# EXPLORING OPEN INNOVATION STRATEGIES: A SIMULATION APPROACH

**Irina Savitskaya**
Lappeenranta University of Technology
Faculty of Technology Management
Prikaatintie, 9
45100, Kouvola, Finland

**Martin Ihrig**
The Wharton School
University of Pennsylvania
418 Vance Hall, 3733 Spruce Street
Philadelphia, PA 19104, USA

## KEYWORDS

Agent-based modeling, simulation research, open innovation, strategic management, knowledge assets.

## ABSTRACT

This paper presents an agent-based simulation tool that allows researchers to model innovation strategies with different degrees of openness in their R&D and commercialization processes. It implements the micro-foundations of open innovation and can be used to explore innovation strategies and their associated financial performance and their knowledge creation potentials in different market environments.

## INTRODUCTION

Recent research on innovation management has been preoccupied with the challenges of openness of innovation processes, with the discussion primarily built upon Chesbrough's *Open Innovation* concept (Chesbrough 2003) and further extensions to it (e.g. Gassmann and Enkel 2004). The concept refers to the process of innovation management when a company provides internally produced knowledge for the market and lets external knowledge flow in for maximizing the value for the company. It can also be described as "both a set of practices for profiting from innovation and a cognitive model for creating, interpreting and researching those practices" (West et al, 2006 p. 286).

Being introduced in 2003, open innovation was first developed as a result of a set of in-depth case studies (Chesbrough 2003) and then further investigated in quantitative research (Gassman and Enkel 2004), suggesting a difference in the open innovation process between inbound and outbound open innovation. Currently, open innovation research is conducted through a multitude of methods and tools. However, there is not yet agreement on what method is more suitable for the study of the open innovation phenomenon and currently used methods do not resolve the main question of whether open innovation is superior to closed innovation (Trott and Hartmann, 2009; Almirall and Casadesus-Masanell 2010). To resolve this dilemma, we suggest conducting virtual experiments modeling the behavior of agents following four innovation strategies. To achieve our goal, we use a unique simulation tool which has already proved its efficiency in strategy simulations (Ihrig and Abrahams 2007; Ihrig 2010, 2011).

## THE CONCEPTUAL BACKGROUND

### Open Innovation

Although innovation is recognized as a key driver of firms' competitive advantage and growth, and collaborative innovation as a source of competitiveness of entire ecosystems (Almirall and Casadesus-Masanell, 2010), there is still no consensus on how to reach the optimal level of openness in collaboration for innovation. The open innovation approach suggests that opening up company borders for inflows and outflows of knowledge is a feasible option, even in lean times (Chesbrough and Garman, 2009). The literature discusses the potential practical implications of such an approach, but it still remains unclear how to manage the internal knowledge under different levels of openness in co-innovation. While open innovation clearly provides several benefits and opportunities for companies – and is therefore often being touted as superior to a closed innovation model (Laursen & Salter, 2006; Chesbrough et al., 2006 and others) – the theoretical grounds of it still stay undefined. The question whether open innovation is a winning strategy has been previously addressed by some researchers (Trott and Hartmann, 2009; Almirall and Casadesus-Masanell 2010), however, there is still no definitive answer to it.

At the same time, if we look back at the definition of the concept of open innovation, knowledge flows are at the center of open innovation transactions, and we can use them to formulate knowledge-based innovation strategies. This approach allows us to view open innovation through the lense of the I-Space framework (Boisot, 1995, 1998) that describes knowledge-flows in different populations of agents. The Information Space or *I-Space* is a conceptual framework which relates the degree of structure of knowledge (i.e. its codification and abstraction) to its diffusibility as that knowledge develops. As will be described below, we draw on this in our simulation modeling.

