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Agent-Based Model of Self-Organized Industrial Symbiosis

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Abstract. Industrial synergies are forms of collaborative partnerships between companies resulting in the sharing of resources or the exchange of material or energy by-products. They generally have both economic and environmental benefits. The creation of such innovative partnerships within a territory leads to the development of an industrial symbiosis (IS), which is a dynamic networks of interconnected industrial actors. IS can develop in different manners, with different levels of planning and serendipity, in which the diffusion of trust and knowledge are generally thought to play a key role. This paper proposes and evaluates a simple agent-based model of self-organized IS development capable of simulating the impacts of social factors (i.e., social structure, trust, and knowledge diffusion) on the creation of industrial synergies, and eventually on the emergence of IS. This model was tested using NetLogo. Its consistency with the original design objectives was validated with a sensitivity analysis that considered several factors. Next, experiments were designed and carried out in order to study the influence of the social structure and dynamics. Results revealed that both factors have an influence on synergy creation, as IS is a function of both social dynamics and structure. However, more analysis is required to better understand the limits of such a model, as well as to validate the model's assumptions.

Keywords. Industrial symbiosis dynamics, agent-based modeling, simulation.

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1 Introduction

Industrial synergies are forms of collaborative partnerships between companies resulting in the sharing of resources or the exchange of material or energy by-products. They typically include by-product synergies (i.e., re-use of by-products), shared infrastructures, and a joint provision of common resources or services (i.e., collaborative provision of non-core business services or resources). They generally have both economic and environmental benefits. The creation of synergies within a territory leads to the development of industrial symbiosis (IS). In this paper, we adopt the framework proposed by Boons *et al*. (2016), who define "*IS as a process of connecting flows among industrial actors through (1) use of secondary material, water, and energy resources and/or (2) utility and service sharing, such as collective use of infrastructure or environmentally related services across a network*." IS are dynamic networks of interconnected industrial actors. They can be initiated in different manners. Boons *et al*. (2016) proposes seven IS dynamics inferred from empirical observations. This paper proposes a simple model capable of simulating self-organized IS (Chertow, 2007).

Modeling and simulating a Complex Adaptive System requires the identification of factors that drive the behavior of its components in terms of decision making and interaction with their environment and each other. In the context of self-organized IS, geographic proximity, social embeddedness, and trust are identified as positive factors and enablers of industrial symbiosis development (Velenturf and Jensen, 2016; Chertow and Ehrenfeld, 2012; Ashton and Bain, 2012; Gibbs, 2003; and Hewes and Lyons, 2008).

Along these lines, the general objective of this paper is to propose and evaluate a simple agent-based model of self-organized IS development capable of simulating the impacts of social factors (i.e., social structure, trust, and knowledge sharing) on the emergence of IS.

This paper is organized as follows. Section 2 presents a literature review of self-organized IS and agent-based models of IS. Section 3 presents the model, while Section 4 presents and discuss the experiments and their results. Section 5 concludes the paper.

2 Literature Review

This literature review first focuses on the concept of self-organized Industrial Symbiosis and its social dimensions. Next, it introduces the paradigm of agent-based modeling, and focuses specifically on agent-based models of IS development.

2.1 Self-organized Industrial Symbiosis

IS can be shaped by different processes, with various degrees of both intentionality and influence from external actors or environmental factors, such as public or private third-party organizations, governments, policies, and culture (Boons *et al*., 2016). Self-organized IS are characterized by self-motivated industrial actors who intentionally or not identify by-product exchanges, or resource or service sharing opportunities. This process exploits, to various extents, an organizations's capacity to acquire the necessary knowledge, and then engage and mobilize with other actors (Boons and Spekkink, 2012). It is a bottom-up process that is influenced by the industrial actors' attributes (e.g., past experience, expertise, financial situation); capacity (e.g., to engage in risky transaction, to acquire knowledge and to mobilize partners); and social environment (e.g., their social interactions, local regulations, culture and social norm) as they develop and make investment decisions in industrial synergies. Because these attributes, capacity and factors can change over time, the processes that shape IS can also evolve as a result of individual or collective learning; the diffusion of the IS philosophy (e.g., from existing local and non-local IS cases); new social ties development; or new policy introduction (e.g., government strategies, environmental regulations, economic and innovation incentives). The next two sections briefly introduce the concepts of social embeddedness, trust and knowledge diffusion and sharing in social networks.

2.1.1 Social embeddedness and trust

As postulated by Chertow and Ehrenfeld (2012), Ashton and Bain (2012), Velenturf and Jensen (2016), and others, self-organized IS dynamics is generally influenced by the social embeddedness of local industrial actors, their mutual trust, and their social structure. Actors in a group are socially embedded if their behavior is influenced by other actors from the group, or by social norms that are shared within that group (Ashton and Bain, 2012). Hence, the nature and structure of social ties within a group influence IS dynamics.

For instance, Doménech and Davies (2011b) analyse the mechanisms and factors of embeddedness, such as trust, information exchange, and joint problem solving, that lead to IS development. The authors highlight the importance of trust-building and its influencing factors as central elements in the process. Similarly, Domenech and Davies (2011a) use Social Network Analysis to study the structure of the by-products exchanges in the Kalundborg Study. Although this study is limited to formal IS exchanges at a specific time (i.e., it does not analyze actual social ties, nor how the social structure evolved, nor how new actors were added to create new IS exchanges), it does give an idea of its underlying social structure: a network of industrial actors with a high degree of centrality (i.e., presence of hub actors with several connections) and a short average distance between the actors (i.e., minimum number of social connections linking two actors).

Another social characteristic of IS development is the organizations' institutional capacity to mobilize the necessary actors (e.g., industry, government, consultant, researcher) to improve the set of opportunities to initiate and implement industrial synergies (Boons and Spekkink, 2012). This capacity requires that other member organizations to have a certain degree of understanding of the others' expertise and their capacity to contribute to synergy creation. This aspect is addressed in the next section.

2.1.2 Knowledge sharing in social networks

Knowledge management (i.e., documenting and sharing of tacit and explicit knowledge within and between organizations) in industrial symbiosis, and how it shapes IS dynamics, has been poorly studied. Although Boons and Spekkink (2012) found that the institutional capacity to acquire and use technical knowledge did not play any role in IS development in a survey of eco-industrial parks in the Netherlands, Schiller *et al.*, (2014) suggest that tacit and explicit knowledge diffusion in industrial networks, and how it is influenced by trust, should be studied, insofar as it is an integral part of the social dimension of IS. In particular, Haskins (2006, pp 324) identifies "*Knowledge about, acceptance of and commitment to the concept (of Eco-Industrial Parks/IS)*" as being one of the critical factors of IS development.

In the context of social networks, knowledge diffusion and sharing -which involves information seeking and learning from others- are influenced by both the structural properties of social connections and the intrinsic properties of these connections (e.g., strength, closeness, nature). In particular, Borgatti and Cross (2003) found that the meta-knowledge about the expertise, the perception of value, and accessibility of an organization's social connections affect positively the diffusion of that expertise between network members. As mentioned earlier, it is also a necessary factor of the institutional capacity to mobilize actors and network members. Thus, the collective learning of this meta-knowledge increases the ability to take advantage of new opportunities. In the context of industrial symbiosis, the development of such meta-knowledge can be fostered by green social networking and dedicated social media platforms, such as those proposed by Ghali *et al*. (2016).

