Agent-Based Simulation in Path Dependence Research: A Network-Theoretic Model*

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Abstract

I suggest a model to research standard diffusion and path dependence in networks of actors (e.g. organizations, organizational units) adopting technologies. The model includes several existing models as special cases. It should enable exploring path dependence in greater detail. The model distinguishes between three phases. First, it looks at standard diffusion in a static network. It afterwards simulates the – potentially path-dependent – growth process. Then path-breaking or -reinforcing interventions in the structures of the network take place. The model sets itself apart from other models by having different forms of network initialization and network growth strategies. First experiments show that I can replicate several existing path dependence models, e.g. Arthur's canonical model, as a special case. This builds confidence in the models' validity. Along the way, I constructed a flexible simulation laboratory ready-to-use for other path dependence researchers. Future directions are described.

Keywords: Path Dependence, Standard Diffusion, Path-Breaking Interventions, Switching Costs, Agent-based Simulation, Network-Theoretic Models

1. Introduction and Motivation

I wish to suggest a new (general) model to research standard diffusion and path dependence in networks of actors adopting standards. The model was constructed with the airline industry in mind where actors manifest in organizations and links may be thought of as codeshare interactions or alliance memberships. The model includes several existing models in the context of path dependence research as special or limiting cases and should thus enable to explore path dependence phenomena in greater detail. It distinguishes strictly between three phases. First, it looks at standard diffusion in a static network. Then, it simulates the network growth process. Finally, interventions in the structures of the network take place. Interventions may occur while the network grows or after it has settled.

Existing path dependence models limit attention to N - the size of the network (cf. Afuah 2013). Arthur's model of path dependence and increasing returns (1989) for instance holds that new agents become influenced by all N existing agents. I refer to these models as N-type models. Furthermore many models (e.g. Weitzel et al. 2006; Petermann 2010; Draisbach et al. 2012) neglect growth processes. They assume static networks. Bringing together standard diffusion in static networks and network growth and stretching the limitations of N-type models, I construct a new model drawing on an agent-based simulation approach (cf. Gilbert and Troitzsch 2010) and models from network analysis (cf. Jackson 2008). In contrast to N-type models, network analysis highlights interaction structures among agents (nodes) to explain phenomena on the macro level. Building on this approach, the proposed model incorporates different forms of network initialization and network growth strategies.

Practical importance is highlighted by inertia overcoming established technical standards in the airline industry. One example is booking classes in airline pricing and distribution – a parameter supporting airlines' profit-oriented revenue management strategies. The booking class standard has enabled airlines to develop advanced pricing strategies (cf. Talluri and van Ryzin 2005). A limitation to 26 discrete booking classes has, however, today become serious limitation for many traditional network carriers (cf. Isler and D'Souza 2009). Moves to alternative pricing strategies – e.g. dynamic pricing (cf. Levin et al. 2009) –, are drawn back by high switching costs and coordination problems (cf. Westermann 2013). The paper aims to facilitate a better understanding of path building and intervention processes in settings with complex interaction structures as illustrated by the airline industry. This intends to inform management thinking in situations with locked in standards.

This paper proceeds as follows: I build the blocks of the model in sec.2. Then I present first results from experiments focusing on the role of interaction structures in growing networks on standard diffusion (sec.3). I end with concluding remarks and future research directions (sec.4).

2. The Model

The initial (static) network consists of a fixed set of *n* nodes (e.g. organizational units, organizations) and links between those nodes. Links represent business interactions exhibiting a positive externality to adopt the same technologies. One may think of codeshares or alliance memberships in the airline industry.

The network structure is generated using different standard network types as depicted in Figure 1. For instance, I initialize the network using a lattice (cf. Figure 1A) or a star structure (cf. Figure 1B). For concreteness, a lattice may be thought of as an organization having decentralized structures because each node depends only on *m* direct neighbors. In contrast, in a star network each node links to one central node. A star network may be thought of as a network with a large "core" organization surrounded by many smaller "peripheral" organizations, each of which is linked to the core organization. This emulates e.g. the network of airline reservation systems. Other standard network types include static random networks (cf. Figure 1D), ring networks (cf. Figure 1C), small world (cf. Figure 1E) or preferential attachment networks (cf. Figure 1F).

