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The Role of Individuals in Innovation Networks: A Simulation Approach in Canadian Biotechnology Network

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***Abstract* – Known as the driving force of biotechnology innovation, scientific individuals contribute significantly to knowledge transfer through their privileged connections with other scientists of the field. The objective of this work is to investigate the role of individual scientists and their collaborations in innovation networks. In order to study the networks in their dynamic context an agent-based simulation model is developed using real data based on the Canadian biotechnology publications. While the repetitiveness of the collaborative relationships among scientists has shown negative effects, the presence of the gatekeepers has proved to be very positive for the overall efficiency of the network. The impact of star scientists on the innovative activities has been found positive, but some negative effects on the flow of knowledge in the network have been detected.**

***Keywords* – Innovation network, Knowledge dynamics, Agent-based modeling, Canadian biotechnology.**

1 INTRODUCTION

Biotechnology as a breakthrough in science-based industries revolutionizes many industry sectors including agriculture, food and medicine and has proved to have a great commercial potential. Nevertheless as a knowledge-based scientific advance, biotechnology is an important focus for many research and development (R&D) activities. Thus, the number of researchers involved in scientific publishing or patenting in this crucial sector is growing continually, and the collaboration of these scientific individuals forms an innovation network that progressively helps in the development and application of biosciences and biotechnology.

Networks are one of the primary sources of new and novel knowledge in the knowledge intensive sectors and specifically in biotechnology industry [Demirkan and Demirkan, 2012]. Due to the high exposure to various sources of knowledge, innovation networks act as an enhancer of the learning process by facilitating the production and circulation of knowledge [Powell et al., 1996; Sternberg, 2000; Fritsch, 2001; Fritsch and Kauffeld-Monz, 2010]. The socially connected individuals are the key generators and transmitters of knowledge [Dahl and Pedersen, 2004], whose collaborations compose the links of the innovation network. Since the survival as well as the success of biotech industry critically relies on the level of innovativeness of their products and procedures, the operational characteristics of innovation networks are of primary importance to improve the performance of such networks and thereby, of the whole industrial sector [Powell et al., 1996]. The raise and the crucial importance of biotechnology innovation systems led to a growing awareness of descriptive literature on this central topic and understanding the efficiency and the effectiveness of biotechnology innovation networks is still the focus of many empirical studies.

The research on innovation networks encompasses several disciplines and has evolved out of various approaches, including systems of innovation [Lundvall, 2010], regional economies [Saxenian, 2001], knowledge dynamics [McFadyen et al., 2009], social capital [Inkpen and Tsang, 2005], and firm knowledge [Ahuja, 2000; Dhanaraj and Parkhe, 2006]. Innovation networks in biotechnology has been of a great interest due to the nature of this emerging sector as a sector in which scientific advancements are collaborative [Oliver 2004] and R&D is increasingly carried out in collaborative networks [Katz and Hicks, 1997]. These research efforts involve several analyses including R&D alliance network [Gay and Dousset, 2005; Baum et al., 2000], inter-organizational collaboration [Powell et al., 1996; Owen-Smith and Powell, 2004, Walker et al., 1997], university industry relationships (UIRs) [Owen-Smith et al., 2002; Whittington et al., 2009; Jong 2008] and scientific collaboration networks [Newman 2001; D'Amore et al., 2013; Shiffauerova and Beaudry, 2011; 2012].

Recently, simulation attempts have been conducted to analyze the combinational characteristics of the innovation networks [Gilbert, 2004; Albino et al., 2006; Pyka et al., 2009; Triulzi and Pyka, 2011; Ahrweiler et al., 2011; Wu and Zeng, 2009; Abrahamson and Rosenkopf, 1997; Tian and Zhang, 2008; Gilbert et al., 2007; 2001]. However, the focus of these studies is at the firm level, while the application of simulation models at the individual level has remained unexplored and requires further studies.

The main objective of this research is to examine the behavior and the innovativeness of individual scientists, with a special focus on star scientists and gatekeepers. In this paper, the term "star scientists" refers to the most prolific scientists in the networks, who are the main sources of new knowledge. They are the scientists who efficiently make use of the knowledge created in the innovation network, and produce significantly more new knowledge than others [Zucker and Darby, 1996; 1995; Hess and Rothaermal, 2011]. Among many definitions proposed for the term "Gatekeeper", in this study we adopt the definition proposed by Schiffauerova and Beaudry [2011] as an individual scientist at the network's frontier who plays a key role for the inflow of the external knowledge to the collaboration network. The main objective of this study is to picture and analyze the dynamics of the Canadian biotechnology innovation networks, deploying an agent-based simulation model (ABM) The uniqueness of this study stems from twofold, the use of real data derived from Canadian biotechnology literature database in our ABM and the performance of analysis at the individual level. This paper explores the role of various scientists in Canadian biotechnology network and elucidates the quality and the duration of their relationships in such networks - i.e. loyalty to their co-authorship partners.

