Facilitating Diffusion of Innovations Through Niche Management Strategies*

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Abstract

Niche-based policies (e.g. strategic niche management (SNM)) that advocate nurturing innovations in protected space (i.e. niches) are among novel policy approaches, which aim to facilitate the adoption of sustainability innovations. Despite being an intuitively appealing approach, there is a remarkable absence of specific guiding principles regarding the design of such policies. This absence is mainly due to the dynamic complexity of the innovation development and diffusion processes. This study aims to analyze niche management strategies, and the resulting diffusion dynamics with the help of an abstract simulation model. Using the model in a test ground for exploration, plausible diffusion cases are identified an analyzed. Furthermore, risky cases that result in "expensive failures" are also highlighted.

Introduction

The 'sustainability' concept stands as a meta-goal and as a guiding principle for the European Union (EU) community at large, which is mainly a consequence of the concerns regarding the current practices of major socio-technical systems, such as energy supply, transportation and healthcare. Transition to a sustainable state is a difficult challenge with two major aspects. The first aspect is related to defining what is sustainable, and to developing new technologies and artifacts that can be part of a sustainable socio-technical system. The second and equally important aspect of the challenge is related to changing large-scale socio-technical systems (e.g. transportation) into more sustainable configurations by integrating sustainable technologies. Although a sustainability transition cannot be reduced simply to an innovation diffusion problem, widespread adoption of a sustainability innovation is an essential part of it. When it comes to facilitating such an adoption, it does not suffice to focus solely on the innovation. The socio-technical context in which we expect the innovation to be integrated plays a crucial role, and it is this very context that creates a set of barriers that make it difficult to achieve a transition.

Differing from an innovation that serves a novel function, in most cases, sustainability innovations are aimed at replacing a formerly used technology for a particular purpose. The presence of such a predecessor, an incumbent technology, is one of the primary reasons underlying those barriers to adoption (Rip & Kemp, 1998). First of all, the needs, expectations and competencies regarding a certain function are shaped over time

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by the incumbent technology (Bijker, 1995; Levitt & March, 1988; Schot & de la Bruheze, 2003; Shove, 2003), and in most cases an innovation fails to deliver a perfect fit to these formerly shaped needs and expectations. Secondly, an innovation carries significant amount of uncertainty about its prospects, and the resulting skepticism among system actors ranging from end-users to investors make it difficult to quit the incumbent technology. Apart from these, the incumbent benefits from a set of mechanisms that create increasing returns, whereas the innovation does not benefit from such factors, yet. These mechanisms are well demonstrated, including scale economies, learning effects, adaptive expectations, and network externalities (Argote & Epple, 1990; Arthur, 1989; Ghemewat & Spence, 1985; Rosenberg, 1982, 1994).

Aforementioned mechanisms create a set of dynamic barriers to adoption that result in a vicious cycle for a sustainability innovation: without significant adoption the barriers cannot be neutralized, and in the presence of these barriers the innovation cannot compete with the incumbent for adoption. The phenomena of lock-in and entrenchment (Arthur, 1989; Cowan & Gunby, 1996; Jacobsson & Johnson, 2000; Mulder & Knot, 2001; Unruh, 2000; Walker, 2000), which refer to the hard-to-change nature of a socio-technical system, are directly related to this deadlock situation. In short, intrinsic dynamic mechanisms (e.g. learning-by-doing, information diffusion) within a socio-technical system make the replacement of an incumbent technology with a sustainability innovation a complex and very challenging process. As observed frequently in the past, even a promising innovation may fail to diffuse into a socio-technical system due to such barriers-to-adoption.

One of the most prominent policy approaches that is proposed to overcome such barriers is the Strategic Niche Management (SNM), which directly aims at creating a level playing field for competition between the incumbent and the innovations (Caniëls & Romijn, 2008; Hoogma, 2002; Kemp, Schot, & Hoogma, 1998; Rip & Kemp, 1998; Schot, Truffer, & Potter, 1999). The SNM approach relies mainly on two ideas. Firstly, an innovation is mostly immature upon its appearance in the system and develops to its true potential over time as a consequence of accumulating experience both in its utilization and supply. This may be due to improvements on the novelty itself, or due to adjustments and institutional developments in the system. The true potential of an innovation in a particular socio-technical context can only be realized through such developments, and the realization of the potential is vital in alleviating the barriers-to-adoption. However, an innovation may not survive to its full potential, which relates to the second key idea in SNM: The market competition an innovation will face in a socio-technical system may result in its disappearance much before it can develop to its true potential (Caniëls & Romijn, 2008; Frank Geels & Raven, 2006; Schot & Geels, 2008; van Eijck & Romijn, 2008; Witkamp, Raven, & Royakkers, 2011). Based mainly on these two premises, SNM as a strategy involves creating niches where innovations can be protected against competition, against the incumbent, and can develop as a consequence of the experience in this protected space (i.e. Niche formation and protection phase). Following this, the strategy involves scaling-up the niche when the innovation is more mature (i.e. Scale-up phase). The last phase of SNM involves withdrawing the support given to the innovation that protects it from competition (i.e. Support withdrawal phase).

Although the niche-based policy proposed in SNM is intuitive and reasonable in the presence of learning-by-doing type of mechanisms (Argote & Epple, 1990; Arthur, 1989; Ghemewat & Spence, 1985; Rosenberg, 1982, 1994), its application is not straightforward. As also highlighted by Rip and Kemp (Rip & Kemp, 1998), there exist multiple key points that play an important role in the success of the approach. These include the size of the niche where the novelty will be nurtured, the timing for scaling-up, the extent to which the novelty will be protected against competition, and the timing for withdrawing the support provided to the novelty. Intertwined dynamic processes such as adoption, scale economies and learning-by-doing make it difficult to comprehend plausible diffusion dynamics of an innovation that is supported through a niche management policy.

This study is a first attempt towards building up a better understanding about the application of SNM as an approach, and aims to study different SNM schemes under different socio-technical scenarios in order to plausible diffusion dynamics conditioned by these policy schemes. The study is mainly based on a stylized model that covers the major processes that play important roles in the entry of an innovation into a market that is dominated by an incumbent technology. This generic model is used in an exploratory manner in order to evaluate several niche management policy designs under an ensemble of conditions. The following section introduces the model that is used. Section 3 discusses the simulation experiments, and general observations. In Section 4, the paper will focus on a set of selected cases with unconventional diffusion dynamics. The final section of the paper summarizes the main findings and discusses future work.

Model Description

The model aims to capture major dynamic processes that are relevant to the evolution of a new artifact and/or practice in a socio-technical system, and to the diffusion of this innovation. The model is aimed to be as simple as possible in order to maintain its benefit as an exploratory ground for comprehension of possible diffusion dynamics under different niche management strategies.

In the market depicted by the model, a single artifact/practice (i.e. the *incumbent*) is assumed to be widely used, and is the dominant option. A novel artifact/practice (i.e. the *innovation*) is introduced to the system at t=0. The *incumbent* and the *innovation* are assumed to serve the same function. It is assumed that there is only a single attribute that differentiates these two options for the users during their adoption decisions. Without loss of generality, it is assumed that lower the attribute level, more preferable the option from the perspective of the users. For the sake of clarity, this attribute can be assumed to be an economical one as operating cost, and more importantly this attribute is dynamic and changes as a consequence of the adoption dynamics.

The attribute of an option (the *incumbent* or the *innovation*) is dynamic and it changes due to two effects. First one is the learning curves effect (i.e. experience-driven change). According to this, the attribute will improve (i.e. its value will decrease) as a consequence of cumulative experience with the option. In its most basic form, the mechanism is implemented as follows;

$$a(t) = a(0) \times \left(\frac{E(t)}{E(0)} \right)^{\alpha} \quad \text{where}$$

$a(t)$: Value of the attribute at time t

$E(t)$: Cumulative experience at time t

α: Learning factor

The learning curve effect represents the supplier-side accumulation of experience and know-how that can potentially translate into improvement in the artifact being offered to the users. In the absence of the innovation, it is assumed that the suppliers have minimum motivation to translate that potential into an actual improvement in the artifact's attributes. This motivation is triggered with competition in the market. In order to capture this in the model, the learning curve effect is active for the innovation throughout the simulation period, whereas for the incumbent option it is activated only when the innovation is perceived as a threat. Simply, an innovation constitutes a threat when it manages to diffuse more than 20% of the system in this model. This is a simplified implementation of the fight-back reflex of the incumbents in the socio-technical systems (F Geels, 2002).

