Monte Carlo-procedure (MCMC) to estimate model parameters on basis of maximum likelihood estimation. For more information about how this MCMC-procedure exactly works, we advise to read the articles of Scott (2015: 7), Harris (2014: 71), and Hunter et al. (2008: 2).

1. Node attributes that specifically relate to individual traits and experiences of the representative. Does the representative, for example, have good communication skills? Is the representative visionary and knowledgeable? Does she or he have many years of relevant work experience? Other possibilities that fall within this category are: the willingness of the representative to initiate a radical policy change (Metselaar, 1997), the extent to which the representative perceives the policy innovation process as meaningful for society (Tummers, 2012: 364), for its clients (Tummers, 2012: 364), and for its own work activities (Holt et al., 2007), etc.

2. Node attributes that consider the influence of the home organization on the practices of the representative. Possible influences that can be considered as such a kind of predictor variables are: the mandate/autonomy of the representative in the collaborative process (Van den Brink et al., 2006), constituent multiplicity (Oliver, 1991: 162), politicking in the home organization (Bouckenooghe et al., 2009), managerial support and control (Parker and Price, 1994; Rhoades and Eisenberger, 2002), and political support by the Minister (Wasserman and Galaskiewicz, 1994: 196).

With regard to exogenous dyadic terms, the most commonly used factors in ERGMs are so-called homophily and heterophily effects (Harris, 2014: 55; Morris et al., 2008). Homophily entails that two nodes share a specific node attribute, whereas heterophily is used to denote that two nodes differ on a node attribute. If we relate these sorts of predictor variables to the actor-dynamics in the generative mechanisms of collaborative policy innovations, a scholar can for instance test in a ERGM if the probability is higher that an actor engages in learning practices with another actor if they belong to the same tier of government (homophily effect), or if they operate in different policy sectors (heterophily effect), as was earlier suggested by Lee et al. (2012: 558-559).

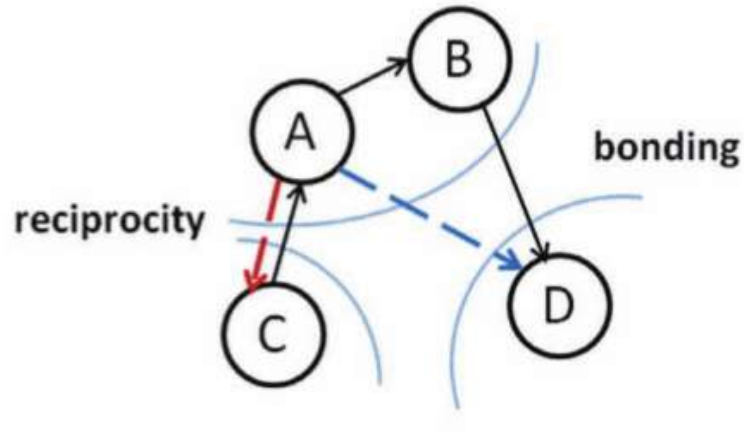
Other statistical terms that fall within the category of exogenous dyadic terms are relational attribute effects or so-called edge attributes (Morris et al., 2008: 6). These are specific factors that consider the relational dynamics between two actors. A good example of such a kind of predictor variable is ‘the degree of divergence that exists between the objectives of two actors in a collaborative policy innovation’, as was inter alia determined by Koppenjan and Klijn (2004: 47-49) and Schön and Rein (1994: 26) as a relevant factor for explaining the interactive dynamics among actors in policy games and policy controversies.

Endogenous Factors and Interaction-terms

Endogenous factors, in contrast, are structural effects inherent to the network itself that are modelled as influences on the behaviour of network members (Boehmke et al., 2016: 128). These network configurations are thus operationalizations of the earlier mentioned tie-independence effects. The complexity of network settings is such that an exhaustive list[6] of endogenous factors cannot meaningfully be given. In point of fact, Handcock et al. (2015) already discuss more than 100 types of possible endogenous factors that can be included in ERGM analysis.

[6] A long list of all possible endogenous variables can be read in the articles of Morris, Handcock and Hunter (2008), Lusher et al. (2013), Snijders et al. (2006) and Handcock et al. (2015).

Figure 3: The endogenous features of reciprocity and transitive triads.



Lee et al.'s (2012) study, however, provides some good examples of possible endogenous hypotheses that can be incorporated in ERGMs for understanding the interactive dynamics in collaborations. These scholars inter alia hypothesized (idem: 555-556) that in collaborative interorganizational development networks, organizations will forge reciprocal relationships (see dotted line in figure 3 from actor A to actor C), and they will bond with partners whose trustworthiness has been scrutinized by others (see the dotted line in figure 3 from actor A to actor D). Hypothesis 1 was subsequently operationalized by including the endogenous feature of reciprocity in the ERGM analysis, while hypothesis 2 was analyzed by working with the endogenous variable of transitive triads.