The paper is organized as follows: the hypotheses are introduced in section 2. Section 3 provides a brief description of the data and the methodology. Finally, the simulation results are discussed in section 4, while conclusions are drawn and policy implications derived in section 5.

2 HYPOTHESES

2.1 The effects of loyalty on the innovation networks

The cooperative relationships among humans are affected by various criteria. The duration as well as the depth of a relationship is highly grounded on its purposes and benefits it provides regularly for engaged partners. In a productive academic environment, the collaboration ties are formed in a way to create new knowledge. The similarity of goals, required skills of the partner, trust, and records of previous successful collaborations are of a great importance when scientists choose their partners [Mat et al., 2009]. Everyday life experience, however, has shown that there also exist personal factors which play a role in the decision process of partner selection, including culture, family, social life, etc. Therefore, it is expected to see some people changing their partners frequently, while others prefer loyalty to their current partners [Buchan et al., 2002].

Since the process of searching for new partners is time-consuming, people are usually willing to remain loyal to their previous partners, even when better choices are available. The loyalty to previous partners, results in a clustered collaborative network [Mat et al., 2009] in which exists a number of heterogeneous closed populations [Amaral et al., 2000]. In this study, the term 'cluster' refers to any partitioning of scientists in the innovation network based on specific characteristics such as geographical location, organization type, working field, etc.

The important factor of an innovation network is the flow of knowledge between its nodes (scientists). The faster and more freely knowledge flows in the network, the faster the innovation grows. The flow of knowledge is closely related to the structure of the network, for example, dynamic links in structured networks help facilitate the flow of knowledge [Zander and Kogut, 1995]. However, loyalty to the previous partners results in a static network in which some nodes might never be connected and some routes for flow of the knowledge might never shape. A high degree of loyalty encourages scientists to stick to their previous partners for their new collaborations and thus forms highly clustered networks which can hinder the innovation production due to its reduced number of potential paths [Van Segbroeck et al., 2009]. Hence, we hypothesize that the innovative production in a network under the high levels of loyalty is lower.

Hypothesis 1a: *Loyalty to the previous partners decreases the productivity of the network*.

In a network with strong social ties, there also exists a challenge for newcomers to find collaborative partners, since the existing scientists prefer to work with their current partners, and usually refuse to start collaborations with new ones. In such a network becoming a scientist requires knowing other people and being involved in a highly socialized context. An access to professional interactions greatly helps scientists to survive and improve their position in the network [Kemelgor and Etkowitz, 2001]. New scientists may then find it difficult to survive in the network if they cannot get involved in scientific collaborations or to find social support, and may become isolated or remain disconnected from pivotal sources of knowledge [Guimera et al., 2005]. Hence, loyalty to a previous partner is expected to have a negative impact on the network structure. We assume that the loyalty increases the repetitiveness of the existing collaborations and thus decreases the number of new collaborative ties as scientists feel less inclined to collaborate with the researchers outside the circle of their existing partners. Moreover, the loyalty reduces the chances of the newcomers to get well interconnected in the network, resulting thereby in more disconnected network architecture. We therefore hypothesize that the efficiency of the knowledge flows in the network will be affected negatively by the high levels of loyalty.

Hypothesis 1b: *Loyalty to the previous partners results in the lower number of collaborators a researcher is connected to.*

Hypothesis 1c: *Loyalty to the previous partners decreases the knowledge transmission capability of the network.*

2.2 The role of star scientists in the innovation networks

Star scientists are the scientists with the extremely high contribution to the scientific output, and their contribution to innovation and development of biotechnology has been much discussed in the literature [e.g. Schiffauerova and Beaudry, 2011; Zucker and Darby, 1995; 1996; Hess and Rothaermal, 2011]. Biotechnology star scientists are the main producers of innovation and knowledge in the network, representing less than 1% of the population of the scientists and the authors of more than 15% of the articles and patents [Zucker and Darby, 1995]. Zucker and Darby [1996] concluded that firm's collaboration with star scientists, results in its success. Therefore, scientists may feel perhaps more inclined to collaborate with stars to gain more fruitful and greater scientific productivity in terms of higher quality of research, better access to the resources (e.g. equipment, funding, knowledge resources), better connection to leading researchers, better chance to get noticed and succeed in their publishing activities. "Trust" is also another factor that is considered as the basis for scientific collaborations in almost all social contexts [Buchan et al., 2002; Storper, 1997] and has a close relation with reputation in the formation of cooperative and exchange structures [Kollock, 1994]. Due to their academic reputation, star scientists are perceived as more trustworthy than other scientists in the network and "trust" overshadows other factors for the selection of potential collaboration partners. Star scientists are thus expected to be selected much more often than ordinary scientists. The literature on biotechnology star scientists also reports that the stars are more likely to repetitively collaborate with the same scientists [Niosi and Banik, 2005], which could consequently result in a less socialized network context and reduce the transmission of knowledge to other scientists in the network. Since the stars are the main sources of knowledge and usually occupy more central positions in the network [Schiffauerova and Beaudry, 2011], the flow of knowledge might be affected by their presence and absence. It is thus expected that a network without star scientists will have more homogeneous structure, and both the links between vertices and the knowledge production would be more evenly distributed among the scientists. On the other hand, the network which includes star scientists will be more centralized, i.e. there will be a greater variation in the centrality of the nodes in the network. It has been shown that the central structure of the network reduces the overall knowledge spillovers among the scientists, resulting in their lower productivity [Eslami et al., 2013]. The reason is that the researchers with high degree centrality can influence the knowledge diffusion by withholding the transmission of information [Chung and Hossain, 2009; Freeman, 1979]. Therefore, we envisage that the presence of star scientists will create more centralized network and thus will reduce the efficiency of knowledge transmission within the network.