In brief, the diffusion and utilization of knowledge to initiate and create industrial synergies and develop IS, are poorly studied. It is not clear which aspects of knowledge sharing and utilization play the most significant role and to what extent. Yet, they are a necessary part of the diffusion of the IS philosophy and the identification of industrial synergy opportunities.

2.2 Agent based modeling and simulation of IS dynamics

Agent-Based Modeling (ABM) is a computational tool used for studying of socio-technical, biological and economic systems by simulating the dynamics of these systems using computer simulation. These types of applications of ABM are referred to as Agent-Based Simulation (ABS). By modeling the individual behaviors and interactions between the key components of Complex Adaptive Systems, ABM enables researchers to anticipate the potential impacts of small behavioral changes (e.g., how components interact, communicate, make decisions, influence one other), or environmental changes from the social, natural, or economic sub-systems (e.g., new regulations, policies, shared infrastructures, material market prices).

In this paradigm, agents are specifically designed to simulate individual behaviors observed in the system, such as reactive (i.e., programmed response to specific stimuli), goal-oriented (i.e., response planned by the agent to achieve some goals), and learning (i.e., response influenced by the agent’s past experience). Agents have specific perceptions of their environment, which can be stochastic and shared with other agents. They also have specific, yet limited, capacity to modify their environment. Similarly, agents are said to be social when they are designed to communicate with others either directly (i.e., signal or message exchange) or indirectly (i.e., share blackboard or databases, modification of their environment, perception of the others’ behavior). Thus, the structure of a “multi-agent collective” is both dynamic and path dependent, as it emerges from both their behavior (i.e., the scope of their decisions and actions) and the way they exchange and perceive information.

Although ABMS is a versatile tool, its value is limited to the anticipation of general trends of systemic behavior due to the intractable complexity of human societies and our limited ability to model this complexity. The next section introduces various IS applications of ABMS.

2.2.1 Agent-Based Models of IS Dynamics

Previous studies have developed and used advanced tools for analyzing material and energy flows and social network structures in IS. However, very few dynamic models have been development to simulate how IS develop over time. The general principle of this approach is to model and simulate certain aspects of IS (e.g., creation of industrial synergies; exchange of knowledge, material or energy; industrial, sorting and handling processes; creation and development of social connections) to anticipate the impacts of various parameters (e.g., market price; landfill fees; social network structure) on specific performance indicators (e.g., volume of material diverted from landfill; number of active industrial synergies). Such studies are difficult or impossible using traditional social science tools, because data may simply not exist. The development of a dynamic IS model enables researchers to investigate specific situations that cannot be observed otherwise.

The ABS application proposed by Bichraoui, *et al*. (2013) aims to anticipate the impacts of potential conditions on IS development (e.g., number of synergies). The authors study the impacts of learning (i.e., by imitation of others' behavior) and cooperation (i.e., willingness to exchange information about output by-products). This model directly simulates by-products production and exchange flows. It considers the notion of proximity as any agent can only learn from other agents within a specific distance. It also includes the notion of plant life cycle. Here the validity of the model is assessed with a sensitivity analysis that quantitatively evaluate the impact of these factors. However, these result are not directly compared to actual data. Therefore, model validation remains largely qualitative (i.e., only general trends are validated).

Albino, *et al*. (2016) propose another application of ABS which aims at evaluating the capacity of simple contract mechanisms to foster a stable IS. Firm agents have the ability to select their actions (i.e., create/maintain a synergy, or do nothing) according to some utility function. They also have a local threshold to specify their willingness to commit to the creation of a synergy. Firm agents belong to any of a specific sequence of production stages. In other words, any firm from a given stage can receive by-products from the previous stage, and send its own by-products to the next stage. This model also considers trust as a parametric probability of maintaining a synergy with another firm. However, it does not evolve during simulation; it has the same value for all agents; and it has no other purpose. Furthermore, this model considers full disclosure of by-product information. In other words, all agents know what other agents produce and use, although they are only interested in the by-products they produce or use. There is also no notion of proximity, unlike in Bichraoui *et al*. (2013). Finally, some parameters are configured using realistic data. However, there is no reported calibration or validation of the model.

Romero and Ruiz (2014) propose an agent-based model of industrial areas that undergo conversion into an eco-industrial park. The model is based on a conceptual framework described in Romero and Ruiz (2013). In this model, agents represent firms and are described with technical (i.e., material/waste/product production/consumption, operational efficiency), economic (i.e., cost/benefit, innovativeness), and social (i.e., trustworthiness) attributes. The value of these attributes is either calculated or randomly configured according to the behavioral category of the agents (i.e., traditional, ecologic, strategic). Like in Albino, *et al*. (2016), the firm agents' decisions are driven by a utility function, which is a weighted average of the economic profit, the environmental impact, the strategic benefit, and the social benefit. Like in Bichraoui, *et al*. (2013), this model also considers firms' life cycle through firm agents' decision-making options, which are to produce, adapt (i.e., according to the social, natural or economic changes), cooperate (i.e., exchange by-product material), and manage disappearance (i.e., when the firm leave the IS). Concerning environmental changes, they are modeled as variations of the unit cost of waste flows, the unit cost of resource flows, and product demand. Therefore, the agents' adaptation capability is implemented as the updating of their attributes. This model also contains a by-product/material substitution knowledgebase used by agents to find industrial synergies. This also suggests a full disclosure of by-product/material information. The authors do not report any implementation or experimental results.

Finally, Couto Mantese and Capaldo Amaral (2017) use agent-based simulation to assess the value of several IS performance indicators for hypothetical scenarios involving simple and theoretical eco-industrial parks. This model primarily focuses on modeling material flows between company agents and a landfill agent. Although it is not based on any specific eco-industrial park, this application is original because its objective is to assess the behavior and usefulness of performance indicators. Again, its usefulness is limited by the relevance of the scenarios and the validity of the model, which are not evaluated.

ABS models of IS development are clearly in their infancy. The limited scope of these models and the lack of detailed data for calibration and validation are limitations that must be overcome to improve their usefulness and accuracy. Nonetheless, they provide valuable modeling insight and perspectives to develop more accurate models. The model presented in the next section contributes to this body of knowledge by providing a first model of social embeddedness in the context of self-organized IS.

3 Agent-based model

This section presents the hypothesis and the details of the proposed model. The general conceptual process is based on the Theory of Planned Behavior (TPB, Figure 1).

3.1 Hypothesis and model overview

Agents represent plants of an industrial park, which, whenever possible and under certain conditions, can create industrial synergies with each other. All plant agents (we use the term "plant" in the remainder of the paper) follow the same generic decision and interaction processes, but have their own corresponding social attributes, values, and levels of knowledge. The proposed self-organized IS structure is heterarchical. Thus, plants exchange knowledge only with their social contacts, and are not aware of what happens in the network as a whole.

