A simulation model for the diffusion of a new technology in an environment populated by heterogeneous agents. The case of business to business (B2B) e-commerce.

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Abstract

In this paper we propose an agent-based simulation model for the diffusion of the *business to business* e-selling technology (B2B) in a population of heterogeneous firms. The model has been implemented using SWARM. The calibration of the model is based on real micro-data derived from a large scale field survey. This survey was conducted on a representative sample of Italian firms all potential adopters of B2B technology in three industrial sectors (mechanical, electromechanical, and electronic industry).

The theoretical underpinnings of our model have two origins. On the one hand, we address the problem of the limits of classical epidemiological models of diffusion (Griliches, 1957; Fourth and Woodlock 1960; Bass, 1969; Mansfield, 1961, 1968) due to the lack of a microfoundation (Davies, 1979; Tanny and Derzko, 1988). This is done by making explicit the decision of adopting the new technology and assuming bounded rationality. Moreover, these models do not take into consideration the heterogeneity of the agents. In classical contagion models the agents are assumed to be homogeneous with respect to both their structural and social characteristics. They differ only in the timing of adoption (structural homogeneity) and have the some probability of meeting each other during the diffusion process (social homogeneity). In the literature of technology diffusion several types of structural heterogeneity have been introduced. Among these are included different values for the structural variables (e.g. size, R&D investment, country etc.) and different positions in some relevant distributions (e.g. rank, order and stock effects: Karshenas and Stoneman, 1983). However, only a few models introduce social heterogeneity, such as when agents

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talk to one other with different probabilities. These probabilities are then represented by a matching matrix.

The second theoretical background has its roots in the literature on network externality effects and increasing returns to adoption (Arthur 1988, 1989, 1990, 1993, 1996; Katz and Shapiro, 1985, 1986; Farrell and Saloner, 1985), which was adapted to the case of B2B technology in a related paper (Bonaccorsi and Rossi, 2001).

In our model, agents change their state (adopter/non adopter) according to the level assumed by an explicit adoption function based on two factors: the intrinsic value of the technology and the network externality effect. The intrinsic value of the technology is approximated by agents subjective expectations regarding future improvements of the technology. We consider improvements with respect to the evolution in data security and in the price of the technology. The network externality effect is captured by variables describing, on one hand, the expectations regarding the diffusion of technology among customers and competitors and, on the other hand, by the actual number of adopters observed in the system.

Social heterogeneity is introduced into the model by attributing to each agent a different number of social contacts, resulting in a different probability to meet other members of the population. The number of contacts is obtained by the micro-data collected in the field survey. The result of social contacts among agents is a change in their expectations. The contacting agent is the one who changes his beliefs on the basis of the expectations of the contacted agent using an appropriate updating rule.

Preliminary results of this study show two different effects caused by the introduction of an explicit adoption function together with structural and social heterogeneity. The diffusion path exhibits two qualitative properties that are sharply different from those of classical epidemiological models. First of all, *the diffusion does not lead to the saturation of the population of potential adopters*. Beyond a certain level of the penetration rate, the strength of beliefs of adopters is not sufficiently high to induce a deep revision of beliefs of the subgroup of non-adopters with pessimistic expectations. Secondly, *the diffusion path at the beginning of the process is more rapid than the S-shaped path* associated with the classical epidemiological contagion model. At the beginning of the process, diffusion is driven by the adoption behaviour of the subgroup with the more optimistic expectations and/or more intense social communication. These two results make clear the implication of structural and social- heterogeneity over general qualitative features of the diffusion process.

A further development of this research is the analysis of the relative importance of the variables dealing with the intrinsic value of technology and with network externality phenomena. In particular, in the presence of increasing returns to adoption, there is the possibility of the emergence of critical masses (Markus, 1987; Lock, Huberman 1998; Roger, 1991, 1996; Economides, 1995). It is then important to test whether critical masses of adopters emerge in our model and whether their time of emergence together with the number of agents forming them vary depending on the model parameters.

