If We Work Together, I Will Have Greater Power: Coalitions in Networked Innovation

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Abstract

The present article uses agent-based social simulation to study rational behaviour in networked innovation. A simulation model that includes network characteristics and network participant's characteristics is run using parameter sweeping, yielding 1450 simulation cases. The notion of coalitions was used to denote partnerships in networked innovation. Coalitions compete against each other and several variables were observed for winning coalitions. Close analysis of the variations and their influence on the average power per winning coalition was analysed using stepwise multiple regression analysis. The analysis brought forward two main conclusions. First, as average betweenness centrality per winning coalition increases, the average power per winning coalition decreases. This implies that having high betweenness centrality as a network participant makes it easier to build a successful coalition, as a coalition needs lower average power to succeed. Second, as the number of network participants increases, the average power per winning coalition decreases. This implies that in a larger network, it may be easier to form a successful coalition. The results form the basis for the development of a utility-based recommendation system that helps people choose optimal partners in an innovation network.

Keywords:
Coalition Formation, Networked Innovation, Creativity, Simulation of Social Networks, Social Behaviour, Complex Networks

Introduction

1.1 The rise of the Internet has sparked off a snowballing development of new technologies. In such a rapidly changing world, it is very hard for companies to remain innovative. Only few companies can retain their market share by relying on their internal R&D departments. An increasing number of companies connect to other parties outside the firm to come up with innovations more easily, faster and more cheaply; this is referred to as *networked innovation*. By sharing their knowledge in their social network, they can profit in a number of ways. To illustrate, Google shares its Android mobile platform technology under an open source license. By doing so, others can advance Google's knowledge. Google is well aware that they do not have to invent new technology themselves in order to make money from it. Instead, they use the expert knowledge that is present among the Android developer community and profit from increased adoption and popularity of their Android platform. If good initiatives arise, Google adopts the technology behind it, works together with its originators, or acquires the technology. They fend off risks of financial failure by making effective and efficient use of the knowledge that is present in their network.

1.2 The value of networked innovation is emphasised by Cassiman and Veugelers (2006), who found that supportive expertise present in an R&D's social network can boost new product development. Furthermore, Kratzer and Lettl (2008) concluded that people that are on the edge of two social networks have more information, as a result thereof being more creative than others in their network. Ronald Burt (2004) coined the term *brokerage* for such situations. Perry-Smith (2006) points out the significance of a central network position and weak ties outside the firm to be more creative.

1.3 In sum, we can be more creative by profiting from knowledge within our network. Yet, the innovative process does not merely consist of one's creative utterances. Good ideas are often generated, but are for some reason not implemented. Klein and Sorra (1996) point out the importance of skilfulness and commitment for the implementation of innovation. Kotter (1996) suggests a powerful guiding coalition to lead organisational change. Such a coalition is not driven by mere organisational hierarchy, but rather by status, information, expertise, reputations and relationships. The guiding coalition can persuade others in the network to support innovation implementation, which is one of the crucial steps in innovation management (Adamides & Karacapilidis 2006).

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resemble reality closely enough. Often, such models tend to *undersimplify*, and yield behaviour that is far from a correct representation of reality. On the other hand, we have Ockham's razor, which suggest that we leave out variables that either contribute little to nothing to the simulation result or make the model unnecessarily complex. Though, there is always the possibility of leaving out too many variables (the model tends to *oversimplify*) his simulation model. Hence, a simulation model should have a complexity that suits the modelling objectives and the available data. In this case, empirical data is not within the authors' reach, which makes it difficult to estimate the model fitness using the same, data-driven supervision employed by Gilbert and Gutierrez (1973) in their plant-aphid-parasite model.