Unlike the models presented earlier, this model does not consider explicitly waste and by-product flows. Instead, potential industrial synergies are randomly pre-defined between pairs of plants. Each of these potential synergies also specifies for each of the concerned plants some investment they must make to operationalize the synergy. These investments, along with random revenues, condition the profitability of the synergy. This modeling approach allows us to control the number of potential synergies in any given network without having to model flows and address their input/output compatibility.

We also do not consider the active search for synergies and the notion of proximity. Instead, we consider serendipitous identification of industrial synergies within the direct social contacts of plants. Consequently, along with the pre-definition of potential synergies, we also pre-define a network of social contacts and introduce randomly during simulation new contacts between plants. Therefore, if a potential synergy is pre-defined between two plants that are never in contact during simulation, then this synergy is never created.

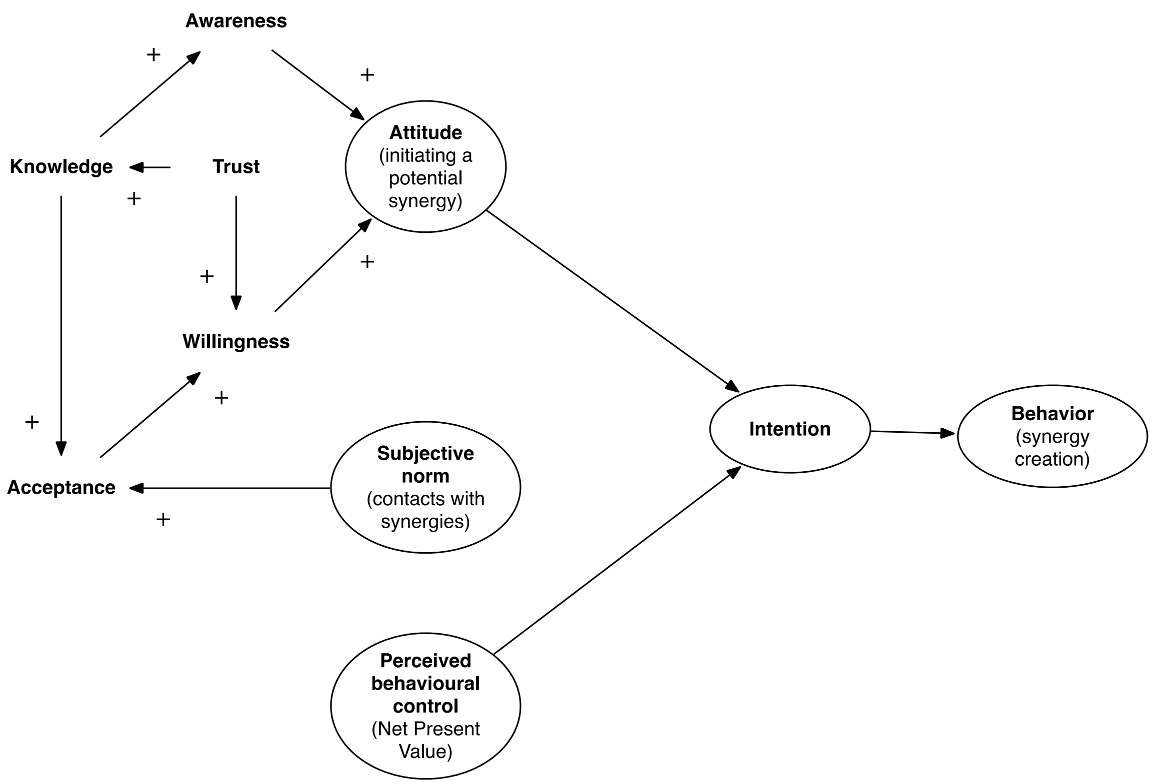


Figure 1: General Planned Behavior of plant agents

Thus, plants only rely on their social contacts and the diffusion of the IS philosophy to identify potential synergies. This diffusion process is modeled as both internal (i.e., within a plant's social contacts) and external processes (i.e., when plants learn from other sources). The internal diffusion process is a function of the trust plants have for each other. Unlike Albino, *et al*. (2016), for whom trust is an attribute of the network, and Romero and Ruiz (2014), for whom trust is an attribute of the plants, we model trust as an attribute of a directed social contact. It is the perception of a given plant of the level of trustworthiness of another plant. It is non-symmetrical and influenced by its reputation within the plant's social contacts.

Finally, knowledge is modeled as a bounded variable representing the level of acquaintance of any plant with respect to the IS philosophy. The diffusion of knowledge from one plant to another is a function that only allows transfer from a higher level of knowledge towards a lower level. Similarly, we do not model knowledge accessibility constraints nor the cost of knowledge sharing. Knowledge is always available between socially connected plants.

Concerning the plants' range of actions, it is limited to knowledge transfer and the creation, or not, of industrial synergies. First, knowledge transfer involves the updating of knowledge and social parameters. To do so, time is discretized, and plants' attributes at any time period are computed using mathematical functions (see details below), their attributes, and other attributes from their environment (i.e., financial parameters, other agents' attributes) at the previous time period. Next, the creation of a synergy follows a decision process that first requires the identification of a potential industrial synergy, which we refer to as *awareness* (Figure 1). If a plant's knowledge level is greater than a particular threshold, then it becomes aware of any existing potential synergies within its own network of contacts and informs the potential partner of its existence. Next, plants must both be willing to create a partnership with each other. We refer to this as *willingness* (Figure 1). It is influenced by trust, as well as how many synergies have been created within a particular plant's social contacts, which represent subjective norm in the TPB framework. Both *awareness* and *willingness* define the plants' *attitude* toward creating -or not- the potential synergy. Once the potential synergy is known by both potential and willing partners, they have access to investment information (i.e., cost, anticipated revenues). They both use it to compute the net present value of the synergy to determine if it is profitable. This defines the *perceived behavioral control* of both plants involved (Figure 1). If and only if both partners find it profitable, then the synergy is created.

3.2 Plant attributes and behavior

The plants' attributes describe their characteristics at any given time period, such as their knowledge level, their level of social influenceability, their level of social interaction with other plants, or their willingness to commit to the creation of an industrial synergy. Some of these attributes are dynamically computed (i.e., variables), while others are pre-determined (parameters). The following sections describe in details the different components of the model.

3.2.1 Social contacts

Each plant could potentially have a social contact with any other plants. We assume that a social contact represents any social relationship between, at least, any two of the managers of two plants. We also assume that social relationships can influence management decisions. These social contacts are, by nature, dynamic. They can be created during simulation; their attributes can evolve in time; and they can be transformed into an industrial synergy. Their existence is modeled as a binary variable γ_{ij}, which represents a social contact between plant *i* and *j*, with $i, j \in P$, P being the set of all plants, and $\gamma_{ij} = \gamma_{ji}$. Variables γ_{ij} for all $j, i \in P$ represent the social network structure of P.

$$\gamma_{ij} = \begin{cases} 1 & if\ plant\ i\ and\ j\ have\ a\ social\ contact \\ 0 & otherwise \end{cases}$$

Next, we define the notion of social network of a plant, or more simply its contacts, as the set of plants C_i with whom plant *i* has a social contact with (i.e., $C_i = \{ j \mid j, i \in P,\ \gamma_{ij} = 1, \}$). The set of all social contacts of any plant is bounded, as we only consider here social contacts within P (i.e., $C_i \subset P, \forall i \in P$). They are characterized by both their structure ($\gamma_{ij},\ \forall i, j \in P$), and their nature, which is represented by other variables and parameters defined below.