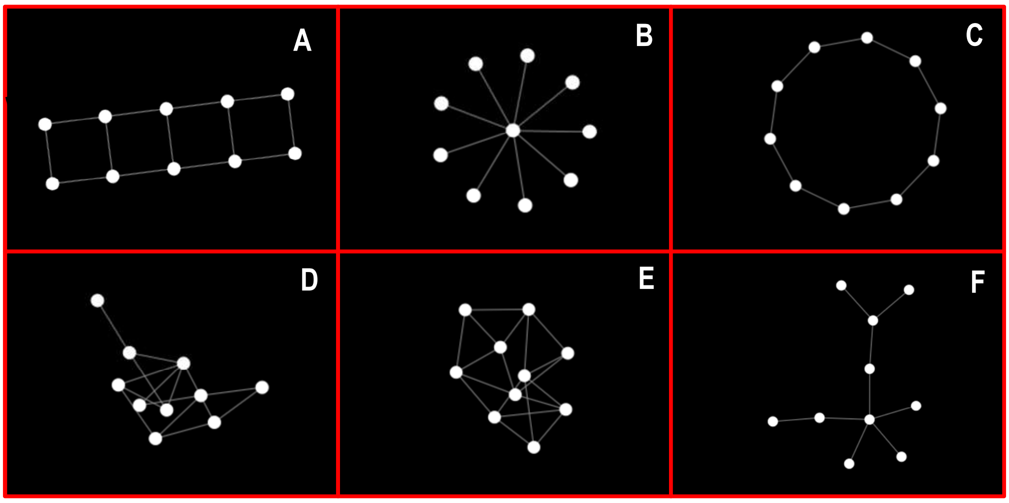

Figure 1 Different types of initial networks with nodes (dotes) and links (lines)

2.1 Standard Diffusion in Static Network

The generated network simulates an initial standardization diffusion process (cf. Botzem and Dobusch 2012: 745), which occurs in a network of fixed size. One may think of a "shadow of the past" and different models may be able to explain standard diffusion in this initial network. In what follows I adapt a model of Tim Weitzel and colleagues (2006). By replicating their model published in a highly ranked IS journal, I aim to gain validity. The process reflects the agents balancing of the utility from the standardization versus the standardization costs (cf. Buxmann et al. 1999; Weitzel et al. 2000).

The model proceeds as follows: Each agent decides locally if she should standardize. That is, she standardizes only if her utility from the standardization outweighs the standardization costs. Given that an agent generally concludes that it is beneficial for her to standardize, she will select one of *q* technologies with the highest (real) value. In general, *q* can take any discrete number of technologies but for reasons of simplicity I restrict the following analyses to two technologies (*A* and *B*).

Agent *i* standardizes only if the payoff $E_i > 0$. Costs K_i are assigned to nodes. The utility c_{ij} is tied to the edge *ij* between node *i* and *j*. The binary variable x_j indicates whether both partners in a network standardize and thus realize the benefit from the standardization. Equation 1 captures this core idea:

$$E_i = \sum_{j \; in \; N(g)} c_{ij} * x_j - K_i \quad with \quad c_{ij} > 0 \tag{1}$$

Where c_{ij} is the utility of agent *i* to standardize with agent *j*, which is realized if and only if *j* also standardizes (indicated by x_j) minus the standardization costs K_i for node *i*. Note that the benefit c_{ij} is summed over all neighbors j of i in the network $N(g)$. For reasons of simplicity without losing generality I assume that $c_{ij} = c_{ji}$. Standardization pays off for both partners equally. Thus, I proceed with an undirected in contrast to a directed network (cf. Weitzel et al. 2006: 494).

Figure 2 gives a two-agent example. If both agents decide according to Equation 1, agent 1 favors standardization as her expected payoff exceeds her standardization costs by 7.5 units (17.5 – 10 = 7.5 units). Agent 2, in contrast, is not willing to standardize as her costs exceed her benefits (17.5 – 20 = – 2.5 units). The benefit is only realized if both agents standardize. If, in contrast, one agent remains non-standardized, the network looses the 5 potential units net benefit [35 (= 17.5 x 2) – 30 (= 20 + 10) = 5 units].

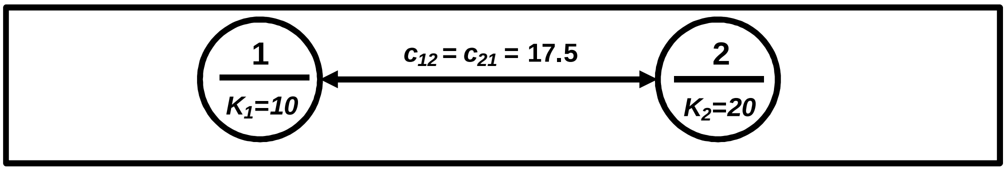

Figure 2 Two-agent example adapted from Weitzel et al. (2006: 494)

In non-pre-standardized networks it turns out that agents can only decide on standardization if they know what the others will do. Agents have to build expectations on the other agents possible decisions (cf. Arthur 1989). In the model each agent therefore determines an expected value *Expected* $[E_i]$. The agent now standardizes if *Expected* $[E_i] > 0$. She incorporates each partners' standardization costs K_j, number of partners φ_j, and standardization utility with her c_{ji} in a probability p_{ij} that replaces the binary variable x_j. Equation 2 describes this expanded reasoning:

$$Expected[E_i] = \sum_{j\ in\ N(g)} p_{ij} \cdot c_{ij} - K_i \quad with\ p_{ij} = \left(\frac{c_{ji} \cdot \varphi_j - K_j}{c_{ji} \cdot \varphi_j}\right) \qquad (2)$$

$$s.t. \quad c_{ij}, c_{ji} > 0$$

Organizations can identify their business partners' parameters orders of magnitude as expert interviews with airline IT managers suggest.