Hypothesis 2: *The presence of star scientists decreases the transmission capability of the network.*

2.3 The role of gatekeepers in the innovation networks

First coined by Allen [1967], the term "gatekeeper" refers to an individual who gathers, processes and transfers knowledge from internal and external procedures. Gatekeepers are usually characterized as firms that transmit the non-local knowledge to the region and thereby play a pivotal role in exposing the region to the outside world [Morrison, 2008] and give higher innovative performance to the local network [Boschma and Ter Wal, 2007]. However, gatekeepers are not only limited to firms, because research universities, cooperative R&D institutions [Steiner and Ploder 2007], and public research organizations [Graf 2011] have been commonly suggested to serve the functions of a gatekeeper as well. Moreover, it has been suggested that the productivity of a firm is highly dependent on individual gatekeepers due to their contribution to the R&D performance through linking the company to its external environment [Allen 2003; Tushman and Katz, 1980; Katz and Tushman, 1981]. Narrowing the focus to individuals we thus hypothesize that gatekeepers will play a positive role in enhancing the production of knowledge in the network.

Hypothesis 3a: *The presence of gatekeepers increases the productivity of the network.*

Due to their well-established external contacts, technological resources and capabilities, the gatekeepers have a better capacity to absorb new knowledge and diffuse it throughout the cluster [Malipiero et al., 2005; Lazaric et al., 2008, Schiffauerova and Beaudry, 2012]. Since the gatekeepers play a vital role of transmitters of information and opportunities, the scientists with no direct or indirect connections to gatekeepers are in danger of getting isolated due to the limited access to information flows. The presence of gatekeepers in the networks is inevitable, since they have emerged naturally and remain in the network by natural requirements and connections that take place in the network [Heikkinen et al., 2007]. It is thus expected that the network structure will benefit from the presence of gatekeepers and the efficiency of the knowledge transmission will improve.

Hypothesis 3b: *The presence of gatekeepers increases the transmission capability of the network.*

3 METHODOLOGY

The system of collaborating scientists is a dynamic system of individuals with certain links interconnecting them through their publishing or patenting collaboration. As a dynamic network, Canadian biotechnology network shows a changing behavior over time in terms of the number of scientists, their collaborations, and the knowledge outputs. . In order to capture the performance of the network and to analyze its characteristics, a model of complex network has been developed.

The simulation modeling of this study is based on Agent Based Modelling introduced in [Gilbert et al., 2001], a learning-by modelling process which is built upon the theory of innovation networks. The multi agent simulation has been largely used to model the knowledge-based innovation and served as a baseline to introduce science and technology policies [Ahrweiler et al., 2004; Gilbert et al., 2007; Pyka et al., 2009; Triulzi and Pyka, 2011]. Firms, researchers, research laboratories, policy actors and other institutions involved in the development of the knowledge-based economies [Godin, 2006] are identified as the main agents, generating 'artefacts' that lead to new discoveries and innovations [Gilbert et al., 2001]. An agents further follows strategies to ameliorate its artefacts by itself or by forming collaborations with other agents, noting that the success of the artefacts is based on the criterion that is not available to the other agents. In this study, agents are Canadian researchers in the field of biotechnology and artefacts are papers authored by this researchers. The success of artefacts are evaluated based on co-authorship network properties of biotechnology researchers.

The ABM is characterized by the interactions among different individuals, which also modifies the individual's knowledge creation and performance. The model enables us to trace the knowledge dynamics in the system and provides us with valuable insights that cannot be obtained by the observation of the reality [Triulzi and Pyka, 2011]. It also allows us to run some experiments, such as examining the effect of the elimination of a class of scientists from the network. We tested our hypotheses by running several scenarios, using real data from the publication database in Canadian biotechnology.

3.1 Innovation Networks

Since we have built our model based on the real data, our innovation networks are formed by a group of individual scientists which are characterized by various real-life attributes (Table 2). These scientists collaborate with each other in order to exchange knowledge and information, and thereby produce new scientific knowledge leading to an innovative output in the network. In the real life, scientists meet for many possible reasons, but not all the connections between two scientists necessarily lead to the creation of the new knowledge. In this paper, the connections between scientists that has resulted in a published paper are studied. Our innovation network is built through mapping the article co-authorship and network links are the co-author relationships which resulted in the publication of a scientific article. Such networks represent the creation of the scientific knowledge and the innovative outcome through a complex system of knowledge-based relationships.