2.4 The agent-based social simulation that we developed comprises a *simulation scenario*. A simulation scenario is a workflow, or a number of actions that has to be performed during the simulations. Actions can be performed multiple times, and they often take place in pre-defined sequences. When multiple sequences are run in a simulation, we call them *iterations*. An iteration often influences the subsequent iteration by means of *reinforcement*, as is the case with our simulation. An iteration consists of multiple *phases*, to distinguish different types of activities performed during the iteration. During an iteration, we start off with an initialisation phase to set up the agent's and environment's parameters; this is followed by a number of phases in which the agents interact. Akin to a simulation of agent coalition formation by Klusch and Gerber (2002), we distinguish four phases (as depicted in Figure 1):

1. Initialisation: The agent and environment parameters are set up
2. Simulation: The candidate coalitions are determined
3. Negotiation: Coalitions are formed
4. Evaluation: The winning coalition and reinforcement is determined

Initialisation

2.5 The simulation commences with setting up the network of agents given a predefined network density (*Setup Network*). Network nodes represent individuals and the edges form their relationships. Two individuals are said to be related when the agents are known to each other. Agents receive initial values for the parameters age, Belbin personality and gender (*Setup Agents*). Based on their position in the network, the agents' betweenness centrality (Brandes 1994) is estimated (*Calculate Betweenness Centrality*). Betweenness centrality tells us how dependent others are on an individual in a network. For instance, when we have two companies A and B, and only one person in company A connects to company B, then the employees in companies A and B are very much dependent on that single person in terms of information exchange. As a result, that person will have high betweenness centrality. Intuitively, having such a good network position leads to increased power. Also, high betweenness centrality will increase the creativity of an agent (*Calculate Creativity*).

Simulation

2.6 During the simulation phase, the initial parameters and the calculations of betweenness centrality and creativity will be used to let the agents generate new 'ideas' (*Generate Ideas*). The ideas are abstract and do not own any content. They receive a value based on the creativity calculation performed in the initialisation phase (*Assign value to ideas*). Based on the idea value and the betweenness centrality, an agent's power is determined (*Compute agents' power*). An agent that has high power is more likely to convince others of the value of an idea. Besides, if it has high betweenness centrality, it may have more decision power, as other agents are dependent on this agent. Power and social similarity (age, gender, personality) (Ibarra 1992; McPherson et al. 2001) contribute to the likelihood that an agent will be selected for cooperation, the so-called agent score (*Find candidate coalitions*). For instance, if agent A has high power and is very similar to agent B, then agent B will most likely choose agent A to cooperate with (and form a coalition).

Negotiation

2.7 We use the Shapley value, a measure well known in game theory, to calculate the value of prospective coalitions. The Shapley value calculates the added value of forming a coalition with another agent over going at it alone (*Calculate Dyads' Strength*). Subsequently, dyads are formed based on the calculated dyad strength: the dyad which has the highest prospective value is formed (*Form Dyads*). It must be noted that a coalition must be at least as strong as the accumulated strength of its members (superadditivity). In fact, a coalition must be stronger than the accumulated strength of its members (monotonicity). In this case, agents are compelled to cooperate by setting the individual gain to zero. The latter reflects that in real life one inherently needs support to have one's idea accepted by the community. To do so, we form coalitions (Kotter 1996). As opposed to humans, agents always play rationally, and thus choose to form a coalition with the highest-scoring prospective coalition. That is, a coalition may consist of zero to multiple dyads (*Accumulate Dyads / Form Coalitions*). Next, the coalitions' strengths are calculated (*Compute Coalitions' Strength*).

Evaluation

2.8 Finally, a winning coalition is determined, that is, the coalition that has the highest accumulated power (*Declare Winning Coalition*). Payoff in the form of additional power (in the next iteration) is given to the agents of the winning coalition (*Payoff Winning Coalition*). Payoff is divided among members of the coalition, relative to their power (*Divide Payoff among Members*). No payoff is given to non-winning agents, for in the next iteration, power for all agents is normalized between 0 and 100, which implies a