So far, I modeled the nodes' binary (yes or no) decision to standardize. To model multi-standard problems, the agents' decision function from Equation 2 is extended as follows:

$$Expected[E_{iq}] = \sum_{j\ in\ N(g)} \left(\frac{c_{ji} \cdot \varphi_j - K_{jq}}{c_{ji} \cdot \varphi_j}\right) \cdot c_{ij} - K_{iq} \qquad (3)$$

Where q denotes the technology and K_{iq} the standardization costs for agent i. K_{jq} is the standardization costs for agent j for technology q. Since standardization costs vary across technologies, one can think of these standardization costs as different efforts to get rid of legacy applications, data and practices when implementing the new standard (cf. Weitzel et al. 2006: 495). One can determine realized (ex-post) saving by extending Equation 1 respectively.

To initialize the simulation, standardization costs K_i are assigned to nodes with a random normally distributed probability (i.e. a mean $\mu(K)$ and a standard deviation $\sigma(K)$). The utility from the standardization c_{ij} is assigned random and normally distributed across nodes (with $\mu(c)$ and $\sigma(c)$). As a result of this initial standardization, agents decide in favor of one technology. Agents may switch in a multi-standard situation as agents gain confidence in their neighbors actual choices (cf. Weitzel et al. 2006: 495). Figure 3 shows the standardization outcome for three example networks[1]. Figure 3A depicts a lattice, where agents standardize almost equally to technology B and A. In Figure 3B, a star network, agents favor technology A. In contrast, the random network depicted in Figure 3C shows a mixed outcome. I find increasing the ratio of standardization costs to standardization benefit causes a

[1] All examples where generated with a network of 24 agents, $q=2$, $\mu(K)=4$, $\sigma(K)=0.5$, $\mu(c)=7$, $\sigma(c)=0.5$, $\lambda= 0.25$. The parameter λ is a link probability necessary to generate static random networks (cf. Jackson 2008: 78)

standardization gap where agents will not standardize despite the global efficiency of standardization (cf. Weitzel et al. 2006: 500). I also observed that increasing the standardization costs' standard deviation *σ(K)* resulted in a larger technological variety to co-exist.

While the model is subject to network externalities (i.e. each node is influenced by its neighbor's state), nodes will not accumulate information over time. Agents build new expectations each period regardless of the state in t-1. No feedback from learning occurs (cf. Arthur 1994). I extend the model now by bringing in network growth processes because they are a natural way to model positive feedback. In addition, I later create memorizing agents as another way to model positive feedback (see section 2.5).

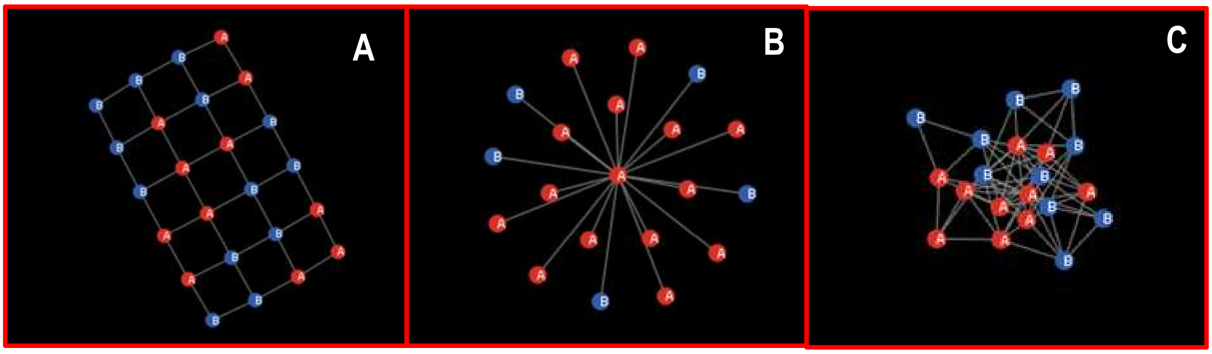

Figure 3 Standard diffusion outcome. In the cases, nodes either standardize to A (red balls) or B (blue balls)

2.2 Network Growth

To model network formation – how new nodes enter the network and connect to others – I construct a simple growth process: Each tick (or simulation period) one new node enters. The new node then connects to *m* pre-existing nodes. Growth is an important process in any organizational setting. Often times, complementary elements thereby tend to cluster together more and more closely (David 1994). One may think of the airline industry where an alliance entry is an important moment of technological choice. Airlines often have to replace or adapt existing technologies as illustrated by Air Berlin joining Oneworld.