In order to acquire the data for the creation of the networks, we extracted the information on biotech-related publications from the Scopus database (over the period 1952-2006). Using SQL, the data is first cleaned and classified according to the Simulation model requirements in order to assign attributes and define variables. Second, each class of data is fed separately to the ARENA Input Analyzer in order to find the best fitting probability function to be further used as random number generators in the simulation model. The simulation model is then developed and used to form various dynamics of the collaboration network. Finally, PAJEK software is employed to perform Social Network Analysis and gain the results.

3.2 Input analysis and model building

The data input analysis is of great importance to the success of our simulation model, since without in-depth input analysis, the simulation results cannot contribute to the effective and inclusive policy making. For this purpose, we conduct a comparative analysis of biotech-related publication activity based on the data extracted from Scopus database. We defined fifteen geographical groups in our analysis, thirteen of which correspond to the Canadian biotechnology clusters, one group includes all the scientists affiliated to the American institutions and one group puts together the scientists from all the other locations in the world. We referred to these groups as geographical clusters in this paper. The list of the geographical clusters and the percentage of scientists in each is represented in Figure 1. The collaborations between each pair of scientists are shown in Figure 2, revealing that most of the collaborations occur inside the cluster. This confirms the literature noting that scientists are more willing to collaborate with partners inside their clusters [Cowan and Jonard, 2004; Frenken et al., 2009]. The simulation model thus applies a distance- based factor, which stimulates scientists from the same clusters to choose each other as collaborators. It is also proposed by [Schiffauerova and Beaudry, 2009] that when the distance between two scientists meets some minimum limit, the geographical location of scientists loses its importance. Accordingly, the model is also designed in a way that for all the distances greater than the average distance between all pairs of clusters, the probability of selection remains the same. The information regarding the organization type of each scientist is derived from his/her affiliation in the database (Figure 3A). 73% of the entire collaborations occur between the partners of the same organization type (Figure 3B). Besides, in more than 70% of the collaborations, at least one scientist is from a university. The selection procedure in the simulation model has been designed in a way which follows this pattern.

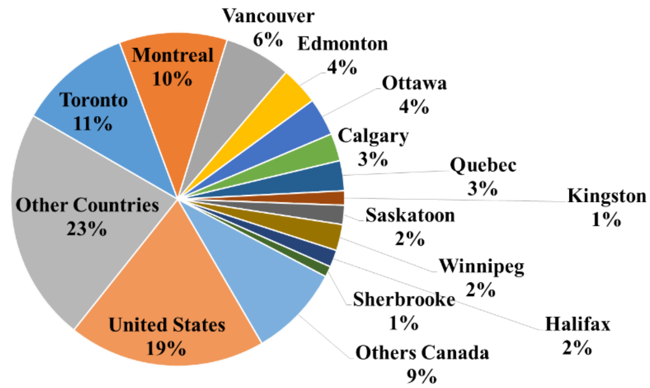

Figure 1. Share of scientists in different geographical clusters

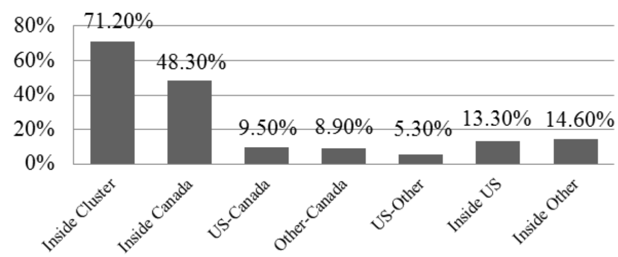

Figure 2. Distribution of collaborations between geographical clusters

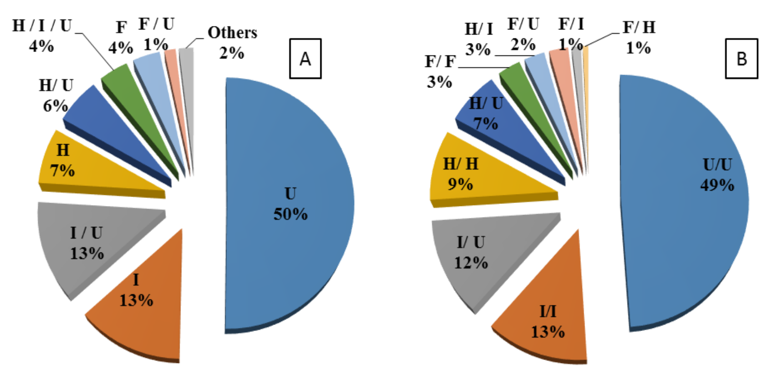

Figure 3. Share of scientists in different types of organizations[1] (Left:A) and in different types of collaborations (Right:B).