3.2.2 Potential industrial synergy

A potential industrial synergy is modeled as the existence of a potential industrial synergy between two plants. It is a binary parameter s_{ij}, which represents the existence or absence of a potential industrial waste exchange between plant *i* and *j*, with $i, j \in P$, and $s_{ij} = s_{ji}$. Variables s_{ij} for all $\forall\ j, i \in P$ represent the set of potential industrial synergies within P.

$$s_{ij} = \begin{cases} 1 & if\ plant\ i\ and\ j\ have\ a\ potential\ industrial\ synergy \\ 0 & otherwise \end{cases}$$

Because these potential synergies are not necessarily known at any time, unless specific conditions are met, we must also define the notion of *awareness*, which represents whether or not the plants involved are aware of any potential exchanges. Thus, we also define binary variable A_{ij}^t, which represents the awareness of plant *i* at time *t* of the existence/absence of a potential synergy with plant *j*, with $i, j \in P$, and $A_{ij}^t \neq A_{ji}^t$. As explained later, the value of A_{ij}^t is a function of the knowledge of plants *i* and s_{ij}.

In order to model the existence of a created synergy, we also define variable S_{ij}^{t} to specify whether two plants *i* and *j* share an industrial synergy at time period *t*, with $S_{ij}^{t} = S_{ji}^{t}$.

$$S_{ij}^{t} = \begin{cases} 1 & if\ plant\ i\ and\ j\ have\ an\ industrial\ synergy\ at\ time\ period\ t \\ 0 & otherwise \end{cases}$$

3.2.3 Trust

We adopt Yu and Singh (2000) formal definition of trust. Hence, the trust rating assigned by plant *i* to *j* at time *t* is a continuous variable ${T_{ij}}^{t}$, with ${T_{ij}}^{t} \in [-1,1]$ (i.e., minimum and maximum trustworthiness). At the beginning of each time period, each plant updates its rating of other plants using Equations (1) and (2) to model how trust evolves over time and how it is propagated through social contacts. We use several parameters to describe how much each plant can be influenced by its own set of contacts, and how much trust can be influenced by other serendipitous external events.

$$\mathrm{T_{ij}}^{t+1} = \begin{cases} \min[\mathrm{T_{ij}}^{t} + \beta_i(\overline{\mathrm{T_{ij}^{t}}}\text{-}\mathrm{T_{ij}}^{t}) + \mathrm{d_{ij}}^{t}; 1] & \text{if} \quad \mathrm{T_{ij}}^{t} \leq \overline{\mathrm{T_{ij}^{t}}} \\ \max[\text{-}1; \mathrm{T_{ij}}^{t} + \beta_i(\overline{\mathrm{T_{ij}^{t}}}\text{-}\mathrm{T_{ij}}^{t}) + \mathrm{d_{ij}}^{t}] & \text{if} \quad \mathrm{T_{ij}}^{t} > \overline{\mathrm{T_{ij}^{t}}} \end{cases} \tag{1}$$

$$\overline{T_{ij}^{t}} = \frac{\sum_{k|k \in C_i \cap C_j} {T_{kj}}^{t}}{|C_i \cap C_j|} \tag{2}$$

with

$i, j \in P$

${T_{ij}}^{t}$ trust rating assigned by plant *i* to *j* at time *t* with ${T_{ij}}^{t} \in [-1,1]$;

$\overline{T_{ij}^{t}}$ reputation of plant *j* assigned by common contacts of plants *i* and *j* at time *t*;

$|C_i \cap C_j|$ number of common social contacts of plant *i* and *j*

β_i social influenceability level of plant *i* with $\beta_i \in [0,1]$;

${d_{ij}}^{t}$ trust increment assigned by plant *i* to *j* at time *t* due to serendipitous social event between *i* to *j* with ${d_{ij}}^{t} \in [-1,1]$.

In brief, Equations (1) and (2) define trust at time period *t* as a continuous variable. It is influenced by the past trust value of agent *j*, its reputation (w.r.t. the common contacts of agents *i* and *j*) and the level of influenceability of agent *i*, and other serendipitous social events.

3.2.4 Knowledge and knowledge transfer

Knowledge is modeled as an aggregated level of awareness ${K_i}^t \in [0,1]$ of plant *i* with respect to the IS philosophy. We assume that, all things being equal, the higher this level of knowledge, the more likely a plant will be to consider the creation of an industrial synergy. This assumption means that if managers are either aware of the IS philosophy or the existence of industrial synergy practices in their own industrial sector, they are more likely to have a positive attitude towards adopting such a solution for their own industrial needs. We also assume that this knowledge can only be gained through knowledge acquisition (e.g., learning or hiring of experts), or sharing, which is a function of the social interaction intensity and trust levels within the social contacts of a plant. To do so, plants also update at the beginning of each time period their knowledge level according to Equation (3).

$$ {K_i}^{t+1} = min\left(1; {K_i}^t + \beta_i . \sum_{j \in C_i | {T_{ij}}^t \geq \breve{t_\iota}} \widehat{K_{\iota J}}^t + l_i^t\right) \tag{3} $$

with

${K_i}^t$ knowledge of plant *i* at time *t* with ${K_i}^t \in [0,1]$

$\widehat{K_{\iota J}}^t = \max\left(0; \sigma_{ij}^t\left(K_j^t - K_i^t\right)\right)$ with $i, j \in P$

$\widehat{K_{\iota J}}^t$ maximum knowledge increment of plant *i* from *j* at time period *t*;

l_i^t knowledge gain at time period *t* due to learning or the hiring with $l_i^t \in [0,1]$;

σ_{ij}^t social interaction intensity of plant *i* and *j* at *t* with $\sigma_{ij}^t \in [0,1]$;

$\breve{t_\iota}$ minimum trust threshold of plant *i* to consider knowledge sharing or a synergy with another plant;

Equation (3) defines the knowledge level of a plant at any given time period, as its knowledge at the previous time period, plus the knowledge gained from social interactions within its trusted contacts, plus the knowledge gained from learning/hiring.

Next, based on Equations (1) and (3), we define the concept of awareness of a potential industrial waste exchange introduced earlier is defined as:

$$ A_{ij}^t = \begin{cases} 1 & \text{if } {K_i}^t \geq \breve{k} \text{ and } s_{ij} = 1 \\ 0 & \text{otherwise} \end{cases} $$

with

$\breve{k}$ minimum knowledge threshold required to be aware of a potential exchange.