In contrast to *N*-type models, I introduce three network formation processes introducing procedures for how new nodes attach to a selected fraction of existing nodes (cf. Jackson 2008: 124-140): *(i)* uniform randomness, *(ii)* preferential attachment, and *(iii)* a hybrid model. Uniform randomness means that a new node picks *m* other nodes uniformly at random (cf. Jackson 2008: 124-130). Preferential attachment, in contrast, prefers nodes that are already well-connected (cf. Jackson 2008: 130 et seq.). The rich get richer. Each new node forms links to *m* partners with probabilities proportional to their degree. Under preferential attachment, more nodes with a high degree form than may be expected for uniform randomness and more nodes with a low degree. The degree distribution displays "fait tails" (Barabasi and Albert 1999).

Hybrid models span between uniform at random and preferential attachment models. They were developed as degree distributions and other characteristics of many empirical networks lie somewhat in between the former two models (cf. Jackson 2008: 134). I draw on a model by Jackson and Rogers (2007). The core idea is that a fraction of nodes is picked uniformly at random and another via searching neighborhoods of friends. The model proceeds as follows: Each new node links to a fraction of nodes she knows from random meetings (parent nodes) and then befriends with friends of the parents nodes[2]. The algorithm first picks *a* nodes uniformly a random (as depicted in Figure 4A) then it begins to look at the friends and picks *1 - a* neighbors of the friends (cf. Figure 4B). A parameter α (0 < α < 1) controls the proportion of random vs. network-based meetings.

[2] This resembles a typical process in social networks where you first get to know some group members by pure chance and then you will get to know their friends and also befriend with them

So far, I considered the level of integration as an absolute number of link partners *m*. This reflects new nodes having limited and fixed capacities to connect to pre-existing nodes. A relative fraction *m*, in contrast, scales with the number of nodes in the network. It is one in a full-density network where each new node connects to all other nodes. Such formation process characterizes, for instance, Brian Arthur's (1989) path dependence model among others (cf. Afuah 2013). This fact points to the possibility of considering Brian Arthur's model as extreme case of this more general model.

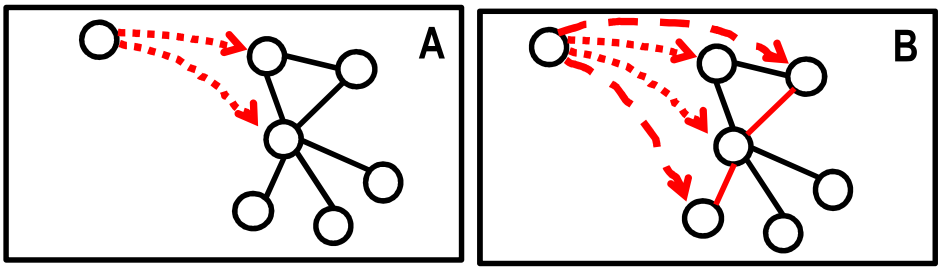

Figure 4 Hybrid network formation process. Random meetings (dotted lines) find an initial number of friends (on the left) and network-based meetings (dashed lines) pick friends of friends (on the right).

I observe that hybrid models fit structures of empirical IT networks well. A pre-study at a recycling company builds confidence in the fact that hybrid models can possibly match data of real-world degree distributions, densities, clustering coefficients and average path lengths. In the example, nodes represented information systems and links represented flows of information. The simulation data fitted structural characteristics of the network – consisting of 212 nodes and 234 edges – as degree distribution, average path length or clustering coefficients.

Strategic agents: I now turn to technology adoption choices of new nodes. In the model new nodes assess a technologies' perceived quality (or base utility) and network externalities (cf. Arthur 1989). The perceived quality b_{qtype} is exogenous and depends on the agent's type. Each agent type holds different lists of technology preferences. Network externalities weight the number of like-minded partners with the effect strength. Equation 4 shows an agent *i's* technology adoption function:

$$U_{iq} = b_{qtype} + nw_{qtype} * \sum_{j \; in \; N(g)} x_q \qquad with \;\; x \in \{0,1\}, \;\; b \;\geq 0 \tag{4}$$

Where the binary variable x_q is one if *i*'s partner has adopted technology *q* (and zero otherwise). I sum over *i's* partners to determine an agents' externalities (cf. Draisbach et al. 2012). If *j* includes all other nodes except *i* the model resembles Arthur's model (cf. 1989).