According to the database, each scientist has some number of links as soon as he/she enters the network and the links are defined based on the co-publications. The average number of initial links

[1] U=University; F=Firm; H=Hospital
Some scientists were affiliated to more than one type of institution (e.g. I/U: a scientist who is affiliated to both university and institution.)

for the first 10 years of publishing activity is shown in Table 1. As an indicator of the quality of the articles we used journal impact factors (based on ISI Web of Knowledge rankings), which are commonly recognized as the paper quality indicators [Weale et al., 2004]. Canadian biotechnology clusters are strongly related to high-class academic research and especially to star scientists [Queenton and Niosi, 2003]. There is no common universal definition of star scientists that provides numerical specifications of their productivity. In order to consider both qualitative and quantitative aspects of the production of the star scientists in the model, we define two criteria to qualify a scientist as a star: minimum of 5 publications and minimum totaled journal impact factor of 10. These criteria correspond to about 5% of the scientists in the Canadian biotechnology database, which is in line with the percentage of stars in Canadian biotechnology network, claimed by Schiffauerova and Beaudry [2011] using the real data. Similarly, in our model, we considered a gatekeeper as a scientist who holds simultaneously at least five links inside and two links outside his/her geographical cluster. This definition accounts for 14.2% of all the individual researchers involved in Canadian biotechnology which again is confirmed in reality by Schiffauerova and Beadry [2012].

Table 1. Number of links per scientist inside and outside of the cluster (%)

Number of Links	0	1	2	3	4	5	Sum
Inside Cluster	6%	18%	31%	12%	25%	8%	100%
Outside Cluster	44%	37%	18%	1%	0%	0%	100%
Sum	50%	55%	49%	13%	25%	8%	-------

Java developer language in accordance with Eclipse coding environment has been used for building the model. The model is further debugged and verified by tracking individual nodes through the model and studying their behavior. After verification, the model is run several times with different scenarios to examine our research hypotheses.

3.3 *Simulation model*

Due to the model's ability to capture structured interactions of multiple agents and to map the emerging patterns at macro-level [Dawid and Fagiolo, 2008], in this study we employed an ABM to scrutinize the dynamics of the Canadian biotechnology innovation. The model is built based on the real life data and thus captures the most important detectable characteristics of the scientists in the two databases. It is structured as follows: At the beginning of each year, a number of new scientists are added to the network, using the trend gained directly from the publications database. For each new scientist, a primary set of attributes and variables are defined. The attributes identify each scientist in the network and remain constant during their life, while the variables indicate the performance of the scientists and may get updated several times. The simulation modeling parameters are listed in Table 2.

At the beginning of each time slot, a distribution function decides whether each scientist should become involved in a new collaboration or not. Afterwards, another function assigns how many partners co-author each new publication. The selection of a new partner in the model is highly dependent on the following conditions: if the two potential collaborators are from the same cluster and from the same organization type, if the fields of research for both scientists are the same, if at least one of the scientists is a star or a gatekeeper, if the geographical distance between the two scientists is less than a threshold, if the difference in the score (a number that holds track of scientist's productivity in the network) of two scientists is less than a threshold. For each condition, a fixed positive number is added to the chooser variable[2] according to the level of priority of the condition.

Any two scientists, whose values of chooser variable match and are greater than each other's chooser threshold, become selected as collaborators. When all the scientists are assigned to a collaboration group, a publication duration time is defined for each group.

The publication duration refers to the time during which the scientists are presumed to be working on a new publication. All the variable values, including the number of articles, and total journal impact factors, are updated for all the involved scientists as soon as the publication duration is over. At the end of each collaboration activity, the model decides whether each scientist remains in the network or dies. In the model, a scientist dies if his/her age in the network passes thirty years (i.e. the longest observed life of one scientist in the database). Whenever two scientists stop working together the age of their connecting link is set to zero. The model further starts to track the age of the mutual links in the network, which is useful in determining the loyalty[3] of partners. The more recent two scientists have worked together, the more probable it is for them to choose each other for another collaboration. The flowchart of the simulation model is presented in Figure 4.

4 RESULTS

The mutual relationships between scientists affect the dynamics of networks over time [Van Segbroeck et al., 2009]. Therefore, in long term, the duration of relationships, i.e. loyalty of mutual partners, determine the structure of networks, which plays a pivotal role in the creation and diffusion of knowledge. By examining the effect of loyalty on the networks, we can measure its effects on knowledge transmission capabilities of networks. The flow of knowledge in the networks is highly dependent on some characteristics of the networks, including degree centrality[4], clustering coefficient[5] and density[6].

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[2] Chooser variable: a decisive factor measured by summing up the levels of advantage in working with a specific partner, i.e. geographical closeness, organization type similarity, history of previous collaborations, level of productivity (their "score" value), field of study similarity, star status and gatekeeper status.

[3] Loyalty in this study is defined as the duration of time in which one scientist prioritizes their previous collaborators over other members of the network to start a new co-authorship.