The second dynamic process related to the attribute is the scale economies (i.e. scale-driven change). Dependent on the scale of instantaneous usage, the attribute of the option changes (i.e. high volume of usage results in better attribute levels). These two attribute-changing processes are depicted in Figure 1.

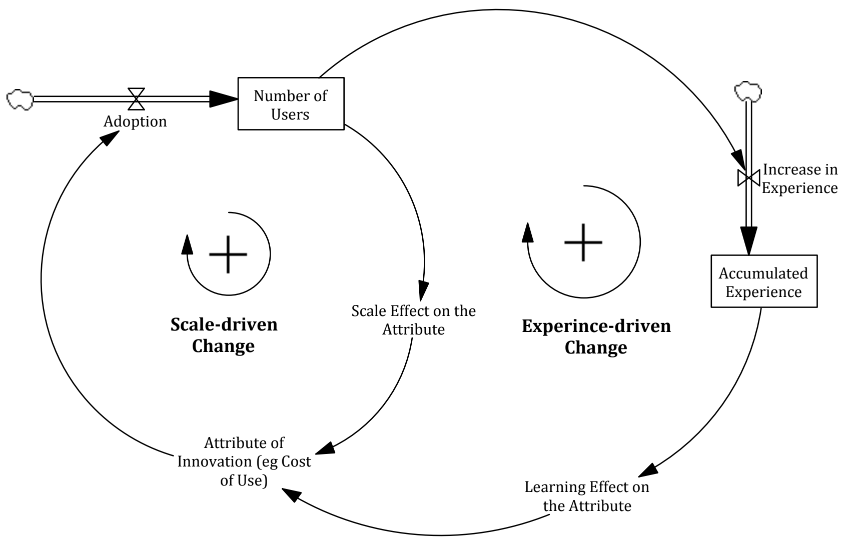

Figure 1. Causal-loop Diagram for the Attribute Improvement Mechanisms

To summarize, the model covers two technological options that have dynamic performance attributes, and also capability of fighting-back with upcoming competition. This competition is all about the users, who choose which option to utilize based on the single attribute of the alternatives.

Since the main objective of the study is to explore diffusion dynamics under different niche management schemes, the model also incorporates a structure that separates a protected niche for the innovation, which can be scaled up to the whole market as time goes by. The niche market is conceptualized as a certain fraction (e.g. 5%) of the total market. The innovation is supported within this niche in order to eliminate the competitive pressures and give the innovation a chance to evolve into its true potential as a consequence of the experience to be gained from its adoption in the niche. In order to represent this aspect, it is assumed that a hypothetical regulator spends 'resources' proportional to the gap between the incumbent and innovation in terms of the attribute represented in the model. In other words, if the innovation is performing worse according to the attribute, the regulator compensates this via external support (e.g. subsidies, etc.) so that it becomes equivalent to, or more attractive than the incumbent option within the niche market. The scale of this support is indicated by percentages in the model, and represents the level it is aimed to take the niche above existing regime. For example, assume that the operation cost is $2 for the incumbent option, and $3 for the innovation. If the support scale is 10%, the regulator compensates the gap between the operating cost of the innovation and the level of $1.8 (i.e. 10% better than the incumbent option), and provides an external subsidy of $1.2 per use in order to make the innovation more attractive within the niche.

Aforementioned issue corresponds to the niche scale and support scale aspects of a niche management strategy. Other two aspects are support withdrawal timing and niche up-scaling. The former represents the time beyond which the regulator will not be supporting the innovation anymore. At some point during the niche management strategy, the regulator starts scaling-up the niche, and this process can be depicted as gradually extending the niche market to the full market size. As can be seen in the simplified stock-flow diagram in Figure 2, this process is modeled through a flow between the niche market and the rest of the market (i.e. Scale-up flows). Once scaling-up starts, the extension of the niche market is captured by gradually including more users from the rest of the market into the niche market.

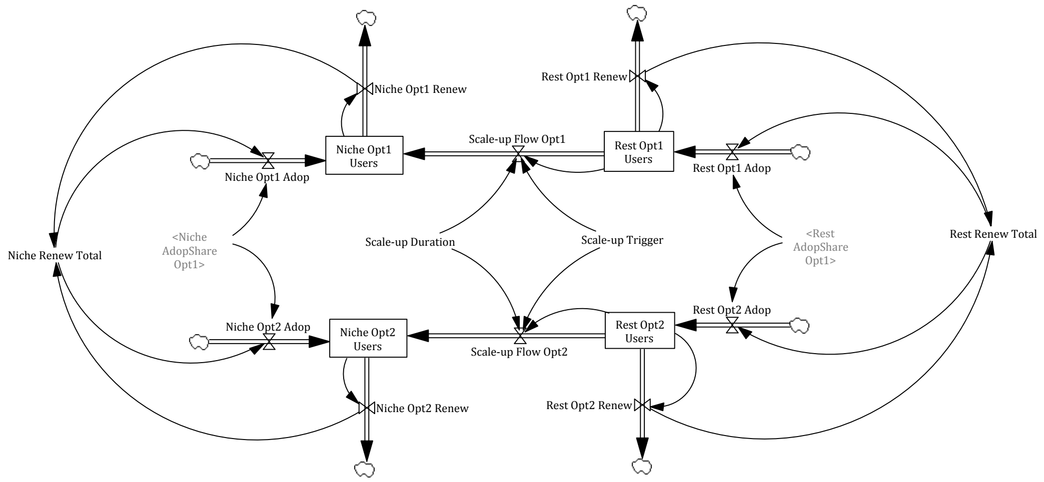

Figure 2. Stock-Flow Structure for the Niche Up-scaling and Adoption

Regarding the adoption decisions, it is assumed that the users both in the niche market and in rest of the market periodically reconsider the option they have been using. As a result, a certain fraction of the users of the both options renew their choices (i.e. Opt1 Renew, Opt2 Renew flows in Figure 2) in every period. These renewing users are allocated to the options using a simple uni-attribute logit formulation, which is formulated as follows;

$$U_{opt1} = e^{\alpha . A_{opt1}}$$

$$A_{opt1}: Attribute\ value\ of\ the\ option\ 1$$

$$AdoptionShare_{opt1} = \frac{U_{opt1}}{U_{opt1} + U_{opt2}}$$

For the niche market users, the allocation is based on the supported attribute of the innovation, whereas in the rest of the market the actual (unsupported) attribute is used in the adoption decisions of the users (see Figure 3).

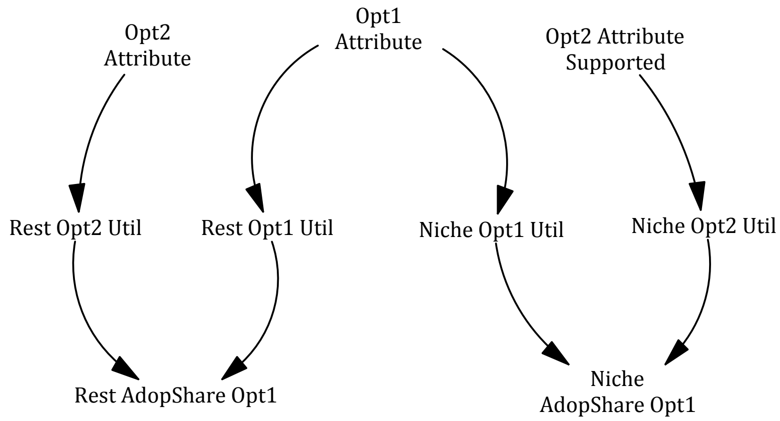

Figure 3. User Allocation for the Niche Market and the Rest of the Market

Initially the innovation is assumed to have a slightly worse attribute value upon release. Additionally, both options are assumed to have the same learning factor alpha, i.e. they are assumed to develop along the identical learning curves. While initializing the options, the parameters are selected such that;

- The innovation has the potential to become better than the incumbent option as a consequence of experience-driven and scale-driven improvement mechanisms.
- If not supported, the innovation will not be adopted by the users, hence will not realize its true potential.
- If supported, the innovation will become better than the incumbent, and dominate the whole market.