2.3 Measuring Lock-Ins

What is the probability of an existing node to re-orientate? What is her ease to switch technologies? The answer depends particularly on how many neighbors of a given node adopt the same technology. That is, how homogeneous is a nodes' neighborhood. The measure is normalized by dividing it by the total number of neighbors *j*. Homogeneity *h* for node *i* is then given by Equation 5:

$$h_i = \frac{\sum_{j \; in \; N(g)} x_{jq}}{j} \qquad with \;\; x \in \{0,1\} \; and \; 0 \leq h \leq 1 \tag{5}$$

Where x_j denotes a binary variable that is one if a neighbor also uses technology *q* (and zero otherwise). The homogeneity is one if *i*'s neighbors entirely uses technology *q*. In contrast, h_i is 0 if none of *i*'s neighbors implements the same technology. To determine the overall homogeneity in the network, I simply average the homogeneity over all the nodes as shown in Equation 6:

$$H = \frac{\sum_{i \; in \; N(g)} h}{n} \qquad with \; 0 \leq h \leq 1 \tag{6}$$

Where *h* is again the heterogeneity of node *i* and *n* is the node count. Figure 5 shows homogeneity examples. Figure 5A is heterogeneous as each node is surrounded by neighbors of different quality.

Under positive network effects the networks will not be stable as nodes will revise their decision in favor of their peers. Figure 5B shows a homogeneous network where each node is surrounded by neighbors of the same quality. If nodes experience positive feedback from their neighbors, the configuration is supposed to remain stable. The Figure 5C network also displays strong homogeneity. But instead of having a single technology regime two technologies govern different clusters. Supplementary diffusion curve analysis (cf. Arthur 1989) is necessary to separate Figure 5B and C.

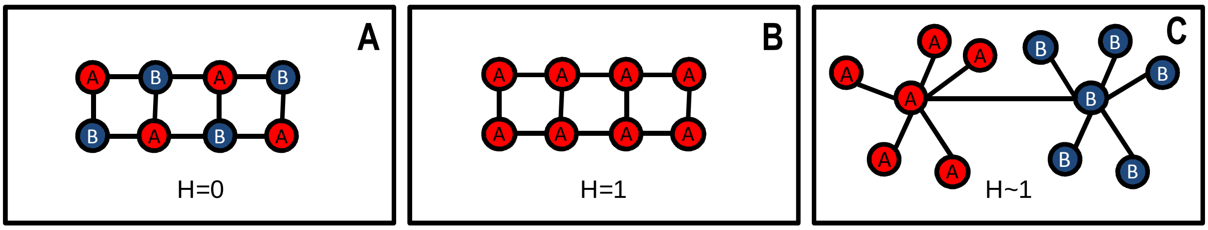

Figure 5 Homogeneity measure for different simple examples

2.4 Interventions

So far, I initialized a network and grew it. I brought everything together to achieve emergent effects. Intervention experiments now aim to extend our understanding on path-breaking and -reinforcement. I conceptualize three intervention types:

- Implantations of new network structures
- Infections inside of a grown network structure
- Environmental dynamics

First, I implant new external structures into the network. I vary the number of nodes. New network components, consisting of several interlinked nodes, enter the network and put stress on the current network configuration. These new structures may utilize existing technologies or bring in new technologies. One may think of an airline joining a strategic alliance. Alliance members may already employ their own technological standard, which may coerce the local airline to adapt its own IT infrastructure. Basically, this extends the simple growth process described earlier. I expect interesting nonlinear effects as implanting components that are internally homogeneous could result in a sudden passing of threshold levels. The network maybe bifurcates and tips towards a technology.

Second, I infect nodes inside a given network structure. Then I observe how changes in the network propagate and when and where agents switch to another technology. Once an infection is triggered, it results in large ripple effects over the entire network. I propose a propagation algorithm that proceeds as follows (see Appendix I for pseudo code snippet): One of the nodes with a maximum degree[3] (i.e. based on the count of link neighbors) is picked as infection target. All first-order neighbors of the node – within a distance of one step - are stored in a 'neighbor list'. They are marked as 'reached' and it is checked whether these nodes benefit from switching their technology. The switching calculus is explained below (see section 2.5). Next, all first-order nodes perform a further, radial search. Basically, the simulation creates a 'waiting list' with all second-order neighbors. This new list replaces the existing 'neighbor list'. It is processed in the next simulation round in the same way. This radial search is continued until no unreached neighbors remain. The propagation algorithm results in a (radial) cascade triggered by the infected node over the entire (reachable) network, i.e. first, second, third, *n-th* order neighbors.

Third, I dynamize the environment. I incorporate environmental changes by manipulating the agents' (technological) preferences. Qualities of technologies change as a function of time. One may think of S-shaped technology maturity curves (cf. Frenken et al. 2012).

[3] Alternative infection targets may be nodes with a high betweeness or eigenvector centrality (cf. Jackson 2008) or "peripheral" nodes. Similarly, Weitzel et al. (2006: 507) reason that large players may standardize anyway and pre-standardization efforts should thus target small players as they are more susceptible to infections.