$\breve{k}$ represents the fact that plants must possess a minimum level of understanding of the IS philosophy to be aware of the existence of any potential synergy. We assume that it is the only necessary condition although in practice, some technical expertise may be involved. Because being aware of the existence of a potential synergy, does not guarantee the plant is ready to adopt that solution, we introduce here the notions of acceptance and willingness.

3.2.5 IS Acceptance and Willingness to commit

The willingness of a plant to commit with another plant represents the non-financial attribute of its willingness to create a synergy with this plant. It is a function of the IS acceptance level of that plant and its trust toward the other plant (Equation 5). The IS acceptance level represents how much a plant is willing to invest in a synergy regardless of its partner. It is influenced by the percentage of his/her social contacts with a synergy (subjective norm), and its recent knowledge acquisition (Equation 4). We did not, however, model the negative impact of synergy creation failure. This results in a strictly increasing level of knowledge and acceptance functions as shown in Equations (3) and (4). We also introduce the notion of self-confidence of a plant, which allows us to model various attitude toward risk with respect to any knowledge acquisition between two consecutive periods.

$$B_i{}^{t+1} = \min\left(1;\ B_i{}^t + \beta_i . \frac{\sum_{p \in C_i} \widehat{S_p^t}}{|C_i|} + \mu_i . (K_i^t - K_i^{t-1})\right) \tag{4}$$

$$W_{ij}^t = \begin{cases} B^t & \text{if } \ T_{ij}{}^t \geq \breve{t_i} \ \text{ and } \ \mathrm{A}_{\mathrm{ij}}^{\mathrm{t}} = 1 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

with

$$\widehat{S_p^t} = \begin{cases} 1 & \text{if plant } p \text{ has an industrial synergy with any plant at time period } t \\ 0 & \text{otherwise} \end{cases}$$

$B_i{}^t$ Acceptance level of plant *i* to create a synergy at time *t* with $B_i{}^t \in [0,1]$;

W_{ij}^t willingness to commit of plant *i* to create a synergy with plant *j* at time *t*

μ_i self-confidence of plant *i* to use its knowledge;

$\breve{w}$ minimum level of willingness to commit to any synergy creation.

The willingness of plant *i* to commit with *j* at *t* takes a non-zero value if and only if *i* is aware of a potential synergy with *j*, and if *i* trusts *j* beyond threshold $\breve{t_\iota}$. Furthermore, it must be larger than $\breve{w}$ for any plant to commit to any synergy creation. It is also a function of its acceptance level.

3.3 Investment decision

To simulate investment decisions, we propose a simple financial analysis carried out during simulation by any plant facing that decision. First, we consider that a potential synergy is modeled as an exchange of a random volume of waste/by-products that is sold annually by its producer to a buyer, at a random market price. Thus, the annual cash flow variation is directly attributable to the synergy and can be expressed as in Equations (6) and (7).

$$R_{producer,t} = V_{exch,t}.\left(C_{landfill,t} + P_{waste,t}\right) \tag{6}$$

$$R_{buyer,t} = V_{exch,t}.\left(P_{resource,t} - P_{waste,t} - C_{transport,t}\right) \tag{7}$$

with

$R_{producer,t}$ net cash flow of the producer during period *t*;

$R_{buyer,t}$ net cash flow of the buyer during period *t*;

$V_{exch,t}$ volume of waste/by-product exchanged between plants *i* and *j*;

$C_{landfill,t}$ landfill cost during period *t*;

$P_{waste,t}$ price of waste/by-product during period *t*;

$P_{resource,t}$ price of new resource during period *t*;

$C_{transport,t}$ transportation cost during period *t*;

$R_{producer,t}$ includes landfill cost savings and revenues from the sale of its waste. In practice, the situation is more complex and can include contracts (Albino, *et al*., 2016). Next, $R_{buyer,t}$ includes the savings from not having to buy new resources, minus the cost of the alternative waste/by-product that must be acquired and transported. Using these values, we calculated the Net Present Value with Equation (8).

$$NPV_{i,j} = \sum_{t=0}^{N} \frac{R_{i,t}}{(1-d)^t} \tag{8}$$

with

$NPV_{i,j}$ Net Present Value of the potential industrial synergy between plant *i* and *j*;

d discount rate

N number of periods to pay off the initial investment.

3.4 Plant behaviors

At the beginning of each time period, each plant executes sequentially two processes: trust and knowledge update (Figure 2), and synergy creations (Figure 3). First, trust and knowledge update consists of updating trust, knowledge, and the acceptance variables. This is done for all social contacts of the plant. Next, synergy creation consists of a series of tests and computations that aim at: (1) identifying if the plant is aware of the potential synergy with a social contact; (2) computing if the plant is willing to commit to an IS with its social contact; and (3) computing the profitability of the potential synergy. If all tests are positive, then the synergy is created. If not, the process continues for all its social contacts. Once both processes have been executed, new random social contacts are added globally, and the social networks (i.e., list of contacts) of the involved plants are updated.

Each computation only involves data calculated at previous periods. The simulation process starts with initial value and ends when a certain number of time periods has been reached. Data are then collected for analysis.

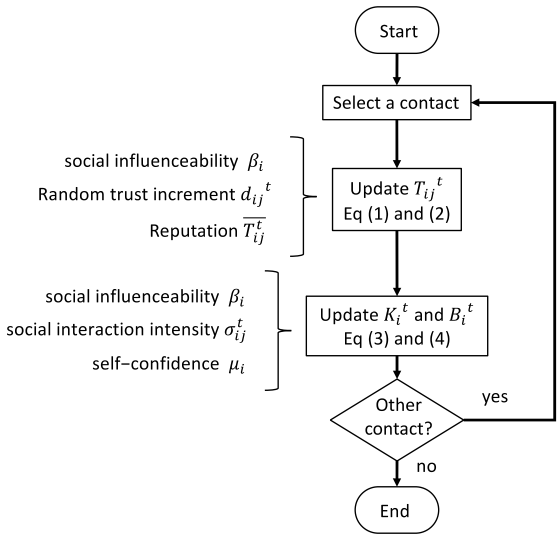


Figure 2:

Trust and knowledge update process

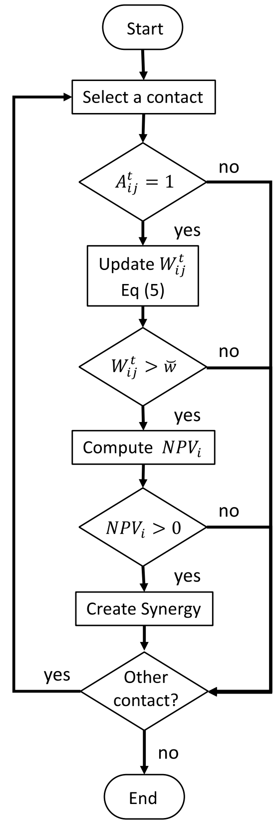


Figure 3:

Industrial synergy creation process

4 Model implementation and experiments

This model was implemented with NetLogo. The next section presents simple calibration and validation experiments we performed.