In short, the innovation is depicted as an option that has the potential to transform into a better choice if it can be nurtured properly upon its introduction to the market.

During the simulation experiments conducted with the model, the objective is set to be achieving the maximum diffusion level for the innovation until a predefined time point (t=800). Numerous scenarios are considered, and different niche management strategies are evaluated based on the eventual level of diffusion of the innovation, as well as the total amount of resources spent while supporting the innovation to attain those diffusion levels.

Simulation Experiments

The stylized model described above can be used to analyze niche management policies under a very broad set of cases. In order to narrow down the scope of analysis, we focused on the development potential of the two options. One of the critical aspects regarding the success of a niche management strategy is definitely about the development potential and pace of the options. On the innovation side, the question is about how much more the option can be developed, and on the incumbent option side, it is more about to what extent it may fight back the upcoming competition (i.e. it can be improved in the face of competition from a novel option). Even in cases where it is assumed that both options have identical development potentials and will follow the identical learning curve, important point is where do they stand on that *learning curve* at the point when novelty is introduced. In other words, what is the level of cumulative experience at t=0 for the new and the old option. Departing from this point, four contextual scenarios are analyzed by varying the initial level of cumulative experience of the options. On the one hand, an incumbent option having a high initial experience level represents a well-established and old technology, but on the other hand a low level represents a dominant option in the system whose dominance does not go far back (i.e. young incumbent). Not every new option is a brand new technology or practice. In some cases they are slightly re-designed/re-engineered versions of previously used/tried options (i.e. old innovation). In these cases, the initial level of cumulative experience with the option is comparatively high considering a truly new option (i.e. young innovation). As a result, the initial values of the cumulative experiences for the two options constitute the main parameters that are used to alter the contextual setting for the evaluation of a niche management policy. Besides these two parameters, we explored a large set of niche management policies by altering the 4 policy-defining parameters; scaling-up time, support withdrawal time, level of the support, and size of the niche. The parameters used to define different simulation experiments, as well as their ranges are given in Table 1.

Table 1

Parameter	Min	Max	Interval
Support Withdrawal Time	0	400	100
Scale-up Time	0	400	100
Init. Niche Scale	5%	25%	10
Support Scale	0%	25%	5
Init. Cumulative Experience (Innovation)	$2{,}5 \times 10^6$	10×10^6	$2{,}5 \times 10^6$
Init. Cumulative Experience (Incumbent)	$1{,}5 \times 10^5$	6×10^5	$1{,}5 \times 10^5$

The resulting 7200 simulation experiments are evaluated according to the extent of the market share gained by the innovations and the extent of external resources spent in order to support it. Therefore, market share and resource per market share are two main outcomes of interest we focus on. Let alone analyzing them, communicating the results of a large set of experiments is challenging. Despite the fact that 16 different contextual cases (i.e. innovation-incumbent combinations) are tested, we confined our discussion to 4 extreme cases among these 16, for the sake of clarity. The observations will be discussed in the following sub-sections.

Case 1: Competition of young options

In this case, the initial experience levels of both options are set to be relatively low (i.e. 2500000 for the incumbent, and 150000 for the innovation). This represents a situation where the innovation is at an early point of its learning curve and steep performance developments are possible. For the incumbent this indicates the feasibility of significant further development, even though not as steep as the innovation's development.

In Figure 4, final market shares of the innovation as a function of different support withdrawal and scale-up time decisions are given. As can be seen from the figure, highest diffusion levels are obtained by early scaling-up and late support withdrawal. The latter point is intuitive and doesn't need further clarification; the more support given, the higher diffusion levels achieved. However, early scale-up indicates that there is almost no need for nurturing the new option in a protected niche. Since the new niche has the potential of a steep performance development, introducing it into a larger user base with a support that makes it attractive makes sense. In this larger user base, the accumulation of experience goes quite fast triggering a very steep development in the performance, which cannot be defeated by the counter development on the incumbent side. However, it is apparent that providing support to this new option not in a small-scale niche, but in a system-wide manner is very expensive in terms of resources allocated for this purpose. That is indeed true. The strategy depicted here as successful (i.e. early scale-up, late support withdrawal) is the most expensive one. However, in terms of cost effectiveness the story is much different. In Figure 5, the ratio of total 'cost' per diffusion level of the new option at the end of the simulation is given. As can be seen, despite being the most expensive one the strategy discussed above is the most cost effective one. The problem with the early support withdrawal strategies is that regime-option fights back effectively and earns back its users. Hence, the support provided is practically a sunk cost since the diffusion of the new option cannot continue without the support and a backlash is observed.

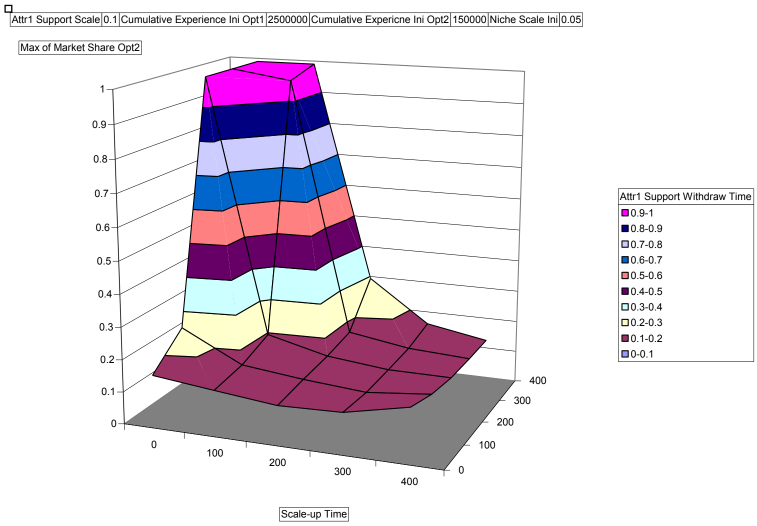

Figure 4

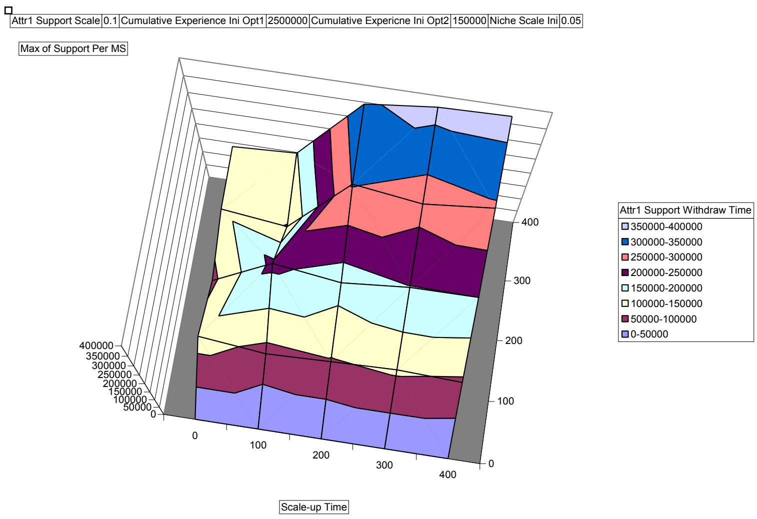

Figure 5

Figure 7 and 8 presents the identical variables, but in a scenario where the scale of the niche is much bigger. In the above case the niche is assumed to be 5% of the total system. In this case, it is assumed to be a considerably large niche, i.e. 25% of the system. Overall conclusions are almost identical for this case also. However, since the size of the protected space has a larger user base, it provides a better ground for fast development of the young niche, and the portfolio of successful strategy designs is bigger in this setting. Even with late scale-up choices, it is possible to observe a full-scale transition in the system.