1. Heterogeneity and network externality in diffusione models

The literature on the diffusion of innovations is vast and encompasses several disciplines other than economics, such as rural sociology (Ryan, Gross, 1943), public health and medical sociology (Coleman et al., 1966), geography (Brown, 1981) or education (Carlson, 1955)–. Starting with the work of Trade (1903) that presents, for the first time, some generalisations[1] about the spread of the innovations[2], diffusion studies have grown very fast in this century. According to Rogers (1995, page xv), in 1962 this topic accounted for 405 publications while in 1995 the contributions approached 4,000. Diffusion scholars form a sort of invisible college (Crane, 1972) sharing a common paradigm that has been deeply influenced by the Ryan s and Gross study about the diffusion of hybrid corn seed among Iowa farmers in the early 1940 s.

Given the interdisciplinary framework, these works analyse very different kinds of innovations ranging from the diffusion of the boiling water in a remote Brazilian village (Wellin, 1955) to the diffusion of complex process innovations among firms. Otherwise, they all share two common results generally considered in the literature as two basic stylised facts (Geroski, 2000). First, diffusion processes take time. Adopting units

[1] Trade was the first author to recognise that the cumulative number of adopters, if plotted against the time, displays an S-Shaped Curve.

[2] In his book the author uses the term imitation

(individuals, firms or other different type of organisations) do not accept the innovation instantaneously and this happens also for those innovations that would lead to a great improvement [3]. Second, if the cumulative number of the adopters is plotted against time, it displays an S-shaped curve. At the start of the process only a few agents accept the innovation[4], then the rate of diffusion takes off[5] and then slows down again until the prevalence is reached.

Focusing on how the economic literature explains these two stylised facts, we can explicitly make reference to two important classes of diffusion models: epidemic and probit (Geroski, 2000). The first ones originated in biology to explain the spread of disease and infections among the populations, and have been transferred in economics in the early 1960 s to illustrate the diffusion of new products (Fourth, Woodlock, 1960; Mansfiled, 1961; Bass, 1969).

In the classical epidemiological paradigm the diffusion of an innovation is essentially a learning process. Individuals become aware of it from mass media (external source), from their peers who have already adopted it (internal source or worth of mouth) or from both sources, as in the mixed influence model proposed by Bass. The amount of information generated in this way reduces the uncertainty that is intrinsic to every new idea, new product or new technology. This determines further adoptions and the consequent reductions of the uncertainty itself. As a result, the innovation spreads into the environment until the prevalence is reached.

However, some weaknesses are present in the structure of these models themselves. Fourth and Woodlock consider only a central source that spread all the information, in every period, reaching a percentage α of non-adopters. This restrictive assumption gives rise to a diffusion path that is a modified exponential curve which does not fit the empirical

[3] Agricultural college of the Iowa University released the hybrid corn seed to Iowa farmer in 1928. It yielded about more then 20% per acre than the open-pollinated variety that it replace. Otherwise it took took 13 year before reaching a 100% prevalence.
The utility of the lemon juice in preventing and curing scurry was demonstrated by Captain Lanchaster in 1601 but English Navy started to imploy it regularly not until 1747.

[4] Rogers, using a classification based on the normality assumption for the distribution of the adopters in each time period, defines these subjects: innovators and early adopters

[5] According to Rogers (1995) and Valente (1995) the take-off point occurs when about the 16% percent of the population has adopted the innovation

regularity of the S-Shaped curve. Mansfield s (1961) model, on the other hand, concentrates on peer to peer information, obtaining an S-shaped curve, but it presupposes that there is at least one adopting agent at time t=0.