Most commonly, the innovation process is considered to follow one of four strategies of openness (Figure 1):

Proceedings 26th European Conference on Modelling and Simulation ©ECMS Klaus G. Troitzsch, Michael Möhring, Ulf Lotzmann (Editors)
ISBN: 978-0-9564944-4-3 / ISBN: 978-0-9564944-5-0 (CD)

*Closed Innovation* (or pure in-house development). Referred to as closed innovation by Chesbrough (2003), it is also known as traditional innovation. The literature shows, that the innovation process has hardly ever been completely closed (besides strategic industries such as the military) and has encompassed to a high extent the cooperation on horizontal and vertical levels. However, in order to cover all the possible strategic options for this research, we include pure in-house development and commercialization of innovation as an extreme case.

*Outbound Open Innovation (Outbound OI)*. This strategy encompasses in-house product development and profits from external exploitation of knowledge. Companies using this strategy are major sources of innovation solutions to the market for technology, as they exploit a big share of their technological discoveries outside the company. Of course they do not sell their core knowledge in order to maintain core competences and the ability to produce innovation.

*Inbound Open Innovation* (*Inbound OI)*. This strategy sees knowledge acquisition as the important contribution to the internal innovation process. Firms purchase technologies and other knowledge in order to complement own developments, to save resources and costs on in-house R&D, and to shorten the time-to-market.

*Open Innovation*. It is the combination of the two aforementioned strategies – Inbound and Outbound OI. Open innovators invest a share of their efforts into in-house development, complement it with knowledge acquisition from the market, and sell and/or license out their intellectual property (IP) in order to accumulate more funds for internal R&D and other activities.

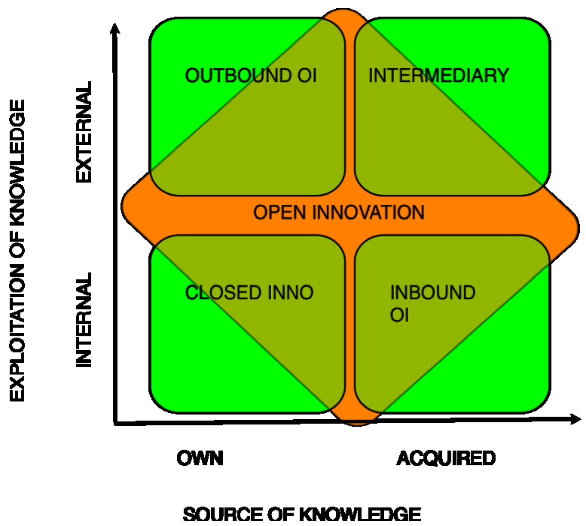


Figure 1: Knowledge-based innovation strategies

These strategies, described through the knowledge lense, constitute the basis of the simulation model presented below. Although we illustrate five potential knowledge-based innovation strategies in the matrix (Figure 1), we exclude the intermediary strategy from the simulation model. The intermediary in this case is buying and selling knowledge as a broker without having its own innovation process, which reflects a different business model, not matching the scope of this research. However, for clarity sake, the intermediary strategy is reflected in the matrix.

## THE SIMULATION SOFTWARE *SIMISPACE2*

Ihrig and Abrahams (2007) offer a comprehensive description of the entire *SimISpace2* environment and explain the technical details. Before discussing the simulation model built in this paper, we must review some of the basics of the *SimISpace2* simulation software.

Two major forms of entities can be modeled with *SimISpace2*: agents and knowledge items/assets. When setting up the simulation, the user defines agent groups and knowledge groups with distinct properties. Individually definable distributions can be assigned to each property of each group. When the simulation runs, the individual group members (agents and knowledge items) are assigned characteristics in accordance with the distribution specified for the corresponding property for the group of which they are a member.