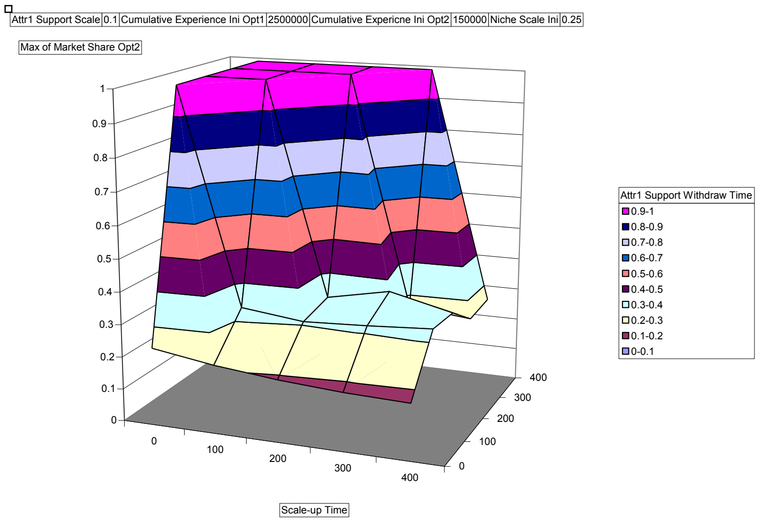

Figure 6

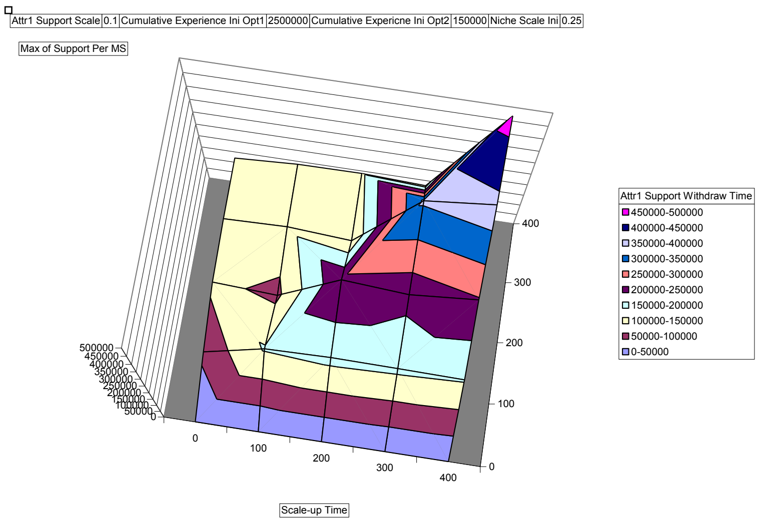

Figure 7

One of the decisions regarding the implementation of the SNM strategy is about the extent of the support to be provided. In the above examples, the new option is introduced to the system being 10% better than the incumbent, with the help of the regulator's support. In the following example, it is introduced as a new option equal in performance to the existing one. Outcome is summarized in Figure 8 and Figure 9. As it can be seen, being equal in performance, the new option does not provide any incentive for breaking the status quo and fail to capture a significant user base in the system, almost independent of the other decision parameters regarding the niche management strategy. In terms of cumulative 'cost', taking the new option to the "10% better" level is observed to cost around 40% more than this strategy. However, the difference between them distinguishes an expensive successful transition versus a costly failure.

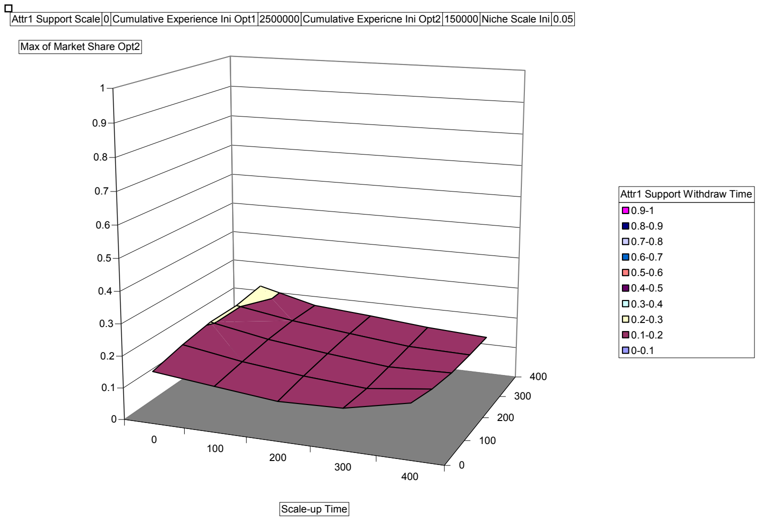

Figure 8

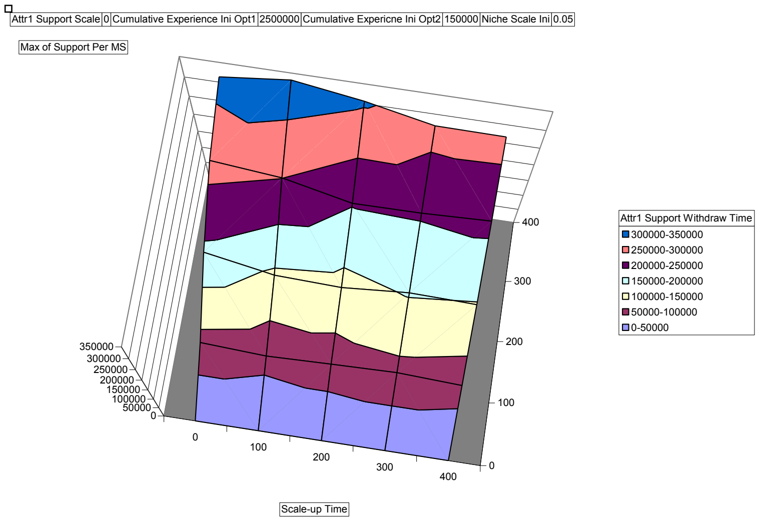

Figure 9

Case 2: Young incumbent option vs. "not promising" innovation

This case constitutes the most challenging scenario for the regulator to achieve a successful transition. Since the incumbent is a relatively young one, it has room for development, which translates into a strong fighting back potential. On the other hand, being a technology/practiced used in other domains and/or systems, the innovation is already realized some level of development. As can be seen in Figure 10, in most cases the outcome is a very limited acceptance level for the new option, i.e. a clear failure. A large-scale diffusion seems to be possible only within a narrow sub-space of the decision space (top-left corner). On the cost effectiveness matter (Figure 11), the worst strategy seems to be a medium-term scale-up coupled with a late support withdrawal. Compared to that early up-scaling is more cost effective since it leads to widespread utilization of the new option. A later up-scaling also seems to be very cost effective, but due to a different reason. Since the utilization level of the new option is significantly low in this case, the total cost of supporting new option usage is also low. Hence, cost effectiveness is not due to a successful transition, but due to minimal support provided. The success of the early up-scaling case is, again, related to introducing the option to a wide enough user base. Since the innovation is an 'old' one, the limited experience to be provided by the small niche can only provide marginal improvements, and this is apparently not enough to compete with the incumbent.