4.1 Model Initialization and calibration

To calibrate the model, we performed a sensitivity analysis with parameters β_i, μ_i, σ_{ij}^t and $\breve{t_\iota}$ to study their influence on the average number of synergies created. To do so, we analyzed the impact of each parameters with 200 plants and random social networks, by setting all other parameters to its midpoint value, and by running 30 simulation runs for several values along its entire range (e.g., 0, 0.25, 0.5, 0.75, 1). Then, we averaged the results for each value point.

First, we observed that their influence is non-linear. When the social influenceability β_i increases, the average number of synergies starts increasing at 0.25, and increases almost linearly after. Concerning self-confidence μ_i, the average number of synergy increases almost linearly and reach a plateau around 0.75. Concerning the social interaction intensity σ_{ij}^{t}, the average number of synergy also increases with a maximum around 0.75. Finally, the minimum knowledge threshold $\breve{t_\iota}$ is the only parameter that does not positively correlate with the average number of synergy, which decreases more or less linearly as it increases. Although it is not possible to quantitatively calibrate these parameters with actual data, their general trends indicate that their influence is as expected and that the model is consistent with the original design objectives. For all other experiments, these parameters are drawn randomly using a uniform distribution with limited ranges of values to create a relatively homogeneous population of plants with respect to their social characteristics (see Table 1 and Table 2).

Table 1: Simulation parameters

Notation	**Description**	**Ranges of parameters**	
	Social Parameters		
$T_{ij}^{t=0}$	initial trust rating assigned by plant *i* to *j*	[-1; 1]	
$K_i^{t=0}$	Initial knowledge level of plant *i*	Experiment *a* [0; 0.5]	Experiment *b* [0; 0.25]
l_i^t	non-social knowledge gain of plant *i* at period *t* due to learning or hiring	Experiment *a* [0; 0.1]	Experiment *b* [0; 0.2]
β_i	social influenceability level of plant *i*	[0.5; 1.0]*	
μ_i	self-confidence of plant *i*	[0.5; 1.0]*	
σ_{ij}^t	Social interaction intensity between plants *i* and *j* at period *t*	[0.5; 1.0]*	
$\breve{t_\iota}$	minimum trust threshold of plant *i* to consider knowledge sharing or a synergy with others	[0.25; 0.75]*	
$\breve{k}$	minimum knowledge threshold to be aware of a potential synergy	[0.75; 1.0]	
$\breve{w}$	minimum willingness threshold of plant *i* to consider creating a synergy with others	[0.5; 1.0]	

* after calibration

Table 2: Economic parameters

Economic Parameters		
$I_{i,j}$	Initial investment of synergy between plant *i* and *j*	$1000
d	discount rate	10%
$V_{exch,t}$	Anticipated volume of exchanged by-products at period *t*	[1000; 10 000]
$C_{landfill,t}$	landfill cost	[$70; $90]
$P_{resource,t}$	selling price of residual	[$1; $150]
$C_{transport,t}$	Transport cost	4$/ton
$P_{resource,t}$	Resource price	[$1; $150]

4.2 Experiments

To illustrate the usefulness of this model, we designed an experiment to study the impact of several factors on the number of synergies created over time, including the number of potential synergies, the number of new social contacts per period, and the type of social network. The next section presents the design of these experiments.

4.2.1 Design of experiment

As shown in Table 1, we performed two series of experiments in order to test two different general knowledge configurations (i.e., experiment *a*, medium average initial knowledge level with small non-social gains; experiment *b*, low average initial knowledge level with medium non-social gains). Next, for each of them, three experimental factors were defined separately (Table 3). The potential synergy level represents the general potential to create a dense IS. Some parks may have more potential synergies than others. The two other factors represent respectively the social dynamics and social structure between plants. More specifically, the number of new social contacts per period is a proxy of the social dynamics. A higher level of new social contacts can be used to simulate the use of a green social media without input-output matching function, or an eco-industrial park with an extension activity program or coordinator in industrial ecology. New social links are randomly added, although they do respect the structure type of the initial social network. This aspect is developed next.

Table 3: Experimental design

<table>
<tr><td colspan="2"></td><td colspan="3">Number of new social contacts per period</td></tr>
<tr><td colspan="2"></td><td>0%</td><td>0.5%</td><td>1%</td></tr>
<tr><td rowspan="6">Potential synergy level</td><td rowspan="2">5%</td><td>scale-free</td><td>scale-free</td><td>scale-free</td></tr>
<tr><td>random</td><td>random</td><td>Random</td></tr>
<tr><td rowspan="2">10%</td><td>scale-free</td><td>scale-free</td><td>scale-free</td></tr>
<tr><td>random</td><td>random</td><td>Random</td></tr>
<tr><td rowspan="2">15%</td><td>scale-free</td><td>scale-free</td><td>scale-free</td></tr>
<tr><td>random</td><td>random</td><td>Random</td></tr>
</table>

All other factors were drawn randomly for uniform distributions with specific ranges of values as presented in Table 1 and Table 2. Furthermore, in all experiments, we consider an industrial park of 50 plants. The number of new social contacts per period is expressed as a percentage of all possible social contacts within a set of 50 plants (i.e., 50 x 49 / 2 = 1225). We consider 3 levels (0%, 0.5%, 1%). The potential synergy level is also expressed as a percentage of all possible pairs of plant. Again, we consider 3 levels (5%, 10%, 15%). Finally, concerning the network structure, we consider two types: scalefree and random networks, as described in the next section. We used a factorial design, so all combinations of factors were simulated 30 times for a total of 36 experiments and 1080 simulation runs (see Table 3).

4.2.2 Network types

We consider two types of network structures to describe social structures: random and scale free networks. Random graphs are generated using random probability distribution, in which each edge of a network has a uniform and independent probability of occurrence. We used a probability of 0.02 in order to match the number of initial social links in the scale-free network. Thus, the expected number of social contacts with 50 plants and a probability of 0.02 is 49, which represents 4% of all possible social contacts. Scale free networks exhibiting power-law degree distribution. In other words, the fraction $f(m)$ of nodes with m links decrease with m according to Equation (9). We built scale-free networks by progressively adding a node n from the initial set of 50 to the network, and by adding a link between node n and another node i from the network with a probability P_{ni} based on the Barabási-Albert model (Equation 10).

$$f(m) \approx a.m^{-k} \tag{9}$$

$$P_{ni} = \frac{k_i}{\sum_j k_j} \tag{10}$$

with

k_i number of social links of plant *i*.

This construction process creates scale-free networks with 49 links. It was also used to add social links during simulation. Scale free networks better represent social structures in which there are many people with few connections, and few people who are very connected.

4.3 Results and discussion

The experimental output studied is the number of synergies initiated each year. The results of the repetitions of each experiment, which are simulated instances of IS dynamic, were averaged for each year. Thus, the graphs shown in the next sub-sections represent an average dynamic for a specific set of conditions.