2.5 When Do Agents Switch?

I conceptualize two opposing forces when agents consider changing their technological orientation: Gains in utility from a new technology promote agents to switch but switching costs counteract. A fine-grained model of switching incorporates the following parameters:

- the quality or base utility of the (new) technology,
- the (positive) network externalities an agent receives from its neighbors,
- an agents' accumulated switching costs and
- switching costs from an agents' network embeddedness.

Equation 4 already specified the first two, utility-driven parameters – quality of the technology b and network externalities $nw_q * \sum_{j\ in\ N(g)} x_q$. I thus concentrate on the switching costs – the later two parameters of the agent's switching calculus. I suggest an endogenous, dynamic model. In the (static) model of standard diffusion (see Equation 1 – 3), I assumed exogenous standardization costs. They became assigned to nodes randomly normally distributed. I expand this notion by assuming that nodes memorize. In a simplest possible case[4] the specific switching costs depend on the number of periods a node has already chosen a solution. One can think of this memory as the amount of legacy functions, applications and data an organization has accumulated that "lock in" the capability (cf. Ross et al. 2006: 50). Consider in this connection a list that holds node *i's* and *j's* memory:

i: [B, B, B, B, B, B, B, B, B]
j: [A, A, A, A, A, B, B, B, B]

The accumulated switching costs *KM* sum over the memory items and pick out the incompatible ones. If for instance, *i* reasons to switch from B to A, she must cope with a serious B legacy when migrating to A. In contrast, *j* faces fewer barriers to switch to A as she already accumulated A-items before.

In addition to accumulated switching costs, I also consider switching costs from agents' network embeddedness. System embeddedness is a key driver for delayed information systems discontinuance decisions (cf. Furneaux and Wade 2011). Switching costs often arise because of potential incompatibilities for working with a new technology (cf. Greenstein 1997) and costs for switching interfaces to other applications (cf. for ERP projects Beatty and Williams (2006)). I assume that interface-related switching costs depend on the number of neighbors that are currently on the same technology as node *i*. As costs to interface often explode with the number of interfaces (cf. Schneberger and McLean 2003), I assume that embeddedness costs *KN* increase quadratically with the number of (legacy) neighbors.

Altogether, Equation 7 shows when an agent *i* switches based on the previous considerations:

$$S_{iq} = U_{iq} - \alpha \sum_{t=1}^{t} KM_{\bar{q}} - \frac{1}{2}\beta \sum_{j\ in\ N(g)} KN_{\bar{q}}^2 \tag{7}$$

$$with\ \ KM, KN\ \geq 0\ \ and\ 0 \leq \alpha, \beta\ \leq 1$$

Where U_{iq} is the utility an agent gains from the technologies quality and the network effects (see Equation 4). The later cost function has two components (*KM* and *KN*). $KM_{\neg q}$ is the number of legacy applications and functions accumulated on the existing (not the new) technological platform. As shown above, each node holds a memory to record its history. *KM* is the sum of this memory over the simulation time *t*. Legacy costs occur only if an entry of *i*'s memory is *not* on the new technology *q*. I used a negation operator (¬) to indicate that fact. *KN* denotes the costs from the network embeddedness. It sums over the neighbors that are not on the new technology. I included α and β for scaling purposes only. I used a linear-quadratic cost function (cf. Ballester et al. 2006) in which the legacy costs *KM* scale linearly with time but interface costs *KN* scale quadratic with the number of neighbors on another technological platform. I did so for the reasons mentioned above. Agents switch if $S > 0$ to the technology *q* with the highest switching payoff.

[4] Advanced memory modeling includes e.g. discounting and forgetting (cf. Gilbert and Troitzsch 2010)

3. First Results

Focusing on the role of different interaction structures (m) in growing networks on standard diffusion, I conducted experiments with a prototypical implementation of the model in Netlogo 5.0.3 including the (new) network extension.

Figure 6 shows outcomes of hybrid random growth processes with varied levels of integration[5] m and $\alpha = 0.1$. The network is concentrated for high levels of integration (cf. Figure 6C). The network is lose for low levels of integration (cf. Figure 6A and Figure 6B). In all cases, the network shows strong homogeneity as may be expected under positive feedback. Homogeneity decreases for higher levels of integration but peaks again for a full-density network. The result of a u-shaped homogeneity curve (see Table 1) may be explained by the fact that for small levels of integration ($m= 1$) agents have little variety in their neighborhood. They solely depend on one friend and its technology choice. For medium levels of integration agents experience larger variety in their circle of friends. In contrast, positive feedback in a strongly integrated network counteracts. Degrees of freedom decrease as most friends adopt similar technologies. For medium levels of integration, it can be observed that the random network growth process results in different technologies thriving in different clusters[6] (cf. Figure 6A, B and C). The full-density network of Figure 6D shows a homogeneous network that entirely dominated by a single technology. This extreme case simulates a path dependent process (cf. Arthur 1989). Table 1 shows a more detailed analysis of the outcomes by averaging the results from different networks over ten runs per parameter.