The external and the internal sources are both present in the analysis conducted by Bass (1969) on the diffusion of durable goods. The process is triggered by innovators who adopt independently of other subjects decisions and is pulled by imitators that follow these early adopters. The result is an S-Shaped curve which is more asymmetric, as the influence of external source is bigger (the innovation coefficient α) than the internal one (imitation coefficient β)[6]. Otherwise, this model presents a limited scope of application. The imitation process may be very important for the decision of an individual agent in choosing new products, but plays a minor role in the case of adoption of a new technology by a firm.

In addition, several criticisms have been raised in the literature towards this kind of approach (Davies, 1979). These criticisms move in several directions.

First of all, these are exclusively *demand-base models* (Stoneman, 1986). They do not take into account the supply side of the market of the diffusing innovation. The possible effects of an improvement in performances of the new technology or of a reductions of its price are completely neglected. Anyway the most important weakness is the absence of microfoundation. There is no explicit consideration of the decisional process of individuals. Diffusion is the result of a macro level process that takes place among individuals and that, in turn, is deeply affected by two restrictive assumptions.

On the one side, the adoption units are homogeneous with respect to their intrinsic characteristics and their preferences for the innovation (Manfredi and Bonaccorsi, 2000). On the other hand, information spread is governed by the assumption of homogeneous mixing. During the diffusion process, individuals have the same probability to meet each other and the nature of social structure is completely neglected.

Probit models overcome some of the limitations present in the epidemiological approach relaxing the hypothesis of the homogeneity of the adopting units and introducing a simple decision mechanism at the individual level. Agents differ with reference to a particular

[6] Empirical studies (Mahajan e Muller 1979) demonstrate that in a successful product imitation coefficient should be bigger than innovation one.

characteristic that has a given distribution $f(x_i)$ across the population. Difference in x_i correspond to difference in the perceived profitability of the innovation. Each individual chooses to adopt it if x_i exceed some threshold level x^*. That is:

x_i ‡~~>=~~x^*.

The diffusion is then the result of the interplay between two factors: the distribution of x across the population and the reduction of x* over time. It can be demonstrated that an S-shaped curve can be obtained assuming that $f(x_i)$ is normal and x^* falls at a costant rate. Typically x correspond to firm s size as in the models proposed ~~that~~ by David (1969) and Davies (1979) that find a positive correlation between firm size and probability of adoption.

3 The model.

Data used in our simulation model have been collected by a large scale field survey that has been addressed to a random sample of 1200 firms via a mail and a web questionnaire. The universe was defined as the list of companies whose purchasing directors are members of a national professional association. The sample is therefore representative of companies that have at least a minimal organisational configuration. Usable responses were 200, with a response rate of almost 17%, which is considered high in mail surveys.

A firm in our simulation model is a particular instantiation of an appropriate class of objects.

Firms can be distinguished in:

1. Firms that already use electronic commerce in B2B transactions, labelled ADOPTERS;
2. Firms that don t use electronic commerce in B2B transactions, labelled NON ADOPTERS.

Firms have social links and exchange information with other members of the collective that already employ the new technology (ADOPTING COMPETITORS) and with other members of the collective that do not employ the new technology (NON ADOPTING COMPETITORS).

The survey allows us to observe the interaction with other agents, that are not member of the collective of competitors, such as suppliers, consultant firms and E-commerce experts.

However, these data are not used in the present model for reasons of simplicity. It will be possible to introduce these agents in further versions of the model.

For the technical requirements of the simulation ~~these~~ special agents, called "secondary agents", are introduced in the model only for reasons of:

- Input Output data management
- Asynchronous time management
- Agents array management

More technical information about these ones can be found in the code appendix (Appendix one).

Consultant firms and experts, in fact, have the function of spreading information about the new technology so they are quite similar to the *"diffusor subject"* studied by Oliver e Marwell in collective action problem[7] and by Witt[8] in diffusion phenomena[9].

3.1 The primary agents

Although data about 200 firms are available in the sample, we consider for the simulation the sub-sample of 100 respondents that answered to *all* questions in the research instrument that are relevant to the calibration of the model[10]:.