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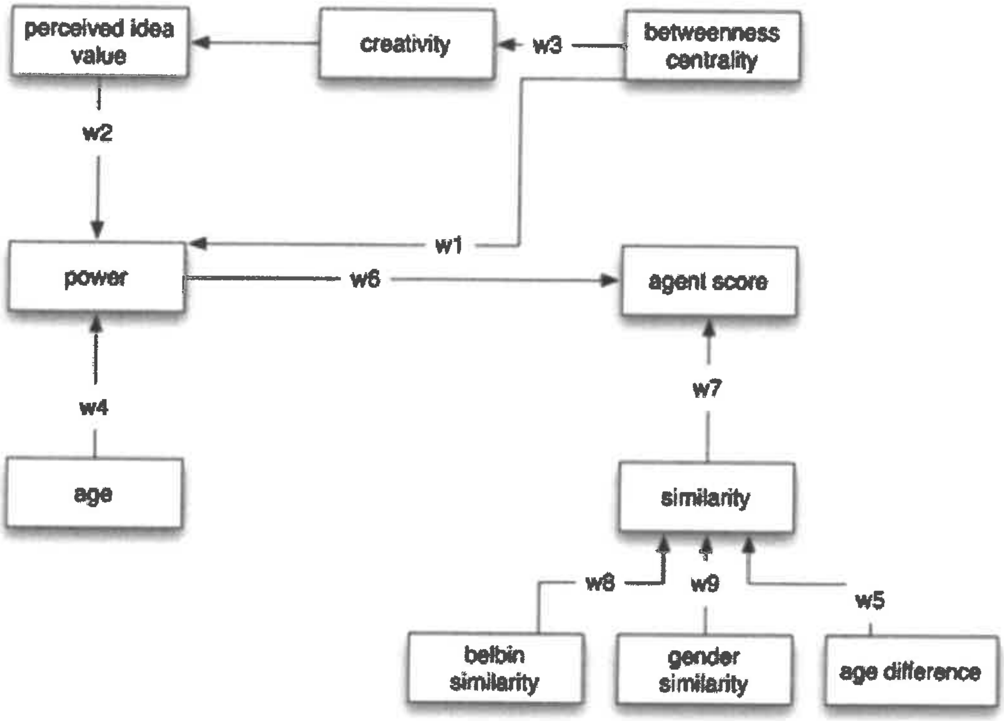

Figure 2. The agent internal reasoning model; for a detailed description, see text

Social network setup

2.11 Two main factors were used to determine the setup the social network: 1) *number of turtles* and 2) *network density*. Let $G_{n,N}$ denote a network having *n* edges and *N* vertices. The vertices *V1* to *VN* are represented by the number of turtles (agents). The edges E_1 to E_n are represented by relationships between the turtles. Network density describes the probability p_e that a relationship E is formed between two turtles ($p_e = N$ * network density). In other words, it is the number of relationships that is formed, as a proportion of the total number of edges that can be formed ((N*$N/2$)). It similar to Erdös and Rényi's formation of a random graph (Erdös & Rényi 1960), yet the probability *p* that an edge *E* is formed between two vertices V_x and V_y, is equal to the network density.

Agent reasoning model

Weights

2.12 There are two factors that mainly influence the decision to form a coalition: 1) power and 2) homophily. Power and the similarity between two individuals (homophily) directly influence the agent's score. The agent's score represents the likelihood that agent A is interested in forming a coalition with agent B. There are seven other factors that indirectly contribute to an agent's score through the two central factors. The factors (including the agent score) are connected through weights (Figure 2), to indicate the effect of one factor on another. The value of the weights is not decided upon arbitrarily; literature was used to determine their value. The value per weight may vary, as is shown in Table 1. Note that it is not a goal to perfectly and precisely display reality in this model. To do so, we would have to include all possible factors and the exact weights between them to exhibit the appropriate behaviour. We merely seek to simulate behaviour that sufficiently closely resembles reality. In fact, it is common knowledge among agent-based modelling researchers that a more complex model often results in a less representative simulation of a situation. In our practice, this means we included relatively few factors in our simulation model to maximise outcome.