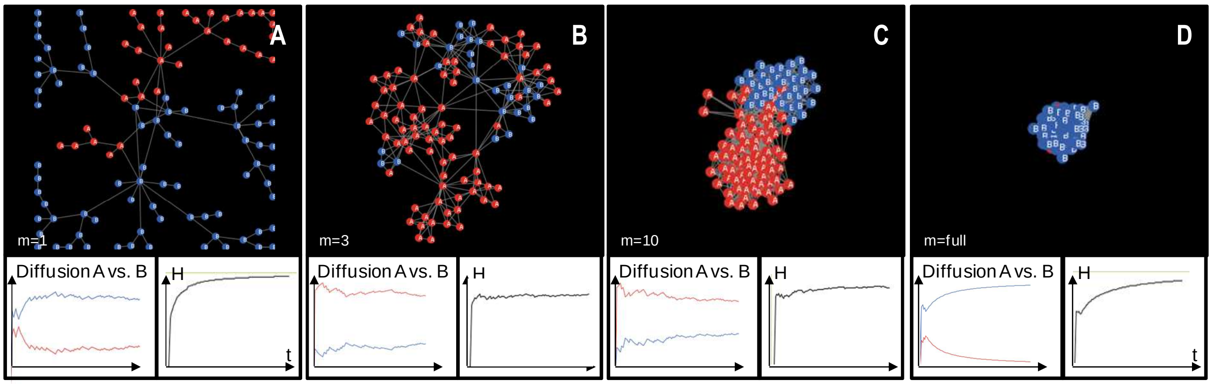

Figure 6 Hybrid network with different levels of integration (after 100 ticks)

Table 1 Averaged results over 10 simulation runs per parameter

	Clustering-Coefficient	Average Path Length	Diffusion win. technology (in %)	Homogeneity
m=1	0,02	5,86	71%	0,98
m=3	0,64	3,43	81%	0,87
m=10	0,54	2,20	77%	0,81
m=full	0,91	1,02	95%	0,98

Figure 7 illustrates results of first interventions. After I grew the network for 100 ticks[7], I implanted a new technology (C) into the network. Agents continued to decide as described in Equation 4. In Figure

[5] Each simulation was initialized with a static random network with $n = 10$, $\lambda = 0.35$, an initial standard diffusion process as described in footnote 1, a hybrid random growth process with varying m's, $q=2$, two types of agents, symmetric base preferences of b=(0.9 0.1) (0.9 0.1) and network magnifiers of (0.8 0.4) (0.4 0.8)

[6] Note that the clustering coefficient is close to zero for $m=1$ (cf. Table 1) because the clustering coefficient is based on a nodes' number of triangles. No triangles are present before $m \geq 2$.

[7] The simulation was initializes using the following parameters: Static random network with $n = 10$, $\lambda = 0.35$, an initial standard diffusion process as described in footnote 1, a hybrid random growth process with $m=2$, $\alpha = 0.5$, $q=2$, one type of agents with b_q= (0.6 0.6) and network magnifiers of (0.4 0.4)

7A, technology *C* was supposed to be twice as attractive as technology A and B (thus, base preferences of agents were 0.6, 0.6 and 1.2). The magnitude of network effects was identical across all technologies (i.e. 0.4, 0.4 and 0.4).

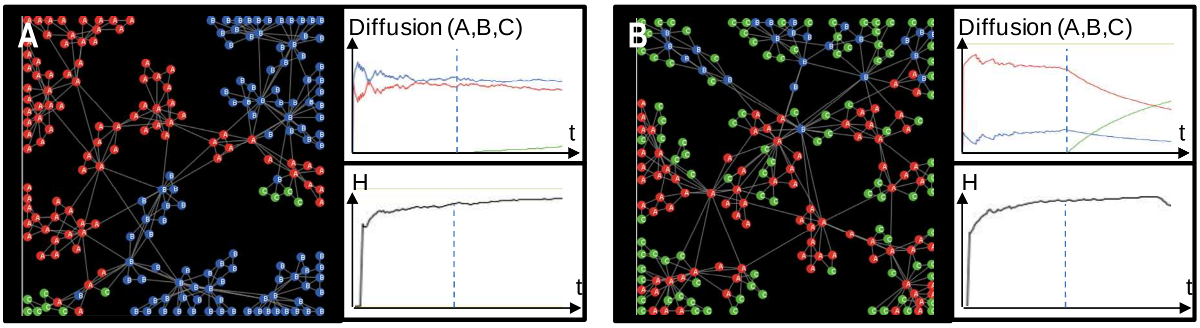

Figure 7 Introducing a new technology with different utilities in a grown network

As shown in the diffusion plot of Figure 7A, technology C does not gain considerable momentum. Only few instances decide in favor of the new technology. This result may be expected as only new nodes that are not coerced by two neighbors of the same technology experience enough degrees of freedom to select technology C. Figure 7B, in contrast, shows considerable dynamics towards the new technology. In the example, I further increased C's attractiveness. Agents now find technology C three times as attractive as A and B (i.e. $b_C = 1.8$). New nodes migrate to C completely as their own utility from the new technology is higher than the costs of overcoming the prevalent network effects.