At the beginning of the simulation, therefore, we have:

1. a group of 92 *NON ADOPTING COMPETITORS*
2. a group of 8 *ADOPTING COMPETITORS.*

In the simulation we consider 100 agents and draw the data for the calibration of the vector of variables from observed data. In future versions we could use any number of agents, fixing the proportion of adopters and non-adopters in order to compare runs with the same initial condition.

[7] Marwell G., Oliver P. (1993).
[8] Witt U. (1997).
[9] For technical requirements of the simulation there are other special agents that are called support agents : more information about these ones can be found in Appendix one.
[10] In the simulation where are *tot* variables, we have eliminate firms that do not answer to *tot* questions

Each agent is characterised by two sets of state variables that are classified as *structural* or *social*, respectively. Structural variables deal with intrinsic characteristics of the agents while social variables regard relationships with other group members.

We can think to the agents characteristics as an array X:

$$X = [y_1, \ldots, y_n, z_1, \ldots, z_m]$$

where $\cancel{y_i, i \in [1,..,n]}$ y_i, i=1, ,n, are the structural variables and z_j, j=1, , m, $\cancel{z_j, j \in [1,..,m]}$ are the social variables. We can think at X as:

$$X = [Y, Z]$$

where Y is the structural variables array and Z is the social variables array.

$$Y = [y_1, \ldots, y_n]$$

$$Z = [z_1, \ldots, z_m]$$

3.2.Structural variables

The structural variables included in the model are ~~as follows~~:

Corporate name (CN). It identifies unambiguously a primary agent in the model.

Agent state (S). It distinguish ADOPTERS from NOT ADOPTERS. It is a binary variable assuming value one if the agent adopts e-selling and value zero otherwise.

Expectation variables:

These variables describe:

- the expected variation of the price of the software for managing e-commerce (Price Expectations, PE);

- the expected percentage of competitors that will sell their products using e-commerce within a year (EX_NCOM),.
- the expected percentage of existing customers that will buy using Internet within a year (EX_NCUS),
- the expected future improvements of the security in Internet transaction (SE)11.

3.3.Social variables

These variables deal with contacts that agents have with competitors who have to choose about the adoption of the new technology and with customers who can give useful information. So we have:

- Contacts with ADOPTING COMPETITORS (CON_ACOM). These are social relationships with agents that already employ the new technology.
- Contacts with NON ADOPTING COMPETITORS (CON_NACOM) This variable is about social relationships with agents that do not employ the new technology.
- Contacts with CUSTOMER (CON_CUS) This variable is about social relationships with agents that use the Internet for procurement.

The questionnaire considers social links activated by each agent in a year period: the previous one for NON ADOPTERS and the year before adoption for ADOPTERS. This difference is justified by the need to keep the right temporal structure of the decision process.

For every kind of contact, we have collected data about:

- *Number of contacts*: this variable gives us the total number of other agents whom each agent has spoken to in the time unity.
- *Frequency*: it gives us the number of times that each agent has activated his social links.

The product between *Number* and *Frequency* gives the agent s total contacts.

[11] Further information about these variables can be found in Appendix II

- *Reliability:* it gives us an appraisal of the judgement given by each agent about the information he has obtained through social links. It can be considered a proxy of the weight that an agent gives to this information in updating his state variables.

3.4 Customers

The questionnaire permits to obtain, for each firm, data about:

- *Total number of customers* (national and foreign customers), labelled T_CUS;
- *Percentage of customers using e-commerce* for the purchasing, labelled PER_CUS.

The latter variable is very important. In fact it is possible to consider the percentage of adopting customers like a state variable of the individual. When a contact happens, the agent uses this variable for deciding if this contact is with an adopting customer or with a non adopting one.