Table 1: Weights, their values, and origin in literature

Weight	Value	Literature
w1	0.45	(Brass 1984; Ibarra 1992, 1993; Krackhardt 1990; Perry-Smith 2006; Simon 1982)
w2	0.45	(Klein & Sorra 1996)
w3	0.67	(Kraatz 1998; Kratzer & Lettl 2008; Tsai & Ghoshal 1998)
w4	0.1	(Burkhardt & Brass 1990)
w5	1	(Ibarra 1993; McPherson et al. 2001)
w6	1	(Ibarra 1992; Kotter 1996)
w7	1	(Ibarra 1993; McPherson et al. 2001)

3 Power (update)	$P_i(t+1)$	$P_i(t+1) = w1 * Cb_i + w2 * v_{ij} + w4 * age_i + P_i(t)$	w1, Cb_i, w2, v_{ij}, w4, age_i, $P_i(t)$
4 Similarity	Sim_{ik}	$Sim_{ik} = w8 * SimBel_{ik} + w9 * SimGen_{ik} - w5 * SimAge_{ik}$	w8, $SimBel_{ik}$, w9, $SimGen_{ik}$, w5, $SimAge_{ik}$
5 Agent score	$Score_j$	$Score_j = w7 * Sim_{ik} + w6 * P_i$	w7, Sim_{ik}, w6, P_i
6 Dyad score	$Dyad_{ij}$	$Dyad_{ij} = Score_i + Score_j - individual\_gain_i - individual\_gain_j$	$Score_i$, $Score_j$, $individual\_gain_i$, $individual\_gain_j$

After the dyads are formed, coalitions are collected by accumulating all dyads that are interconnected. That is, if dyads *{i,j}* and *{j,k}* are formed, the resulting coalition is *{i,j,k}*. The strength of this coalition *{i,j,k}* is calculated by taking the sum of strengths of its members *i*, *j*, and *k*.

Procedure and data collection

2.17 During execution of the simulation model we set two parameters using *parameter sweeping* to see how they influence coalition formation among agents: 1) *network density* (number of relationships divided by the number of total possible relationships) and 2) *number of turtles* (number of network participants). In parameter sweeping, we vary the values for these independent variables in a structured way within a predefined range. Parameter sweeping allows one to report and analyse the dynamics of simulations within a wide parameter space. It requires little human effort, as one does not have to enter all parameter combinations manually (Brueckner & Van Dyke Parunak 2003). The range of the *network density* parameter varies from .01 to 0.05 with an increment of .01 (5 values). The range of the *number of turtles* parameter varies from 2 to 30, with an increment of 1 (29 values). This results in 145 possible combinations of parameters. Each combination of the parameters (simulation run) is executed 10 times to yield stable results. This implies that in total we run 1450 simulations. We observe the following parameters for their fluctuations and to find relationships with the average power per winning coalition:

- network density: The extent to which relationships are formed as a function of all possible relationships
- number of turtles: The total number of participants in the network
- average-betweenness-per-winning-coalition: We measure the average betweenness centrality of the members of a winning coalition to see if there is a relationship between the independent variables and this dependent variable
- average-idea-value-per-winning-coalition: We measure the average idea value of the members of a winning coalition to see if there is a relationship between the independent variables and this dependent variable
- max-power-per-winning-coalition: We measure the highest power of a member of a winning coalition to see if there is a relationship between the independent variables and this dependent variable
- max-idea-value-per-winning-coalition: We measure the highest idea value of a member of a winning coalition to see if there is a relationship between the independent variables and this dependent variable

Data Analysis

2.18 We will analyse the simulation results in two steps. First, we use multiple regression analysis to create a model that uses the independent variables to predict the dependent variable *average power per winning coalition.* Second, we investigate the validity of the model by analysing the correlation between its residuals (Durbin-Watson statistic), as regression assumes absence of such correlation. A Durbin-Watson statistic near 2 implies that there is no correlation between adjacent residuals. When using regression, it is key that the residuals be independent.