4. Concluding Remarks

I presented a new (general) model to research standard diffusion and path dependence in networks of organizations adopting technologies. I breed an artificial "in-vitro" network and penetrate it rigorously. To summarize briefly, the model sets itself apart from previous models by having different forms of network initialization and network growth strategies. First experiments (see Table 1) show that several existing path dependence models, e.g. Arthurs model (cf. 1989), can be reproduced as special or limiting cases of the model. In this way I aim to build confidence in the models' validity. As a byproduct, I constructed a flexible laboratory ready-to-use for other path dependence researchers.

I acknowledge that the experimental setup and the simulation results are yet limited. Focusing on the role of interaction structures in growing networks on standard diffusion, the model shows that growth processes will influence standard diffusion. Arthur's model – where one standard dominates an entire network of agents – is certainly an extreme case. Other settings will exhibit higher levels of diversity, e.g. islands of shared technologies. In addition to carrying out systematic interventions (see section 2.4), I see five particularly promising ways to proceed further: *First*, expanding the analysis to more than two technologies is a natural next step. Do findings differ in quality in contrast to the simple case? The possible outcomes of the arising heterogeneity are yet hard to foresee. This presents interesting challenges for future research.

Second, another next step may be to replicate the polya-urn experiments (cf. Arthur 1994: 7). Thereby, the probability of drawing a ball of a particular color depends on the systems' current state. My simulation environment should be equipped to reproduce the models' findings. Another area of replication is the unified model of standard diffusion (cf. Weitzel et al. 2006). Further research may show in more detail the existence of a "standardization gap" (see section 2.1). This must include solving the linear program on the standardization problem in the investigated networks.

Third, additional research may enhance the random network growth process (see section 2.2) towards a strategic network formation process (cf. Jackson 2008: 153 et seq.). Strategic network growth models provide answers to *why* networks take particular forms, rather than just *how* they take these forms. This would include explicitly modeling the costs and benefits that arise from various networks (ibid: 153). New nodes may base their decision on which links to form not only on pure chance but on a deliberate choice of which pre-existing nodes are attractive technology partners. This could exhibit interesting nonlinear features and resemble empirical technology diffusion curves.

Forth, expanding the homogeneity measure (see section 2.3) to sub clusters of the network is an interesting conceptual challenge. The data suggests situations with strong homogeneity in sub clusters without strong overall homogeneity. When and where is path dependence local? Diagnosing such situations will profit from advanced clustering procedures such as k-means and by identifying the number of clusters and their internal homogeneity automatically.

Fifth, changes in technological networks propagate because ripple effects are promoted by "cascades of complementarities" (cf. Dobusch 2010) or "ramified webs of externalities" (Ciborra et al. 2000: 2). Thereby stronger integration of nodes may favor contagion (cf. Aral et al. 2009: 21545), probably in a nonlinear way (cf. Elliott et al. 2012). I concentrated on the (sole) number of links to model integration (see section 2.4 and 2.5), but there are certainly other possibilities. Future research could especially consider the strength of integration. This presents interesting challenges.

Appendix

Appendix 1 Algorithm for propagating changes through the network. Note that I did not include the procedure for checking whether all nodes lie in the giant component and several technical commands

```
To propagate-changes
      if t = 0 [
            set lst-radius[]
            ask one-of turtles with [count link-neighbors = max-degree]
            [
                  set reached? true
                  let i 0
                  while [i < count (nw:turtles-in-radius 1)]
                  [
                        set  lst-radius  lput  (item  i  (sort  nw:turtles-in-radius
                        1)) lst-radius
                        set i i + 1
                  ]
                  set t t + 1
            ]
      ]
      if t > 0
      [
           let x 0
           while [x < length lst-radius]
           [
             ask item x lst-radius
             [
                  set reached? true
                  check-switching
             ]
             set x x + 1
           ]
           ifelse any? turtles with [not reached?]
                  [ set lst-radius radial-search lst-radius ]
                  [ show "no more neighbors!" ]
           set t t + 1
            ]
      ]
end

To radial-search [my-list]
   let wait-lst[]
   let j 0
   while [j < length my-list]
   [
       ask item j my-list [
         let k 0
         while [k < count nw:turtles-in-radius 1]
         [
           if not [reached?] of item k sort nw:turtles-in-radius 1
           [
             set wait-lst lput (item k sort nw:turtles-in-radius 1) wait-lst
           ]
           set k k + 1
       ]]
       set j j + 1
   ]]
   report wait-lst
end
```

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