Other endogenous effects that are usually included in ERGM-models are outdegree, which represents the basic tendency of actors to have relationships at all (Wasserman and Faust, 1994), the earlier-mentioned tendency towards transitivity (Davis, 1970; Holland and Leinhardt, 1971), and specific popularity effects that consider the cumulative advantage of some stakeholders in collaborations.

Like in many other statistical tests, ERGM also allows to include interaction-terms in the model to test theoretically interesting hypotheses. In studies on tie-formation in collaborative policy innovations, a scholar can for example test an interaction-term between the endogenous variable of 'reciprocity' and 'same minister', as a means to find out if representatives of organizations that work for the same minister are more likely to learn from each other's perceptions (i.e. reciprocal learning) with regard to the problem situation and possible solutions for the cross-cutting issue, than representatives of organizations that work for different ministers.

The Limitations of ERGMs

There are, however, also certain limitations and drawbacks to the use of ERGM-models. First of all, the statistical network method is limited by an inability to accommodate actor networks with valued ties. This means that the outcome variable in ERGMs is binary in nature: an actor has either a connection with another actor or not. Though, recent extensions by Wyatt et al. (2010), Desmarais and Cranmer (2012), Krivitsky (2012), and Scott (2015) may provide the key to overcome this limitation. Second, one assumption explicit to ERGMs is that the researcher has a strong theoretical grasp of the dynamics in the network of actors under study and is capable of specifying the objective function to perform the analysis. If the researcher has therefore little theory about the interactive dynamics in the collaboration, than the method of ERGM would probably not be appropriate. In such a situation, it would be better to use the case study method. That being said, when theory is strong, and there is a direct interest of the researcher in testing for specific predictor variables, a method such as ERGM is preferable (Desmarais and Cranmer, 2012: 431).

Conclusion

This paper calls attention to the importance of more explanatory research focusing on the interactive (generative) dynamics in collaborative processes of policy innovation. In the first sections, we elaborated on the definition of collaborative policy innovation and discussed the current state of the art of the research niche. While earlier studies have certainly contributed to our understanding of the general conditions that hinder or stimulate actors in collaborations in their endeavors to develop, realize and propagate policy innovations, we argued that there are also certain shortcomings in our current knowledge on collaborative policy innovations. These relate, especially, to the interactive dynamics between actors and practices of resource-sharing, commitment-building and learning.

Our first argument is not so much that previous studies failed to look at the generative processes (i.e. learning, synergy and commitment) that cause the collaboration that leads to policy innovation, but rather that the way in which earlier research on these generative mechanisms was conducted did not provide us with clear insights into *why* actors in collaborations are likely to connect with some actors but not, or to a lesser extent, with others during processes of collaborative policy innovation. Hence, we suggested that in prospective studies scholars should devote more attention to the determinants that explain why actors have the propensity to engage in practices of learning, resource-sharing, and commitment-building with only a selected group of actors in collaborations, as has been indicated by several of the existing case studies. Such an analysis would further allow scrutinizing some of the accepted truisms about the benefits of collaborative interaction for policy innovation.

Subsequently, we made our second point in the paper by arguing that traditional research methods, like case-study research and regression models, for different reasons are not very suited to study the interactive dynamics in collaborative processes of policy innovation. Studying network data (like collaborations) with the case study method can become a very labor-intensive and time-consuming research endeavor, while using regression models for this research activity leads to flawed outcomes due to issues of data multiplication and independence of errors.

Therefore, we introduced the statistical network method of Exponential Random Graph Modelling as a valuable methodological alternative. Additionally, we offered some relevant literature suggestions and a basic description of how ERGM works as a means to reduce the amount of insecurity applied political scientists may experience when employing ERGM-models. We particularly explained that the great merits of ERGM, in comparison to the aforementioned research methods, are that the method is capable of performing inferential tests on the interactive dynamics in both relatively small, as well as extremely large actor networks, while accounting for the aspect of tie-interdependence in its analysis by also considering so-called endogenous factors as predictor variables.

Of course, the method of Expontential Random Graph Moddeling is not the only (relatively) new methodology that is capable of studying the role of the individual agency in collaborative processes (of policy innovation). This is also not something we want to claim. There has, for example, also been an interesting study by Jin Im (2013: 115) that used the Qualitative Comparative Analysis methodology to examine the impact of an organization's culture on the way it collaborates with other actors in collaborations.

In the end, we just hope that this paper contributes to the exploration of new venues in the field of collaborative policy innovation, and encourages scholars to add new equipment to their methodological toolbox by making use of relatively new research methods, like Exponential Random Graph Modelling.

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