Knowledge in the simulation environment is defined as a ‘global proposition’. The basic entities are *knowledge items*. Based on the *knowledge group* they belong to, those knowledge items have certain characteristics. All knowledge items together make up the *knowledge ocean* – a global pool of knowledge. Agents access the knowledge ocean, pick up knowledge items, and deposit them in knowledge stores. A knowledge store is an agent’s personal storage place for a knowledge item. Each knowledge store is local to an agent, i.e. possessed by a single agent. Knowledge stores as containers *hold* knowledge items as their contents. This happens after agents obtain a knowledge item. Examples of a knowledge store include books, files, tools, diskettes, and sections of an agent’s brain. There is only one knowledge item per knowledge store, i.e. each knowledge item that an agent possesses has its own knowledge store. If an agent gets a new knowledge item (whether directly from the knowledge ocean or from other agents’ knowledge stores), a new knowledge store for that item is generated to hold it. The knowledge item is held at a certain level of abstraction and codification in that knowledge store. Knowledge stores are about the *form*, knowledge items about the *content* of knowledge.

*Discovered Through Investment (DTI) Knowledge.* DTI knowledge is a special kind of knowledge, which is discovered through investing in related (child) knowledge. DTI knowledge items cannot be discovered through scanning the knowledge ocean. The user chooses a set of knowledge items to be children of a DTI knowledge item (DTI network; separate from linked knowledge). The only way for an agent to discover DTI items is to successfully scan the children and then to codify and abstract (or absorb and impact) them above (or below) a certain user-set value. Once the specified codification and abstraction levels are reached, the agent automatically obtains the DTI knowledge item. Investing in the child items, i.e. scanning, codifying and abstracting them, is the primary means of getting DTI knowledge. Once an agent has discovered a DTI item, it is treated like a regular knowledge item, i.e. other agents are then able to scan it from the agent that possesses it. By specifying the value characteristics of the DTI knowledge item, the user can indirectly determine the value of the respective DTI network.

The agents in the simulation are able to perform various *actions* and thereby to adopt different role types. Actions are assumed to have zero duration, start and end in the same period and are purposefully taken by agents.

The state of the world as well as that of the agent (and the knowledge) changes after an action is successfully undertaken.

What follows next is a description of each action-type. When deciding what to do in a period, agents pick from this list of actions.

*Scanning (storing).* An agent can scan knowledge. Scanning means picking up a random knowledge item, whether from the knowledge ocean or from other agents' knowledge stores. The probability of scanning from the knowledge ocean is specified by the agent-group-level property 'Propensity To Scan From Ocean'. An agent can scan any knowledge item in the knowledge ocean, but can only scan knowledge items in knowledge stores within its vision. Vision determines how far the agent can see spatially. An agent's vision is a certain radius from its current location within which it can *scan* and call for *meetings*. Thereby, it establishes the size of the market within which the agent operates. Some will be village markets and some will be global markets. An agent can scan knowledge possessed or owned (patented or copyrighted) by other agents within its vision. Agents only try to pick up knowledge items that they do not already possess at that level of abstraction and codification. If a knowledge item is successfully scanned, it starts off in a new knowledge store possessed (but not owned) by the agent. Depending on the origin of the knowledge item, the new knowledge store picks up the level of codification and abstraction from the knowledge group the knowledge item belongs to (knowledge item from knowledge ocean) or from the knowledge store it found the item in (knowledge item from other agent). If the agent fails to find a store he does not already know (has a store with the same codification level and abstraction level) then the action will fail and the agent will lose his turn.

Once an agent has scanned all the child items of a DTI knowledge item and has codified and abstracted them up to a certain level, then the agent automatically gets the DTI knowledge item associated with that DTI network. The action that is triggered if all the conditions for obtaining a particular DTI are met (set of knowledge items, codification and abstraction threshold) is called *discover*.

*Codifying.* An agent can codify knowledge. Codification only occurs on knowledge stores (form), not on knowledge items (content). The agent must possess the knowledge store to carry out codification. Each codification action creates a new string-of-pearl store with an increased level of codification. Codification of the new knowledge store increases by the codification increment specified for the knowledge item in the store. The level of codification cannot exceed one.