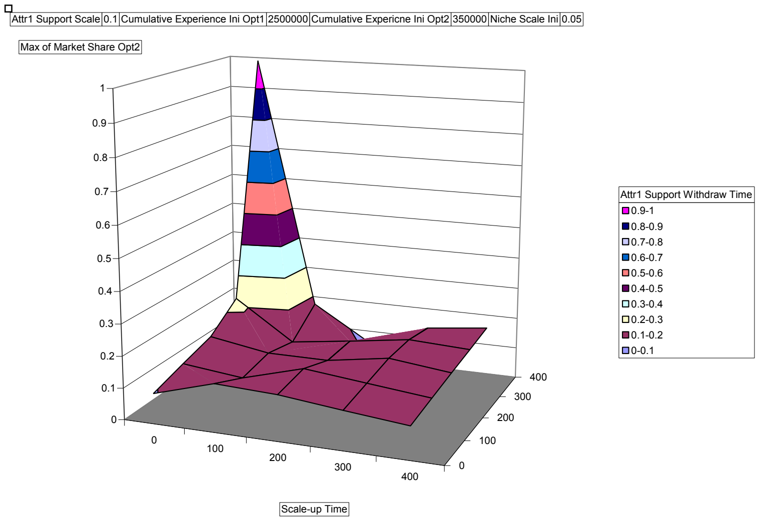

Figure 10

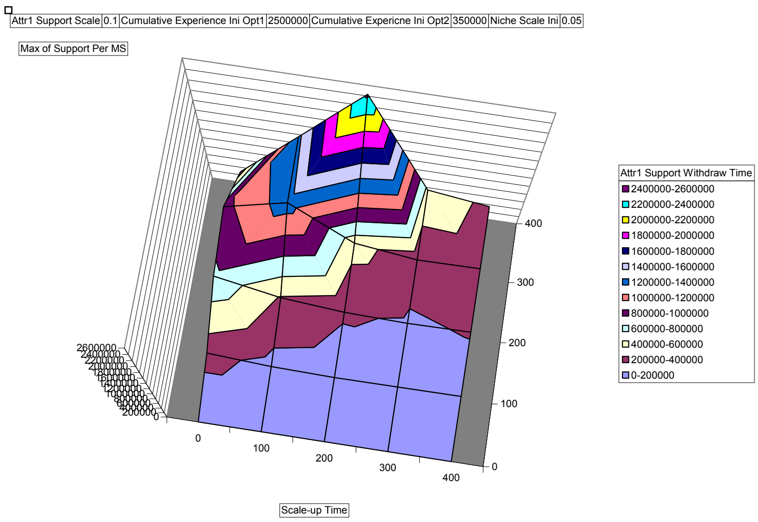

Figure 11

Case 3: Old incumbent vs. Young innovation

Contrary to the case 2, this scenario is the one in which the success of the niche management strategy is viable with different implementations. The established and old incumbent option in this case is on a late point on its learning curve, and there is almost no room for extra development. On the other hand, the innovation has a great potential for improvement with increasing experience. As can be seen in Figure 12, there is no strict border between the full success and failure, as was the case in the former observations.

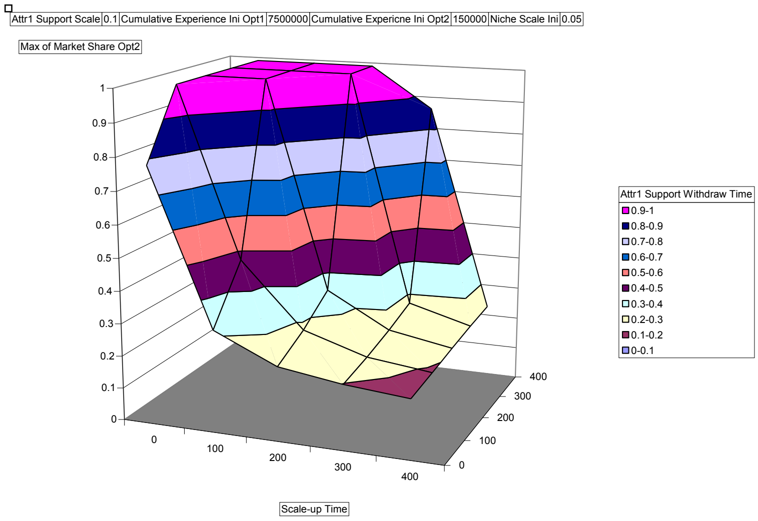

Figure 12

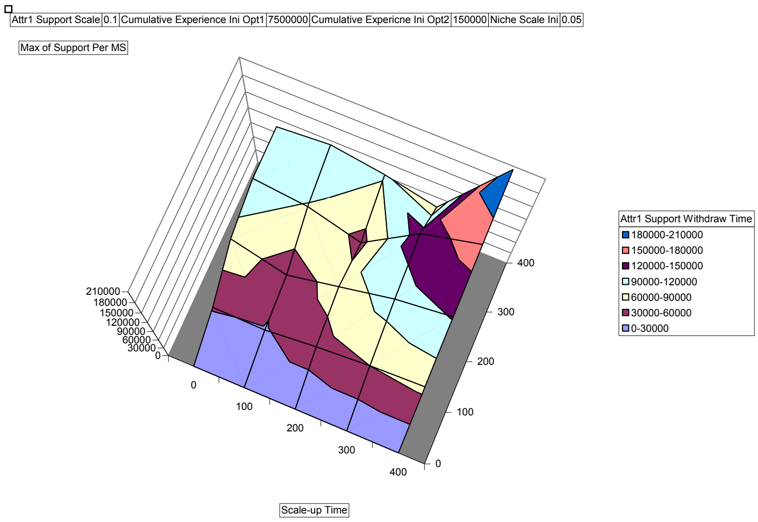

Figure 13

Contrary to some of the cases discussed previously, increasing the duration of support always has a positive return in terms of acceptance level of the new option, independent of the timing for scale-up. However, the observation in terms of cost effectiveness reveals some difference between scale-up decisions. In the *late scale-up* case (i.e. 400), despite the increase in the acceptance level as a consequence of longer support duration, the additional cost burden seems to overweight this marginal increase in the acceptance levels. Hence, a very steep increase in the late scale-up case is observed in the cost effectiveness graph (Figure 13).

Case 4: Old incumbent-option vs. "not-promising" innovation

The observations in terms of acceptance levels in this case are pretty much in line with the observations from the first case. The difference between these two cases is that the pace of development is much slower compared to the case 1, but the development in the innovation and in the incumbent option are relatively similar in these two cases. On the other hand, a shift of peak in the cost effectiveness graph is observed comparing these two cases; long support with medium term scale-up seems to be the worst case in this scenario (Figure 15).

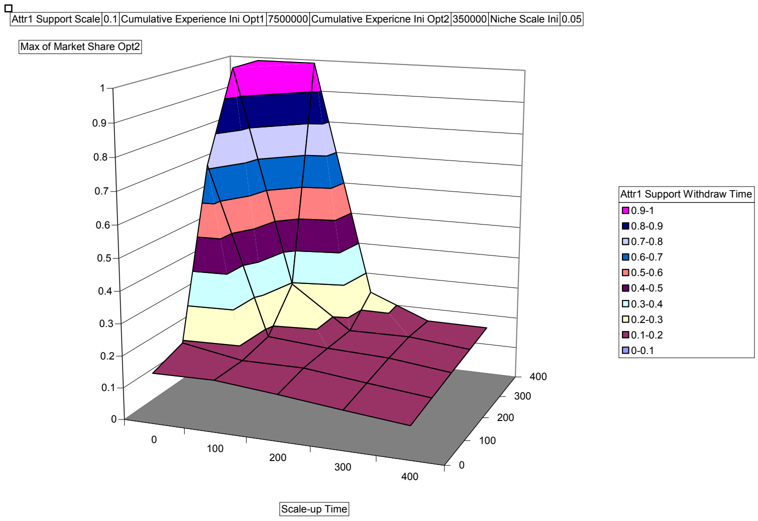

Figure 14

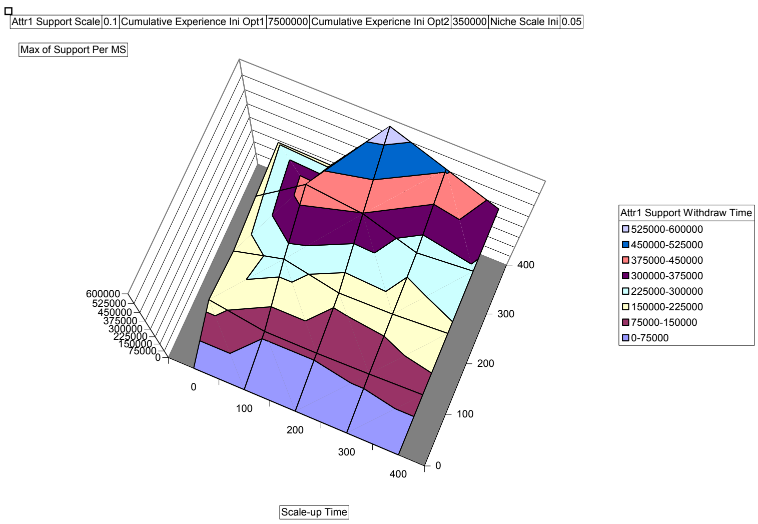

Figure 15

Diffusion Dynamics

The large number of simulation experiments considered in the previous section makes it almost impossible to analyze the individual cases individually in depth. Therefore, the analysis in the preceding section is confined to the final value of the market share for the innovation. Although such an analysis gives interesting insights, it is blind to the dynamics; i.e. the analysis does not pay attention to the overall dynamics of the diffusion process that led to a particular market share at the end of the simulation experiments. In this section, we focus on a set of selected diffusion dynamics and analyze the conditions that lead to their emergence.