[4] The degree centrality is a measure of graph theory that indicates the number of lines connected to each vertex. In the simulation model of innovation network, since the vertexes are scientists, this number indicates the number of collaborators for each scientist in the network. Degree centralization is calculated by dividing the variation of nodes' degrees by the highest possible variation in a network of the same size [Nooy et al., 2005].

[5] The clustering coefficient of a network measures the tendency of scientific individuals to form interconnected communities (clusters) within a network.

[6] The density of a graph represents the proportion of ties in the graph to the total number of possible ties of a graph with the same number of nodes.

Table 2. List of simulation modeling parameters

Set of Attributes	
Scientist ID	A number assigned to each researcher involved in Canadian biotechnology publishing
Geographical cluster ID	Assigns a geographical cluster to each scientist
Entrance year	Indicates the time when each scientist enters the simulation system
Organization type ID	Assigns an organization type to each scientist
Research field	Sets the research field of each scientist
Chooser threshold	A random number assigned to each scientist determining how strict he/she is in selecting a new partner
Set of Variables	
Idle/Busy status	Shows whether a researcher is involved in a collaboration or not at any time
Number of articles	Indicates the quantity of scientist's publication activities
Journal's impact factor	Represent the quality of the publications a scientist is involved in
Number of links inside the cluster	Keeps track of the active collaborators a scientist has inside his own cluster at any time
Number of links outside the cluster	Keeps track of the active collaborators a scientist has outside his own cluster at any time
Score	Represent the productivity of each scientist based on the quantity and quality of publications
Age in the network	Keeps track of the years a scientist exists in the network
Star status	Indicates if a scientist is star
Gatekeeper status	Indicated if a scientist is gatekeeper