*Patenting.* An agent can patent knowledge for a certain duration and with a specific strength. An agent can only patent a knowledge item it possesses, and only if it holds the knowledge item in a knowledge store that has an abstraction and a codification level above a user-set level. That is, an agent can usually only invest in patenting after it has invested in codifying and abstracting.

Each patent has a particular strength and duration. The user can assign a distribution for both characteristics (general setting for all knowledge). The user can set the number of periods a patent lasts and specify the strength of it. The strength of a patent has an influence on whether agents who possess but not own a particular knowledge item can exploit it. The value for strength should be between zero and one. It influences an agent's effectiveness of exploiting knowledge that has been patented or copyrighted. Agents that do not have the patent for a particular knowledge item should be less likely to succeed in exploiting the knowledge.

Once an agent patents an item, it owns that item. Consequently, all of the agent's knowledge stores that hold the newly patented knowledge item are then eligible for the actions that require ownership (e.g., trading).

An agent may not patent a knowledge item that is already possessed by a user-defined number of other agents (diffusion threshold). This is because knowledge that is in the public domain cannot be patented or copyrighted. 'In the public domain' is defined as follows. First, 'in the public domain' means that other agents also possess the knowledge item in question. Knowledge that is widely diffused cannot be patented or copyrighted, and it is up to the user to specify what widely diffused means by setting an appropriate level of absolute diffusion. Once a patent or copyright is requested for a knowledge item that has surpassed the diffusion threshold, that knowledge item will permanently be in the public domain, i.e. the knowledge item is no longer available for copyright or patent protection. The threshold is specified as the minimum number of agents that must hold the knowledge item in order for it to be considered public domain. Second, all knowledge items with expired copyrights or patents automatically become public domain. Third, the user can opt to put all knowledge items of a group into the public domain. This means, from period one on, these knowledge items will be in the public domain and cannot be patented or copyrighted during the simulation.

*Learning.* An agent can learn, i.e. register, existing knowledge. Learning enables agents to exploit the knowledge items they learned of. This means that before knowledge items can be exploited, learning has to take place. Agents can only learn from a knowledge store they possess. The more string-of-pearl knowledge stores an agent possesses for a particular knowledge item, the more probable it is that this knowledge item will be learned first. An agent's chance of successfully learning is higher for more codified knowledge.

*Exploiting.* An agent can exploit knowledge to gain value. Exploitation means capitalizing on internalized knowledge. This means that an agent must register the knowledge prior to exploiting it, i.e. perform the learning action on the knowledge item. The financial funds of the exploiter agent are increased by the value of the exploiting. Exploiting increases the financial funds of the agent by the intrinsic *base value* of the knowledge item multiplied by the *exploit revenue multiplier*. The level of codification and abstraction, the degree of diffusion, and obsolescence are also taken into account.

*Meeting.* An agent can meet with another agent. Only agents who have initiated the meeting (initiator) and those who have responded positively (responder) are allowed to attend. An agent can only initiate a meeting with agents within its vision. Meeting is a prerequisite for a trade.

*Buying knowledge and selling knowledge (trading).* An agent can buy (sell) knowledge from (to) another agent for a certain price (sale amount). In contrast to scanning, buying only targets knowledge that is owned by other agents. Meeting is a prerequisite for trading, and mutual consensus is necessary. Agents can only sell knowledge stores that they own, i.e. knowledge stores with a knowledge item that is copyrighted or patented. The buyer acquires ownership and the seller loses ownership. This means that the patent or copyright for the underlying knowledge item is terminated for the seller, and the rest of the patent or copyright (remaining time) is transferred to the buyer. Note that the seller still possesses the knowledge and is still in a position to learn and to exploit it.

Only knowledge that the acquiring agent has not previously owned will be traded. The financial funds of the seller agent are increased by the sale value for the trade, and the financial funds of the buyer agent are decreased by the sale value for the trade.