Unfortunately, identifying different diffusion patterns among 7200 simulation experiments is not a straightforward task. Looking at a summary plot of the 7200 experiments for the innovation's market share, we observe an envelope plot as in Figure 16, which basically suggests that anything is possible. When we plot the individual diffusion curves for the 7200 experiments, we get Figure 17. Although a variety of different dynamic patterns are visible in this plot, it is not easy to isolate them and identify the parameter values that lead to this pattern.

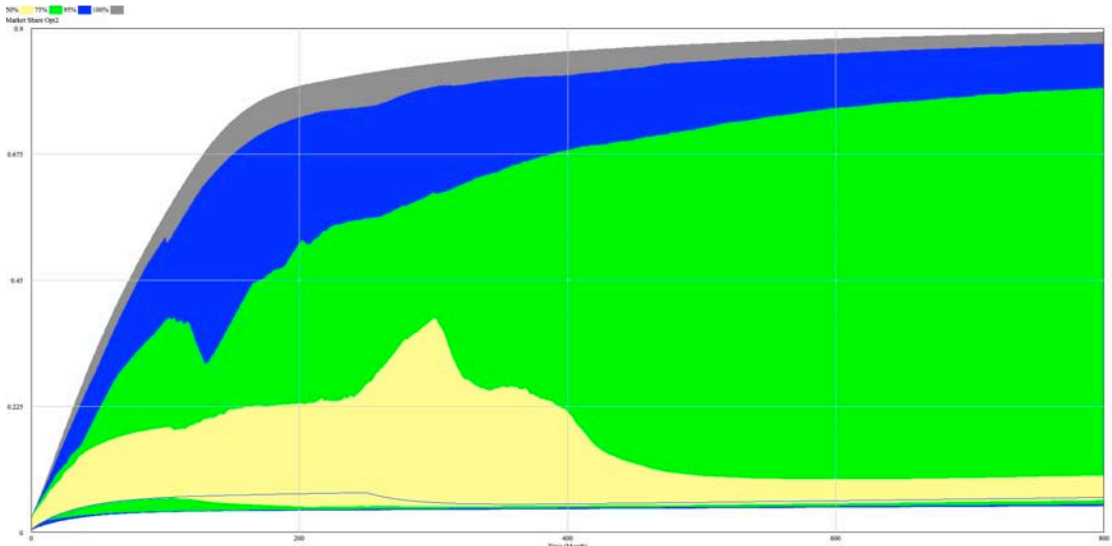

Figure 16

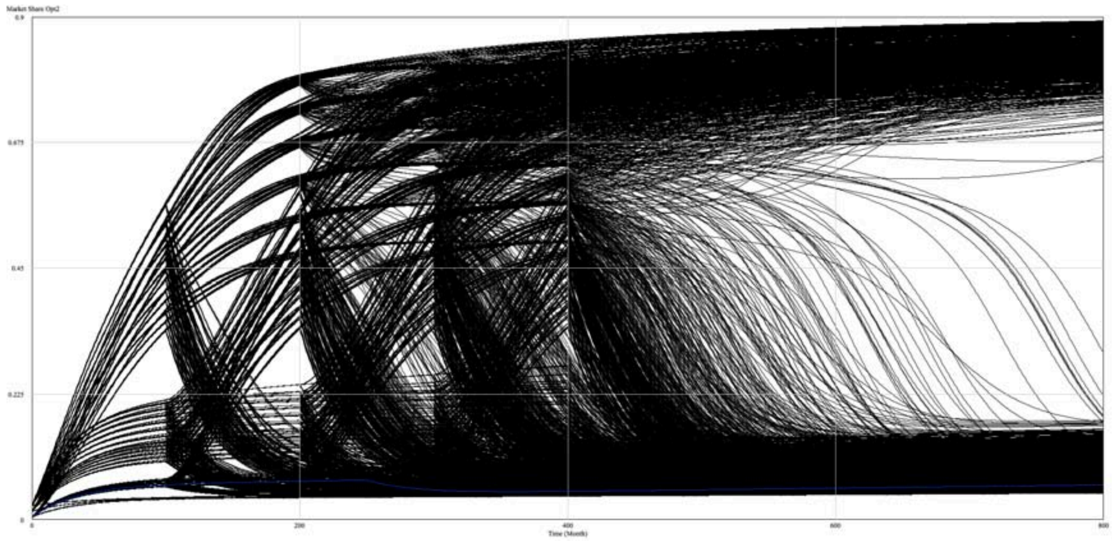

Figure 17

In order to identify and isolate different diffusion patterns, we utilized the behavior clustering algorithm by Yücel (Yücel, 2012). This algorithm measures the similarity between two model output in terms of their pattern features, and identifies several clusters of diffusion dynamics. The clustering algorithm, which is embedded into the exploratory modeling and analysis workbench developed by TU Delft Policy Analysis Simulation Lab (PA Simulation Lab, 2013), also enables selecting sample instances from each cluster and focus on that particular simulation experiment.

Within the 7200 market share behaviors, the clustering algorithm identified several clusters of dynamic patterns including the ones depicted in Figure 18 through Figure 22.

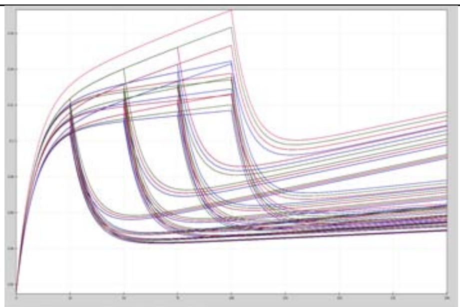

Figure 18

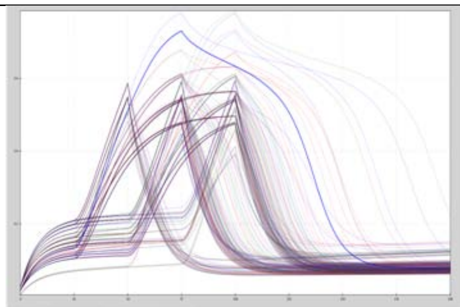

Figure 19

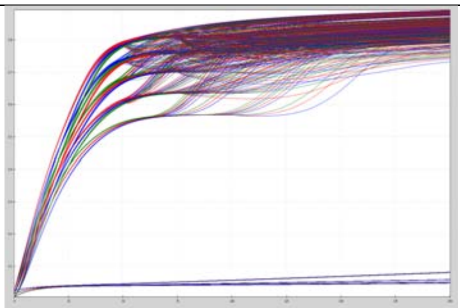

Figure 20

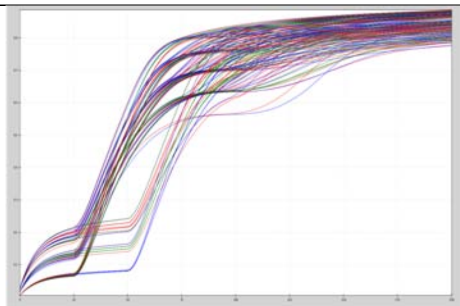

Figure 21

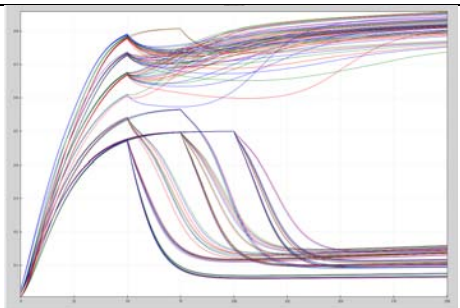

Figure 22

Investigating the diffusion clusters, we identified a set of cases and analyzed them further in detail. First set of diffusion case considered in this way can be labeled as the backlash cases. Two of these cases can be seen in Figure 23 and Figure 24[†].