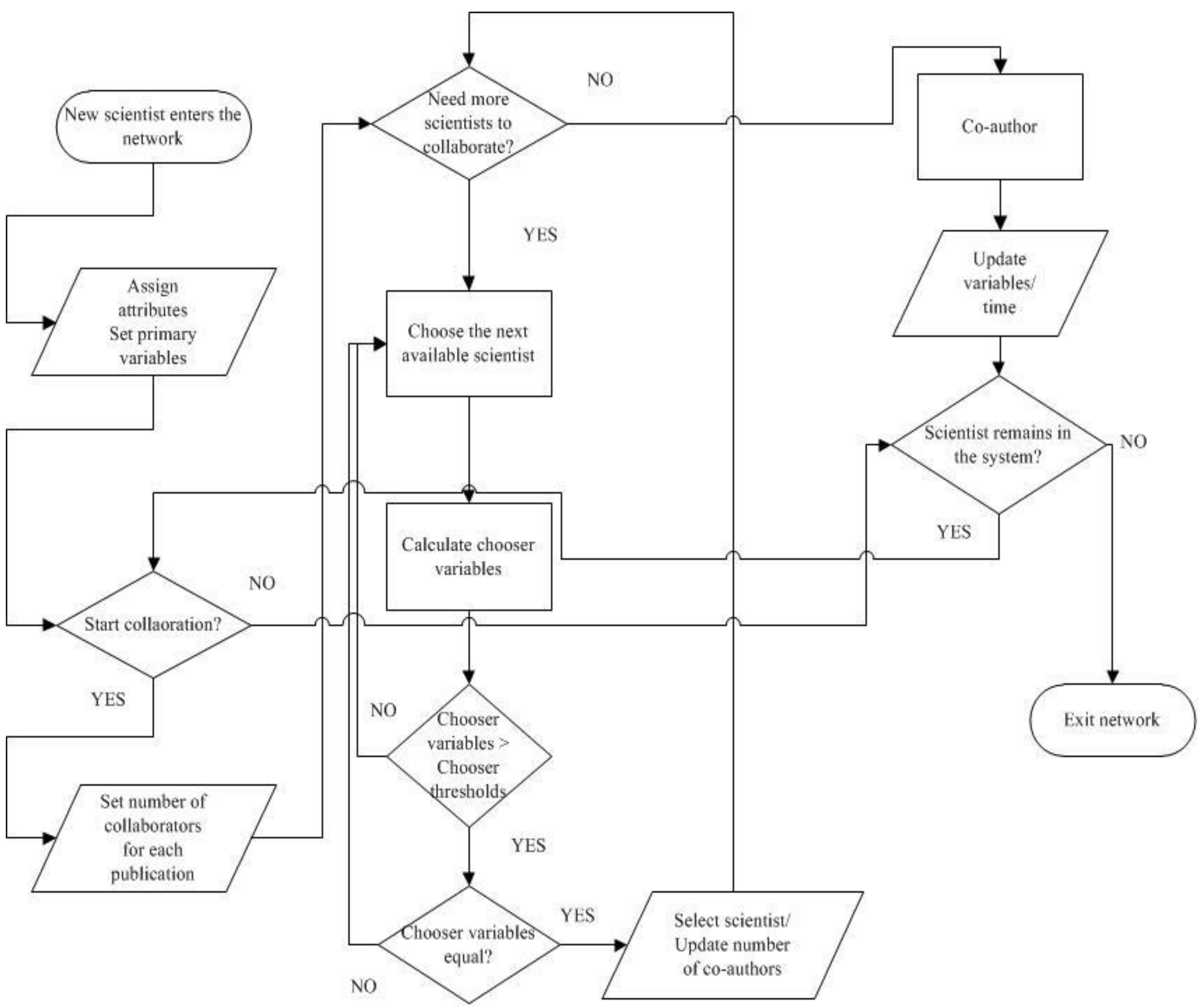

Figure 4. Flow chart simulation model

The first series of scenarios examine the effect of the repetitiveness of the collaborative relationships (the loyalty) among scientists on the overall efficiency of the innovation network in terms of its innovative productivity and its knowledge transmission capability. We use the duration of collaborative relationships as an indicator of loyalty between partners. The model is built in a way that scientists take into account their previous partnerships while searching for new collaborators. In this regard, there is a higher probability for a scientist to be selected if there is a record of mutual collaborations in a specific period in the past. In order to analyze the effects of loyalty on the innovation networks, the average age of links between partners is considered as an independent variable. The link ages thus represent various strengths of social ties and various levels of the loyalty in the network.

To compare all the various scenarios, the network characteristics were calculated and analyzed using PAJEK Social Network Analysis software. The simulation experiment has been run for various levels of loyalty to previous partners (various link ages), ranging from 0 year to 30 years. The results showed that the average rate of publication per scientist declines as the social ties among loyal partners become stronger in the network (Figure 5). This confirmed our ***Hypothesis 1a.*** On the other hand, the average degree of centrality increases together with the loyalty level (Figure 6), revealing the existence of greater number of active links connected to a scientist in higher loyalty levels and thus rejecting ***Hypothesis 1b.***

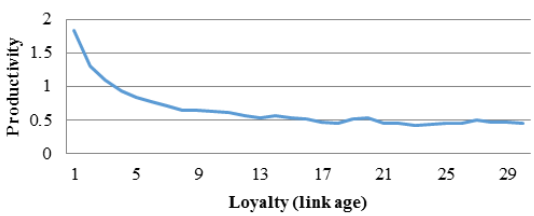

Figure 5. Network productivity (average number of publication per scientist)

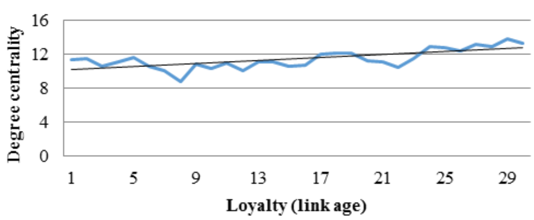

Figure 6. Average degree centrality of the network

The simulation model showed that long-lasting collaborative relationships—i.e. repetitive co-publications with the same partners—can affect the structure of the innovation network negatively, resulting in less flow of knowledge among agents of the network. Increased loyalty in the network caused the network characteristics that account for knowledge transmission capabilities to deteriorate (increasing degree centralization, decreasing density) (Figure 7). Therefore, the results confirmed the ***Hypothesis 1c***.

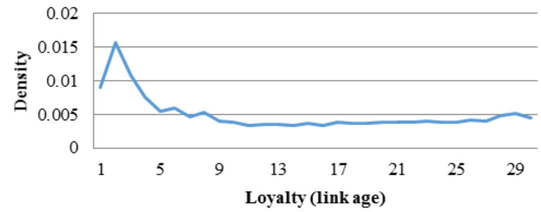

Figure 7. Network density

The following hypothesis is grounded on the role of star scientists in the creation of the knowledge within the network and in shaping the network structure. This has been investigated through the comparison of the effects of their presence and their absence on the characteristics of the networks. To analyze the network without star scientists, the primary settings of the model were modified in a way that star scientists neither exist in the beginning of the experiment nor are able to become defined as stars further in the iterations. Two scenarios, which consider either the presence or the absence of the stars in the network, are experimented by the simulation model. The results of five iterations of the model for each scenario—namely star included and star excluded—are compared and the characteristics of the innovation network are then analyzed. As it could be predicted due to the higher productivity level of star scientist, the simulation experiment has shown that the average innovative productivity of the network is higher in the star-included scenario. In addition, in a network without stars, there exists higher network density, and lower average degree centralization, showing that the network has an advantage in terms of interconnectivity and capability of knowledge transfer. Moreover, there is a higher chance for new scientists to be selected as partners, resulting in less isolated components in the network (Table 3). We conclude that the presence of stars and the reduction in the interconnectivity of the scientists could hinder the flow of knowledge in the network and thus on the efficiency of the knowledge transmission through this network, which confirms ***Hypothesis 2***.