## THE SIMULATION MODEL *KnOISim*

After explaining the simulation software, we can now proceed with describing the *KnOISim* model, designed for open innovation strategy simulations, as well as its properties, agents, and knowledge groups.

### Agents

Following the conceptual framework, we have introduced four groups of agents, each corresponding to the innovation strategy of a different level of openness (Figure 1). Strategies in the model are differentiated by the ability of agents to perform certain actions. Two major distinguishing categories are source and exploitation of knowledge. 'Own' source of knowledge is implemented by the activity of knowledge *scanning.* Agents can either scan from the ocean (which is own ideation of the agent – coming up with the insight by themselves) or from other agents, or both. The scanning is mediated by vision – some agents will have better vision than others, hence they can see more other agents with potentially useful knowledge. Additionally, some agents can also buy knowledge from other agents.

When it comes to exploitation of knowledge, all agents use the *exploit* action, and all agents protect their knowledge through patenting (all knowledge can be patented with a patent duration of 1000 periods, for details see section on Knowledge). However, only some agents are able to sell knowledge.

In order to develop an initial idea into knowledge about an innovation and to successfully capitalize on it, agents can *codify* and *learn.* Knowledge can only be learned after it has been obtained, and only exploited after it has been learned. For agent to capitalize on certain knowledge, this knowledge should reach a certain level of codification.

The differences of agent groups in their actions and the propensity to perform these actions are reflected in Table 1.

Table 1: Agent groups' actions

| **Agent Action Properties:** | **Closed** | **Outbound** | **Inbound** | **Open** |
|---|---|---|---|---|
| ***Propensity*** | | | | |
| Scanning | 1 | 1 | 1 | 1 |
| Learning | 1 | 1 | 1 | 1 |
| Codifying | 1 | 1 | 1 | 1 |
| Patenting | 1 | 1 | 1 | 1 |
| Exploiting | 1 | 1 | 1 | 1 |
| Propensity Scan from Ocean | 1 | 1 | 0.5 | 0.5 |
| Meeting (Initiator) | 0 | 1 | 1 | 1 |
| Buying (Initiator) | 0 | 0 | 1 | 1 |
| Selling (Initiator) | 0 | 1 | 0 | 1 |
| Vision | Small | All | All | All |

It should also be noted that in order to buy or sell knowledge, agents have to first meet. Additionally, depending on the strategy, agents can also initiate and/or respond to certain actions.

There are ten agents in each agent group. All agents start with financial funds of 100. Open Innovators, Closed Innovators, Inbound OI'ers and Outbound OI'ers are randomly spread in the SimWorld (uniform distribution 0-100 for x and y location)

**Knowledge**

We use both basic knowledge and the higher-level DTI knowledge in *KnOISim*. There are three basic knowledge groups *Business Knowledge, Engineering Private Knowledge*, and *Engineering Public Knowledge.* In the beginning, all agents only have Engineering Private Knowledge and Business Knowledge, but no Engineering Public Knowledge.

*Business Knowledge* represents the general understanding of companies of how to do business. This knowledge is required for managing innovation processes, being able to learn new things and to capitalize on innovation. It starts at low levels of codification and abstraction (0.4) since it is primarily the tacit knowledge of business managers and has a base value of 10. This knowledge has an abstraction and codification increment of 0.1.

*Engineering Private Knowledge* represents the technical skills of personnel responsible for innovation (corresponding to R&D scientists, engineers etc.). This is the basis for innovation to emerge and be developed and exploited by the company (here – agent). This knowledge starts at codification and abstraction levels of 0.5 as it is both tacit knowledge of engineering staff and some more codified technical knowledge. It has a codification and abstraction increment of 0.1 and a base value of 15.