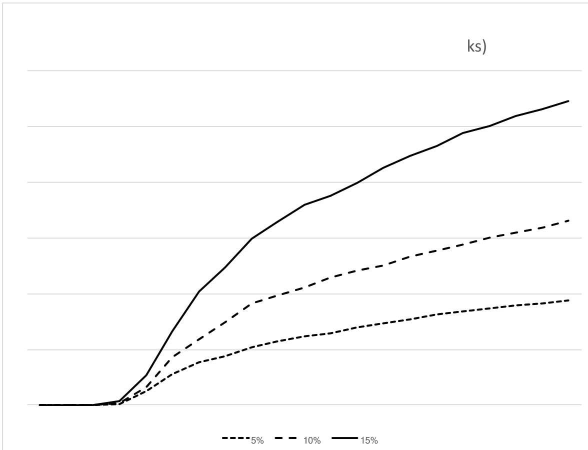
4.3.1 Impact of potential industrial synergy level

Figure 4(a, c) illustrates (for 0.5% of new social links and the knowledge configuration of experiment *a* -the average plants' initial knowledge level is 0.25; the average non-social knowledge gain per year is 0.05; and the average minimum knowledge level to be aware of a potential synergy is 0.875-) how the average number of synergy evolves for both types of network. We can see that, on average, there is no synergy created before year 5. With the configuration of experiment *a*, knowledge sharing through social links was necessary to reach the minimum level of knowledge required in 5 years on average, and so, regardless of the level of potential synergies. Figure 4(a, c) also shows that a higher level of potential synergy increases the number of industrial synergies initiated, which is to be expected because the higher the number of potential synergies, the larger the overlap of the sets of potential synergies and social links.

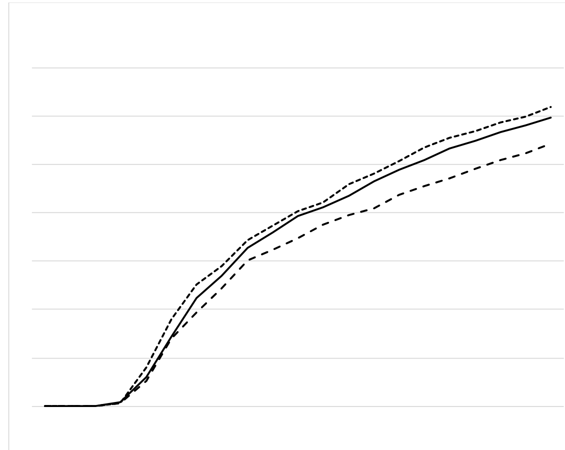
Also, although new social links are added linearly, their impact is not, as it slows as time progresses. This lag is due to learning. As the average overlap between social links and potential synergies increases linearly, it takes time for knowledge to reach the minimum level for these potential synergies to be discovered. Once this level is achieved, many of these synergies are implemented rapidly until there is no new potential synergy to discover. This is also shown in Figure 6(a) for both types of network and no new social links added, where no new synergies are discovered after 10 years. It is also suggested in Figure 4(b and d), where the number of initiated synergies is expressed as a percentage of the number of potential synergies. It shows that this measure of IS dynamics is independent of the level of potential synergies, which suggests that social dynamics (e.g., social interaction level, number of new social links, network structure, trust level) and learning (e.g., from non-social learning or hiring) might be factors constraining the ability of the entire network to identify potential synergies. As discussed in the next section, this is furthermore suggested by the fact that a higher level of social dynamics (i.e., number of new social links) significantly increases the percentage of the number of potential synergy initiated for all three levels of potential synergies (Table 4). These results are similar for all experimental setups (Table 4). Consequently, more experiments are needed to investigate this phenomenon, which suggests that, in purely self-organized IS, both learning and social dynamics are enablers of synergy creation.

Table 4: Impact of social dynamics on the total percentage of potential synergy initiated (random network)

		Number of new social links		
		0%	***0.5%***	***1%***
Potential synergy level	***5%***	12.4%	65.6%	72.8%
	10%	13.0%	64.6%	71.9%
	15%	10.8%	64.3%	74.8%
Average		***12.1%***	***64.8%***	***73.2%***



(a)



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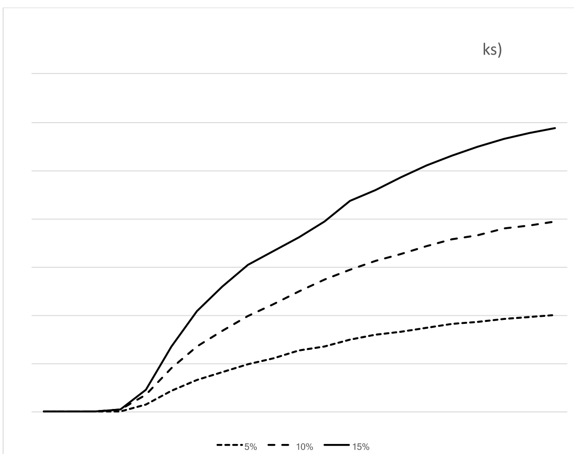
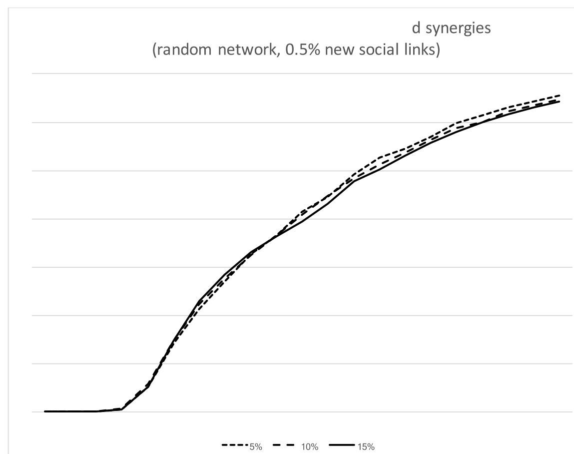


(c)

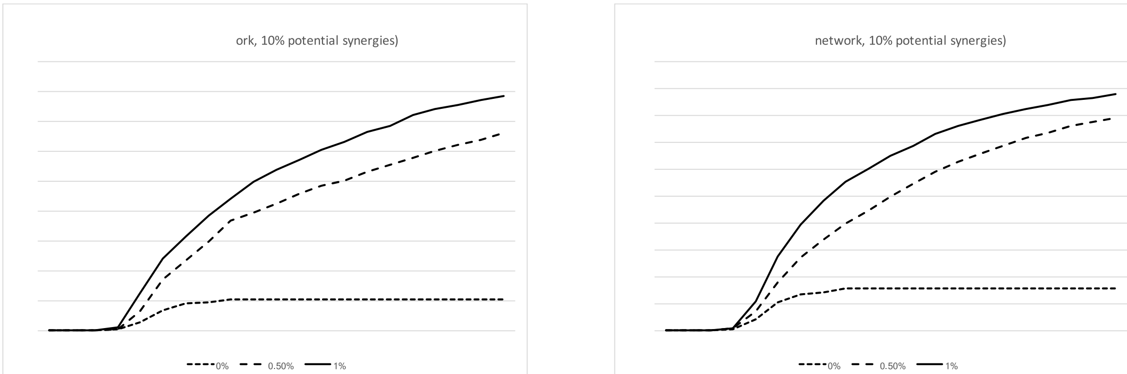


(d)

Figure 4: Impact of potential synergy level on the number of synergy initiated (a, scale free network; c random network) and the percentage of potential synergy initiated (b scale free network; d random network)

4.3.2 Impacts of social dynamics

As shown in Figure 5 (a, b) for 10% of potential synergies and both types of networks, the higher the number of new social links, the higher the average number of initiated synergies. These results are similar for all experimental setups. We can see that even a slight increase of social activity from 0% to 0.5%, increases the likelihood of creating synergies. However, a similar increase from 0.5% to 1% has a much smaller impact for both types of networks. This suggest that more work is needed to better understand how social dynamics affects self-organized IS dynamics. It also implies that mechanisms, actors, or social media capable of facilitating the creation of social links between plants may increase the creation of industrial synergies in an industrial park, although its impact may vary according to its pre-existing social dynamics as well as its synergistic potential.