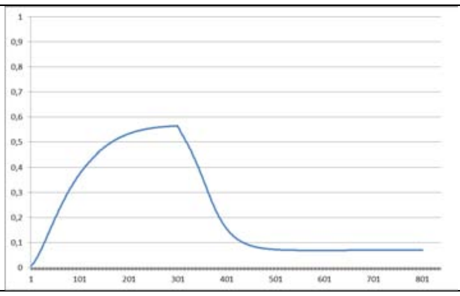

Figure 23. Market share of the innovation (case # 2102)

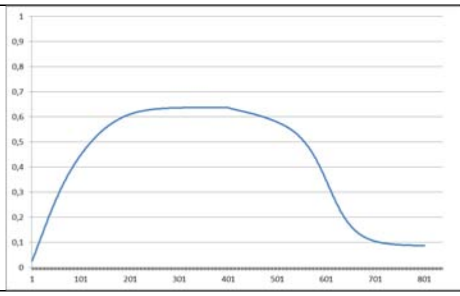

Figure 24. Market share of the innovation (case # 3551)

In the case 2102, the innovation has limited room for experience-driven improvement. Therefore, the nurturing period fails to provide the improvement that is required to

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[†] Each case is identified with an ID number. The parameter values that yield to the given case are given in the appendix of this paper.

beat the incumbent. As soon as the support is withdrawn, the incumbent becomes the preferred option and a steep backlash in the market share of the innovation is observed. In the case 3551, the options are almost equivalent at the point of support withdrawal. The plateau at the market share graph is a competition period where the incumbent is also being improved. Eventually, the incumbent gains back the market dominance. In both of these cases, the innovation is not a very young technology, hence it has limited room for improvement. The difference between the diffusion dynamics mainly stems from the extent of support provided. In 2102, the innovation is supported to be 5% better, and in 3551 to be 10% better. This difference lets the innovation enjoy a larger market share during the protection period, which translates into higher scale-economies, and more experience-driven improvement. Still, the learning process fails to deliver the required improvement. In the case where the support is higher (i.e. 15% better), a very similar pattern is observed in the first half (Figure 25). However, this time the larger user base that is attained during the protection phase delivers the required improvement, and the innovation manages to protect its user base after the support is withdrawn. Beyond that point the innovation diffuses further in a steady pace as the experience-driven learning process yields additional improvement in its attribute levels.

Considering these three case (2102, 3551 and 4751), in all of them the innovation stands at a relatively flat portion of its learning curve. In such a case, the best strategy seems to provide a significant advantage through external support, so that the innovation can benefit from scale-economies. This requires much more resources to support the innovation at the first glance, however eventually it proves to be very effective in terms of resources spent per market share (see Appendix B for the dynamics of total resources spent, and resources spent per market share attained)

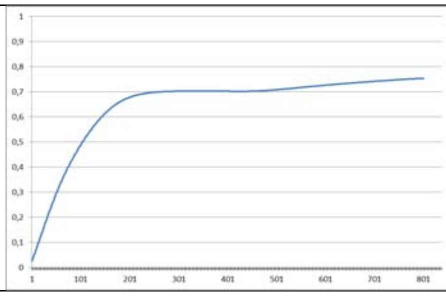

Figure 25. Market share of the innovation (case # 4751)

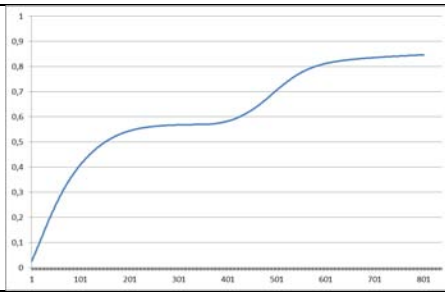

Figure 26. Market share of the innovation (case # 2276)

A second group of interesting diffusion patterns identified as the multi-stage diffusion cases (see Figure 27, Figure 28 and Figure 29). The common characteristic of these three cases is the high improvement potential of the innovation. After even a short period of protection, the innovation improves to a level at which in can outperform the incumbent option. The first stage in these patterns correspond to the diffusion of the innovation within the protected niche (In case 2276, the niche is scaled up starting from t=0. Therefore, this stage is missing in that case). The second stage starts with the niche scaling up process, which extends the potential user base for the innovation. The increase in the user base during this second phase both provides improvement through learning curve and through scale-economies. Furthermore, the loss of market share causes the incumbent option to lose the scale-economies effect. The joint outcome of these developments is the third period of accelerated adoption. This third stage of diffusion slows down with the saturation of the whole market.

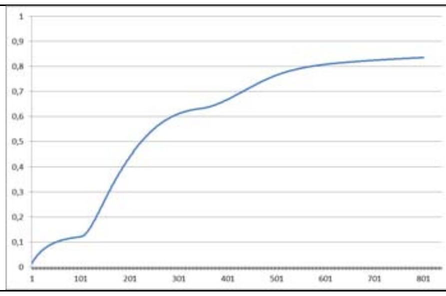

Figure 27. Market share of the innovation (case # 3457)

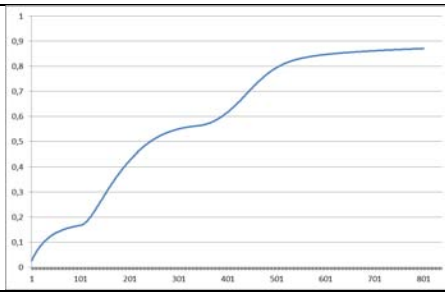

Figure 28. Market share of the innovation (case # 2202)

The above mentioned multi stage diffusion dynamics are all success stories where everything goes fine for the innovation; i.e. at the time of support withdrawal the innovation is developed well enough to compete with the incumbent. The cases depicted in Figure 29 and Figure 30 are two cases where this is not the case. In the case 6778, the attribute levels of the two options are very close, but the incumbent is still more preferable, which causes the disruption in the diffusion pattern around t = 300. However, the innovation already has a user base, which drives the experience-driven learning process. The resulting improvement in the attribute value of the innovation suffices to stop the backlash and trigger a final stage of diffusion. The dynamic story is pretty much similar in the case 5854. The only difference is that the experience-driven improvements cannot close the gap between the innovation's and the incumbent's performance after the support withdrawal point. Therefore, the innovation cannot recover from the backlash of its market share. These two cases suggest that it may be still acceptable to withdraw the support even when the innovation is slightly worse than the incumbent. If the innovation acquired a critical user base, the learning processes may help to close this performance gap (case 6778). However, the borderline between success and failure seems to be very thin, as backlash may be so strong and quick that the innovation may not recover (case 5854).

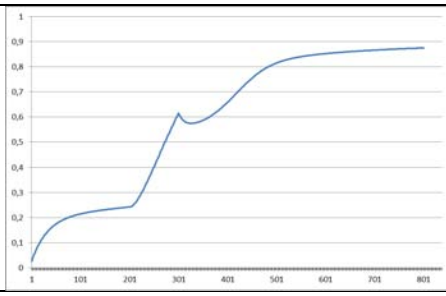

Figure 29. Market share of the innovation (case #6778)

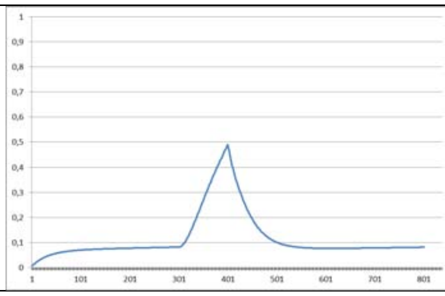

Figure 30. Market share of the innovation (case #5854)

Conclusions

The strategy proposed in niche management relies on the idea of protecting the novel options from competitive environment until they develop enough to compete with the dominant option in the system with the help of experience obtained in the protected niche. However, even considering a limited set of dynamic mechanisms in the diffusion processes success of such a strategy in terms of the extent of diffusion, and in terms of cost effectiveness is not straightforward. The consequences in terms of important strategy variables like when to up-scale the novel option, or until when to continue support may vary significantly.