*Engineering Public Knowledge* is the commonly available technical knowledge in a very structured form. It can be available in the market both as public good – prior knowledge in the forms of manuals, instructions, process descriptions, etc. – and as the engineering knowledge offered for sale by other agents. As this knowledge is more structured, its codification and abstraction level is 0.8. However, the increment is lower than for other knowledge groups – 0.05 – to account for the additional effort needed when integrating external knowledge into own processes. Engineering Public Knowledge has a base value of 10, and it starts in the public domain and hence cannot be patented by the agents without combining it with other knowledge.

There are ten knowledge items in each knowledge group, all groups have obsolescence rates of zero and no per period gain or cost.

*Innovations*

We use DTI knowledge to model innovations. Once an agent possesses an item each from Business Knowledge, Engineering Private Knowledge and Engineering Public Knowledge in knowledge stores with codification levels greater than 0.7 it obtains the corresponding DTI, i.e. the agent 'discovers' an innovation. There are 20 DTIs each of them being based on the combination of the n-th item of each basic knowledge group (e.g., required knowledge items for DTI 1 are knowledge item 1 of Business Knowledge, knowledge item 1 of Engineering Private Knowledge and knowledge item 1 of Engineering Public Knowledge). DTI knowledge items have a high starting level of codification and abstraction (0.8), a high base value of 2500, an obsolescence rate of zero, a codification and abstraction increment of 0.1, and no per period carrying gain or cost.

Agents obtain innovations in different ways: (1) they can achieve innovation through internal development, by combining all underlying knowledge items, codifying them up to the necessary threshold and hence 'discovering' the innovation as a reward. The missing knowledge items can be obtained directly from the knowledge ocean or from knowledge stores of others. Agents can also trade the missing knowledge items. (2) Alternatively, agents can scan DTIs from other agents. However, since knowledge above a codification and abstraction threshold of 0.6 can be patented, agents might have to get into a trade to acquire and exploit DTIs.

**VIRTUAL EXPERIMENTS**

The simulation originally included 40 runs, each 2000 periods. Because of the complexity of our simulation, the data storage and processing capacities required are extremely high. So for being able to analyze the outcomes in full scale, we had to limit the simulation to 10 runs to maintain the 2000 periods, allowing us to follow certain trajectories and the extended full set of required actions. We compared results received from 40 runs with results received from 10 runs and did not discover apparent difference between the results. Hence, we used the 10 runs simulation to construct the results graphs below.

One period of the simulation run is expected to correspond to a particular period in a real-life environment. This will be however industry dependent and can for example be calculated by observing the trends in the industry and approximating the amount of time needed to come up with innovation in a particular sector.

Figure 3 displays the financial funds results of our four agent groups. The graph shows the average across all runs and also demonstrates the standard deviation (black bands). We can clearly see the outcomes of the groups following different innovation strategies. The financial performance profiles differ in early periods and later periods: Outbound OI and Closed Innovation show higher profits in the *short-term*, when they are focused on exploiting their innovations. Since they do not have any intake of fresh ideas other than own resources however, they run out of innovations to exploit in the *longer-term*, whereas the Inbound OI and Open Innovator make profits from commercializing knowledge they have acquired earlier. As profit maximization is one of the most important targets of companies, we can indeed support the claim that openness is the preferred long-term strategy.

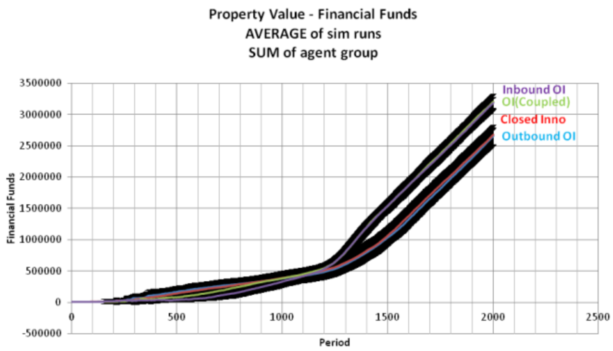

Figure 3: Financial Funds, four agent groups

*Insight 1*: Open innovation is a beneficial long-term strategy. However, there is indication that the Inbound side of it is more profitable than the Outbound side or pure OI.