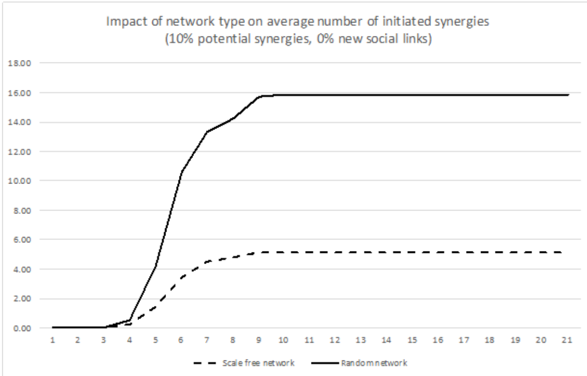


(a) (b)

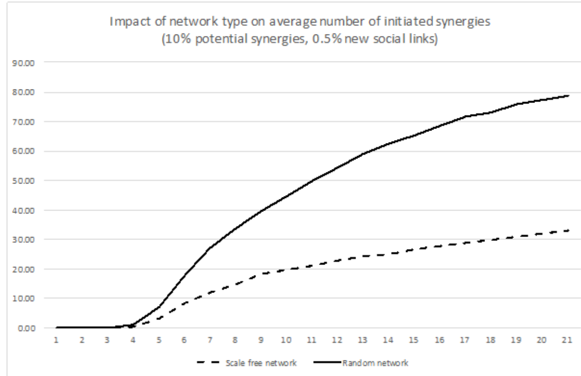
Figure 5: Impact of social dynamics on the number of initiated synergies.

4.3.3 Impact of network type

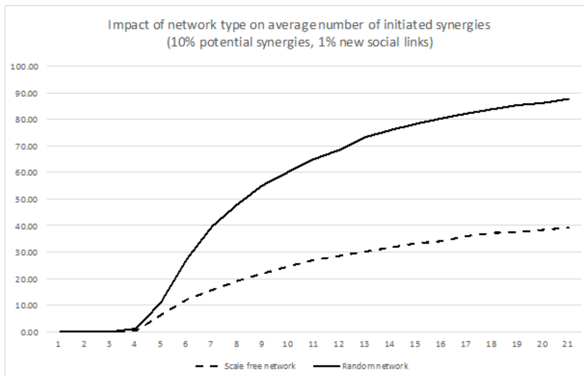
Figure 6(a, b, c) presents the impacts of types of network structure for, respectively, 0%, 0.5% and 1% of new social links. We can see that random networks always outperform scale-free networks. This is true for all tested configurations and knowledge conditions. However, this result must be investigated further insofar as the network structure of potential synergies was random. Consequently, the hub-like structure of scale-free social networks has a smaller overlap with random networks of potential synergies, which certainly affects its performance. Furthermore, synergy networks are not necessarily random as shown by Domenech and Davies (2011a) who mention a hub-like structure in the case of the Kalundborg study. Again, future work will require a thorough analysis of IS structures, as well as more simulation of realistic initial network structure conditions.



(a)



(b)



(c)

Figure 6: Impact of network type (10% potential synergy level; (a) 0%, (b) 0.5%, (c) 1% of new social links)

4.3.4 Impacts of Knowledge conditions

Figure 7 presents the impact of different knowledge conditions (i.e., initial knowledge level and knowledge gain due to learning or hiring) from experiments *a* and *b*. Only the results for 0% new social link, scale free network, and 15% potential synergy are presented, because there is no difference between both conditions as soon as new social links are added, which suggest that, for the tested conditions, social dynamics tend to dominate initial knowledge and non-social learning conditions. However, a small difference appears with no new social links. As expected, we can see that a smaller level of initial knowledge tends to delay slightly the creation of synergies (it takes more time to become aware of potential synergies), although the end results are comparable. This is observed for all level of potential synergies and both types of network. Again, this calls for more in-depth analysis of the impact of initial knowledge level, and how plants learn in a non-social manner, on IS development.

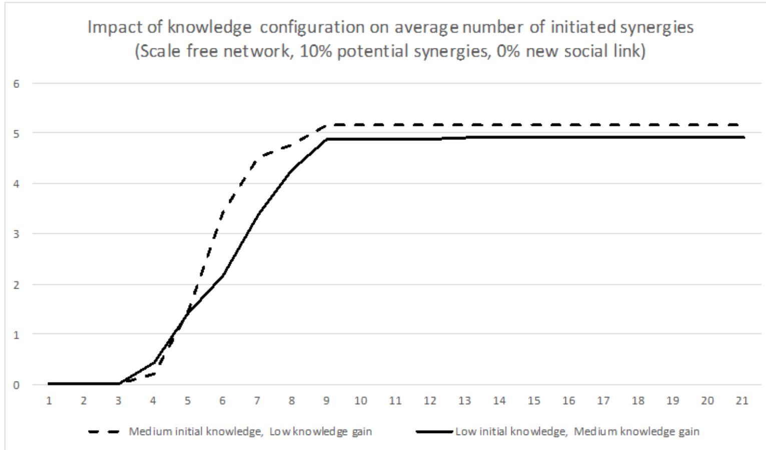


Figure 7: Impact of knowledge conditions

5 Conclusion

The agent-based model of self-organized IS dynamic is the first to explicitly model trust as an attribute of a directed social link between two plants, and to include it in the processes of knowledge diffusion and synergy creation. Although the experiments reported here show how IS attributes can emerge from the interactions and behavior of individual plants, this model remains simplistic and many assumptions were made. The experiments also illustrate how such a model could be used as a complementary tool for case studies, surveys, and other empirical studies, which provide the knowledge required to model appropriately.

In order to improve it, there are many different opportunities. For instance, we can address the stability of supply, both in quality and quantity, which is required to consider explicitly waste flows. Furthermore, we can also consider the dynamic introduction of new plants that can be more or less proactively added to create more synergies. Along this line, we should improve the discrete modeling of time and model more accurately, per month or even week, along with exchange flows, their price and cost, as well as raw material and market fluctuations. Other factors could also be included such as purchase contracts. Finally, we should also study the actual network structures of synergies in IS, and simulate these structures to improve the accuracy of our model.

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