Table 3. Simulation results for the role of star scientists

	Ave. degree centrality	Ave. density	Ave. Clustering coefficient	Ave. Productivity
Star included	11.362	0.006	0.79	0.86
Star excluded	10.476	0.007	0.85	0.75

The last two hypotheses examine the role of gatekeepers as the intermediaries of the knowledge exchange in the networks. Similar to the analysis of star scientists, two scenarios, i.e. the network in the presence and in the absence of the gatekeepers, were experimented by the simulation model. In the first scenario, the gatekeeper status of a scientist is set as variable in the selection procedure of partners whereas the gatekeepers have the same probability of being selected for collaboration as other scientists in the second scenario. The two scenarios were simulated and the results are compared.

The results of the simulation runs suggest that the presence of the gatekeepers benefits the innovation network significantly, both in terms of its enhanced innovative productivity and its structural properties and leads to higher flow of knowledge through the network (Table 4). It can be also concluded that most of the scientists from other geographical clusters prefer to bridge through intermediaries rather than directly connecting to scientists from other clusters. These results thus confirm both ***Hypothesis 3a*** and ***Hypothesis 3b***.

Table 4. Simulation results for the role of gatekeepers

	Ave. degree centrality	Ave. density	Ave. Clustering coefficient	Ave. Productivity
Gatekeeper included	11.362	0.006	0.79	0.86
Gatekeeper excluded	13.521	0.004	0.77	0.43

5 CONCLUSIONS

This study has been the first attempt applying simulation modeling to address the role of individual scientists in Canadian biotechnology innovation network. We used the database of articles to collect the data and study the properties of the Canadian biotechnology network. An agent-based simulation model of the scientists was developed and the simulation experiment was employed for various scenarios to examine the behavior of the model. We introduced three hypotheses related to the loyalty of the scientists out of which two were confirmed and formulated a hypotheses related to the role of star scientists and two associated with the importance of gatekeepers which were supported by our analyses. This study shows that loyalty to previous partners in innovative and scientific collaborations leads to a static network, which hinders knowledge flow and lowers knowledge transmission capability of this network. The reduced number of potential paths as a result of highly clustered and embedded network structure acts as a disadvantage for the scientific innovation productivity. However, long-lasting levels of collaborations in Canadian biotechnology networks indicate no negative effect on the number of collaborators a researcher is connected to, showing that biotech scientists are willing to collaborate with other researchers despite of their loyalty to their previous partners.

The presence of the prominent individual scientists and inventors plays an important role in knowledge and innovation generation and diffusion. Star scientists, on one hand, attract collaborations from many other scientists. However, they usually focus on repetitive long-lasting partnerships by which they create a less socialized network that reduces the transmission of knowledge to other scientists in the network. The increased number of isolated network components of scientists who are unable to find collaborators and the lack of interconnectivity impede the process of knowledge transmission in the network. Gatekeepers, on the other hand, contribute very positively to the active flow of knowledge and they channel the new knowledge from distant sources and easily bridge over the whole network, thereby increasing the efficiency and the speed of knowledge transmission. Gatekeepers may not necessarily be very productive in terms of publications, but they expose other scientific individuals to new knowledge which could not be easily reached otherwise. Their positive impact on connectivity can compensate its reduction in the network caused by star scientists, and hence these two roles can complement each other.

The contribution of this work is twofold. First, this study is the pioneer attempt which uses the real data in the study of the dynamics of the innovation networks. Second, even though the importance of star scientists and gatekeepers for the knowledge generation and innovation production has been accepted by the scientific community, their complementary roles have less been studied empirically in a dynamic environment and complex setting. The use of ABM helped us to define different characteristics for each individual scientist, enabling us to explore these characteristics in a situation that cannot be implemented in the real world. More specifically, the model made it possible to make some experiments by eliminating stars and gatekeepers from the scientific population and provided us with insights that could not be obtained or verified in reality.

This work represents another step towards the understanding of the influence of knowledge networks on the innovative activities and on the role of individual scientists in these networks. The findings of this study can be used to improve Canadian biotechnology policies. The research productivity decreases as researchers remain loyal to their collaboration partners. Hence we suggest providing some incentives for biotech researchers to establish new co-authorship relationships in terms of funding incentives or innovative research programs, i.e. conferences, forums, research centers, or a place where biotech researchers present their work and meet regularly, collaborate and exchange ideas.

Furthermore, to highlight the significant role of gatekeepers, we recommend government to identify the gatekeepers involved in biotech publishing and provide them with some incentives in order to keep them in the network, for example by appointing them to leading positions at research centers or other research institutions. Besides, to benefit from the complementary role of stars and gatekeepers, it is recommended to link them through conferences, forums, or research centers.

We intend to continue exploring the exact role played by networks and their importance in the chain of knowledge creation. One avenue for future research is to gather real-life data about other critical factors such as funding, collaboration costs, and collaboration durations in the modeling. The drawback effect of cost of establishing new connections can be used to perform optimization research and propose applicable regulations and policies for organizations and government in order to facilitate the circulation of knowledge and improve the innovation production in the networks.

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