Figure 4 shows how the different agent groups discover innovations. In order to create innovations, our agents have to accumulate all three types of knowledge described in the simulation settings. As we see, inbound and open innovators discover innovations faster, which goes in line with one of the main arguments in open innovation theory – companies open up in order to optimize their time to market. However, in the longer term, once the R&D process of in-house innovators produce new knowledge, they come up with more innovations in absolute terms, and this advantage looks sustainable for one fourth of our simulation time (periods 1400 to 2000). Apparently, open innovators and inbound innovators are missing certain in-house R&D intensity to catch up or are simply too busy operating at technology markets. However, this lagging in terms of innovativeness is compensated by monetizing the existing innovations (as demonstrated by financial performance in Figure 3).

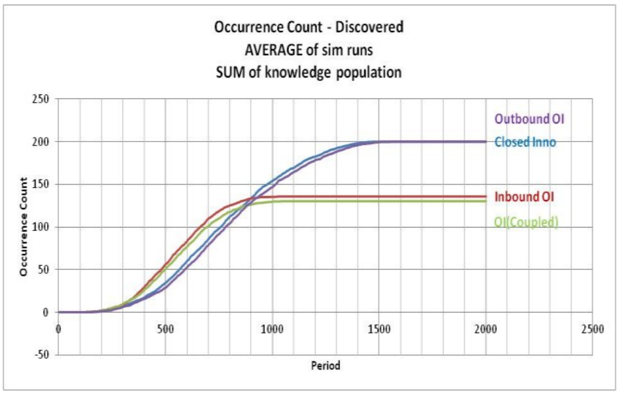

Figure 4: Discovered Innovations

*Insight 2*: Inbound OI and Open Innovation are indeed faster strategies for creating innovations. However, once agents are actively engaged in knowledge exchange and scanning activities, Outbound OI and Closed Innovators, who stick to in-house R&D, discover more innovations. Hence, they have potentially a higher probability to come up with radical innovations.

Figure 5 shows the patterns of knowledge trade by those agents that are involved in trading knowledge. One can see how trading behaviors are changing through the periods, starting with the trade of originally proprietary knowledge and coming to the trade with new innovative knowledge (DTIs). Once Open Innovators and Inbound Innovators are trying to maximize their profits by acquiring existing innovations from the market, the closed and outbound innovators continue to generate innovations and, in the end, discover all possible innovations (DTIs) as we can see looking back at Figure 3. Hence, one can conclude, that the time spent for activities at the markets for technology is taken from the other important activities in the company, e.g. R&D.

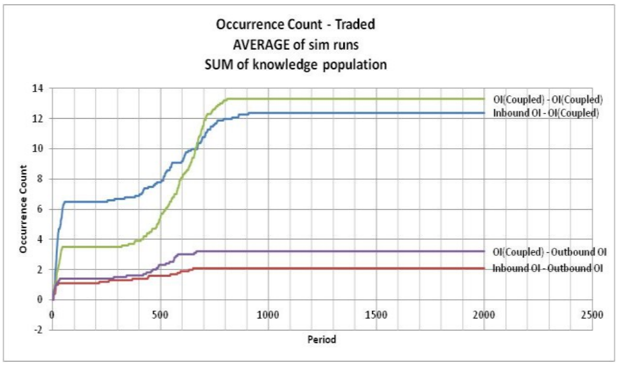

Figure 5: Knowledge Trade

Of course we model a 'perfect' scenario in the sense that agents (or companies) do not differ in their resource base from one another and are only differentiated by important activities in the company, e.g. R&D actions they perform, but this allows us to isolate the performance effects of the four distinct competitive strategies.