Results

3.1 A total of nine variables were exported from the simulation to determine if and to what extent they predicted the *average power per winning coalition.* The correlation coefficients for the variables using Pearson Bi-variate correlation are provided in Table 4. High correlation exists between the pairs {*total number of coalitions, number of turtles*}, {*max betweenness per winning coalition, average betweenness per winning coalition*}, {*max idea value per winning coalition, average idea value per winning coalition*}. Moderate correlation exists between the pairs {*max betweenness per winning coalition, average power per winning coalition*},

Table 4: Correlation coefficients for each of the variables.

	average power per winning coalition	network density	number of turtles	average betweenness per winning coalition	average idea value per winning coalition	max power per winning coalition	max idea value per winning coalition
average power per winning coalition	1.00						

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4.3 Another value that stands out is the network density. The reason for this is that we used relatively small variations of the network density, thus compensating for the supposedly high association observed in Table 5.

4.4 A notable observation we find in a combination of Tables 4 and 5. *Average betweenness per winning coalition* correlates moderately high with the *average power per winning coalition* (-.57). Besides, it has a negative predictive power on the *average power per winning coalition*. A high betweenness often means that one has a lot of contacts in one's social network that others do not have. Having lots of contacts implies one cannot maintain close relationship with all contacts, leading to an increased number of weak ties. Literature is suggestive of the strength of weak ties (Granovetter 1973; Hauser et al. 2007) in social networks (Granovetter 1973). Especially, networked learning (Jones et al. 2008) and networked innovation (Burt 2004; Hauser et al. 2007) value weak ties as predictors of successful cooperation in networks. Our results imply practically the same; Table 5 shows that average betweenness per winning coalition has negative predictive power for the average power per winning coalition. In other words, having high betweenness centrality makes it easier to build a successful coalition as one needs a lower average power to succeed.

4.5 Another interesting observation lies in the negative association with the *number of turtles* on the *average power per winning coalition* (Table 5). This implies that as the network size increases, it becomes easier to build a successful coalition. Although other factors may influence the process as well, we may conclude that it may be easier to form a successful coalition in a larger network.

4.6 There are two implementations of the Shapley value. First, we have the situation in which all agents form a coalition at once, the one that we used in this simulation. Second, the agents may join a coalition one after another. In case of a high-betweenness agent attracting a lot of partners, we could consider using the second method of coalition formation to further optimise the simulation. Besides improving the way the Shapley value is calculated and used for the formation of coalitions, we may decide to implement the nucleolus. The Shapley value does not consider the expected contribution of an agent to a coalition, whereas the nucleolus (Schmeidler 1969) does. During payoff distribution, the nucleolus tries to minimise the maximum dissatisfaction of participants in a coalition.

Conclusion

5.1 The present study investigated whether network characteristics and network member's characteristics influence the average power per winning coalition. To aid people in their search for optimal coalitions, we studied the dynamics of coalitions in networked innovation. We ran a simulation of networked innovation under rational behaviour (to yield optimal decisions), and monitored the variable variations. Multiple regression analysis led to a model that predicts the average power per winning coalition as a function of network size and network density.

5.2 The current study allows us to make two interesting observations. First, average betweenness negatively influences the average power per winning coalition. This means that having high betweenness centrality makes it easier to build a successful coalition, as one needs lower average power to succeed as a coalition. Second, the number of network participants negatively influences the average power per winning coalition. This implies that in a larger network, it may be easier to form a successful coalition.

5.3 The regression model presented in this paper offers interesting uses. Our simulation presumes rational play by network participants. In other words, optimal decisions are made concerning the formation of coalitions. Assuming rational play, we compute how coalitions should ideally be formed within networked innovation. An important implication of this model is that we can assist in real life networked innovation by recommendation of optimal coalitions (with a necessary average power or betweenness centrality), given that we know what the network density and network size are.

Future Work

6.1 The model presented in this work was based on extensive literature review. The research articles that we studied employ empirical methods to determine if and what relationships between variables exist. We combined the outcomes of several influential studies to develop a simulation model. We programmed agents on an individual level to study the emergent dynamics of networked innovation (macro level), an approach that is characteristic for agent-based social simulation. The next step in the process of deriving a model that correctly describes reality is the validation of the model. We plan to validate our model by testing its behaviour against empirical data. Subsequently, we will use the model to generate optimal coalitions for innovation in networks in an empirical setting.

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