In this study a simple abstract model that incorporates some of the fundamental dynamic mechanisms relevant to innovation diffusion, and it is used in as an experimental ground to develop a better comprehension about the way these dynamics interact and condition the diffusion dynamics under varying niche management strategies. The results discussed reveal the risk that the border between a successful implementation and a failure may be very thin dependent on the way strategy is implemented, and it is the strategy design that determines the consequence, not unexpected environmental factors. One common, and unexpected observation is that in all scenarios discussed, early up-scaling seems to more successful, which makes the need for an isolated niche space questionable. This points that in cases where the conventional learning-by-doing mechanism is in operation, locking the novelty in a niche seems to hinder its pace of development. However, in cases where focused and concentrated experience yields a much faster development, the real contribution of the niche isolation may be realized. This is a point being explored with recent versions of the model.

The model is far more simplistic than the detail level required in order to draw any conclusion for a specific diffusion problem. However, the quantified model makes the discussion on interacting mechanisms and dynamic complexity more concrete and highlights important aspects to be considered. In that sense, the model outcomes should be considered as intellectual exploration in a structured manner in order to supplement a more comprehensive theoretical development process for meta-niche management strategies.

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Appendix A. Parameter values for the analyzed cases

Case ID: 2101

"Scale-up Time"	0
Attr1 Support Scale	0,05
Attr1 Support Withdraw Time	300
Cumulative Expericne Ini Opt2	800000
Cumulative Experience Ini Opt1	2,50E+06
Niche Scale Ini	0,05

Case ID: 2202

"Scale-up Time"	100
Attr1 Support Scale	0,05
Attr1 Support Withdraw Time	400
Cumulative Expericne Ini Opt2	200000
Cumulative Experience Ini Opt1	7,50E+06
Niche Scale Ini	0,25

Case ID: 2276

"Scale-up Time"	0
Attr1 Support Scale	0,05
Attr1 Support Withdraw Time	400
Cumulative Expericne Ini Opt2	400000
Cumulative Experience Ini Opt1	1,00E+07
Niche Scale Ini	0,25

Case ID: 3457

"Scale-up Time"	100
Attr1 Support Scale	0,1
Attr1 Support Withdraw Time	400
Cumulative Expericne Ini Opt2	400000
Cumulative Experience Ini Opt1	7,50E+06
Niche Scale Ini	0,15

Case ID: 3551

"Scale-up Time"	0
Attr1 Support Scale	0,1
Attr1 Support Withdraw Time	400
Cumulative Expericne Ini Opt2	800000
Cumulative Experience Ini Opt1	2,50E+06
Niche Scale Ini	0,25

Case ID: 4751

"Scale-up Time"	0
Attr1 Support Scale	0,15

Attr1 Support Withdraw Time	400
Cumulative Expericne Ini Opt2	800000
Cumulative Experience Ini Opt1	2,50E+06
Niche Scale Ini	0,25

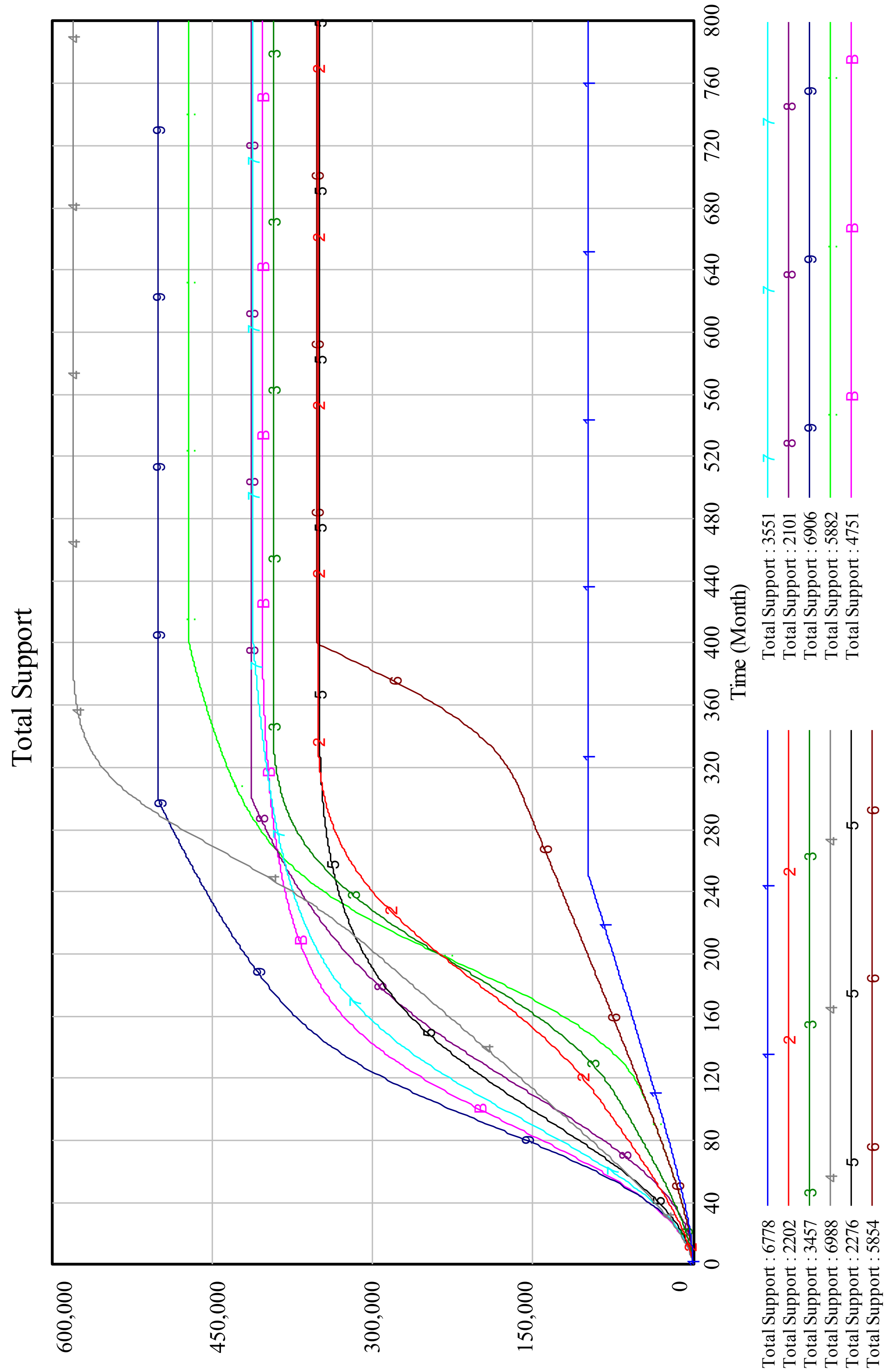
Case ID: 5854

"Scale-up Time"	300
Attr1 Support Scale	0,2
Attr1 Support Withdraw Time	400
Cumulative Expericne Ini Opt2	600000
Cumulative Experience Ini Opt1	2,50E+06
Niche Scale Ini	0,05
Total Support	0

Case ID: 6778

"Scale-up Time"	200
Attr1 Support Scale	0,25
Attr1 Support Withdraw Time	300
Cumulative Expericne Ini Opt2	200000
Cumulative Experience Ini Opt1	1,00E+07
Niche Scale Ini	0,25
Total Support	0

Appendix B. Comparative dynamics of the discussed cases



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