*Insight 3*: The resources spent for knowledge acquisition are shifted from the common resource base of the company and hence the in-house development gets fewer resources allocated, thus, endangering the innovative output of the company.

## CONCLUSION

In this paper, we used the *SimISpace2* simulation software to model knowledge-based innovation strategies and to measure financial pay-offs of different innovation strategies and general innovation-related performance of agents.

The simulation model allowed for comparing the performances of different strategies and, on a practical level, to get a deeper understanding of the strategic choices in the orientation of a company, either on innovativeness (aiming at radical innovation) or on profit-making, which would define the selection of a particular innovation strategy at a specific point in time.

Hence, the application of such a model (and its further development) for analyzing strategic innovation decisions of companies is very promising. It allows for observing the influences of pure strategic decisions under the conditions of no external interferences. Additionally, by adding external factors to the next versions of the model we expect to be able to simulate the innovation strategies' performance in diverse environments.

Moreover, our insights will have to be further tested, by increasing the level of complexity of the model and observing if the assumptions still hold. We suggest further extensions of the simulation model to encompass less pure strategies, to include more actions (e.g. in addition to trading knowledge, add the licensing aspects of the trade), and to test the replication of those in different environments, simulating for example developed versus developing markets.

## REFERENCES

Almiral E, Casadesus-Masanell R. 2010. Open versus closed innovation: a model of discovery and divergence, *Academy of Management Review,* **25**(1): 27-47

Boisot MH. 1995. *Information space: a framework for learning in organizations, institutions and culture,* Routledge: London

Boisot MH. 1998. *Knowledge assets – securing competitive advantage in the information economy.* Oxford University Press: New York

Chesbrough HW. 2003. *Open Innovation: the new imperative for creating and profiting from technology.* Harvard Business Press Boston, MA.

Chesbrough, H. and Garman A. 2009. How Open Innovation Can Help You Cope in Lean Times. *Harvard Business Review*; 87(12): 68-76

Ihrig M, Abrahams AS. 2007. Breaking new ground in simulation knowledge management processes: SimISpace2. In I Zelinka, Z Oplatkova, A Orsoni (Eds.), *21st European Conference on Modelling and Simulation (ECMS 2007):* Prague

Trott, P. & Hartmann, D. 2009. Why "open innovation" is old wine in new bottles. *International Journal of Innovation Management,* 13(4): 715-736.

West J, Vanhaverbeke W, Chesbrough H. 2006. Open Innovation: a research agenda, In: Chesbrough H, Vanhaverbeke W., West J. (Eds) *Open innovation: researching a new paradigm,* Oxford University Press, New York, NY

## AUTHOR BIOGRAPHIES

**Irina Savitskaya,** Dr.Sc. (Technology), is a project researcher at Lappeenranta University of Technology, Kouvola research unit, Finland. Her main research focus is on open innovation paradigm, and more specifically on the external to firm barriers towards its implementation in diverse cultural contexts. Additional research interests include regional and national innovation systems, open innovation, and specifically outbound open innovation and cultural aspect of its implementation. The results of her research have been presented at scientific conferences (ECEI, IAMOT, ISPIM) and published in academic journals (IJIBR, JOTMI and others).
Her e-mail address is irina.savitskaya@lut.fi.

**Martin Ihrig** is an Adjunct Assistant Professor at the *Wharton School* of the *University of Pennsylvania* (USA), a Visiting Professor at *Lappeenranta University of Technology* (Finland), and President of *I-Space Institute, LLC* (USA). He holds a Master of Business Studies from *UCD Michael Smurfit School of Business* (Ireland) and a Doctor of Business Administration from *Technische Universität Berlin* (Germany).
The research initiative he manages at Wharton's *Snider Entrepreneurial Research Center* focuses on the strategic and entrepreneurial management of knowledge. In his simulation research, he is studying entrepreneurial opportunity recognition strategies with the help of agent-based models.
His e-mail address is ihrig@wharton.upenn.edu.