The mechanism may be the following:

1. A number between 0 and 1 is extracted from an uniform distribution
2. This number is compared to the percentage of customers using e-purchasing. If the value of the random number is less or equal than the percentage of adopting customers, then the contacted customer uses e-commerce for the purchasing, otherwise he is considered a non adopter

We can use PER_CUS in another way: if PER_CUS_i is the percentage of adopters and (1- PER_CUS_i) is the percentage of adopters for agent *i*, his contact with a customer will be with an adopting one with probability PER_CUS_i and a non adopting one with probability (1- PER_CUS_i).

The problem with this methodology is given by missing data: several firms did not answer to the question about percentage of customer employing e-commerce. Like for other variables, in this case we will replace missing data with the mean of adopting and non adopting firms.

4 The interaction mechanism

In a generic iteration of the simulation the following events happen:

1. Extraction of an agent who is woken up and has a contact [12]. The probability that a given individual is extracted is proportional to the average number of contacts he has with competitors and customers, whose data are given by the questionnaire. Therefore the probability of taking an active part in iteration varies among agents, depending on social characteristics of the agents and explicitly reflecting social heterogeneity. In other words, if an agent activates (on average) many social links then the intervals after which he will participate again in a new iteration will be shorter than for individuals with few contacts (exponential distribution).
2. Collection of the ~~time~~ system s time (time of simulation) which is contained in an appropriate variable[13].
3. Verification of the type of contact (with a competitor or with a customer) .
4. Activation of the contact and modification of the agent s state variables. This happens in a different way for contacts with a competitor or a customer.
5. Valuation of the adoption function of the agent, who ~~can~~ may change his state (becoming an adopter if he is a non adopter and vice versa)
6. Calculations of the time for next contact of the same type of the one just activated.
7. Insertion of the Agent in a waiting list for another contact[14]

4.1 Effects of contacts with competitors

In a pure epidemiological model with word of mouth [15] there is a direct contagion mechanism: when a NON ADOPTER meets an ADOPTER his state changes instantaneously and he becomes an ADOPTER too, perhaps with a given probability. This

[12] See Appendix I for a more detailed explanation.
[13] See Appendix I for a more detailed explanation.
[14] Appendix I for more detailed explanations.
[15] For instance: Martilla J.A (1971).; Tapiero C. S. (1983); Ellison G., Fudenberg D.(1995).

is quite unrealistic. In fact it is unlikely that a firm decides to use e-commerce just because its chief executive meets the chief executive of another firm using e-commerce, although in probability. We try to model a more complex scenario. When an agent activates a link with a non adopting or with an adopting competitor, a flow of information passes from one subject to the other. These information are about their structural variables. In particular there is no immediate change of agent s state (S), but the modification involves other variables:

PE, EX_NCOM, EX_NCUS, SE.

The updating of variables takes place only for agents who *have* contacted and not for agents who *have been* contacted. We assume that the agent activating the contact is looking for useful information in order to change his thinking about the characteristics of the new technology.

4.2 Updating rules in contacts with competitors

Each agent uses information obtained by a competitor in order to update his own variables. We can consider various updating rules which are shared by the whole group and we could imagine also a situation in which different rules are distributed among the population: individuals are heterogeneous in the way of solving the same problem [16]. In the first version of the model the hypothesis of homogeneity is accepted and we assume that all agents follow the same rule.

According to this, on one hand we could consider subjects that simply *replace* the values of their state variables with those of the contacted individuals, trusting the received information, while on the other hand there may be subjects that don t modify their state variables after the interaction. An intermediate solution is to assume that every state variable becomes equal to the *average* between a *contacting* agent (before the interaction) and a *contacted* agent. An appropriate formula considers a *weighted average* with weights proportional to the reliability that contacting agents give to received information. For every

[16] Lane and Vescovini (1992).

category of contacts, reliability is collected in the questionnaire by asking the firms whether they consider the information received from that category: Not reliable, Enough reliable, Very reliable~~, respectively~~.

For using the variable on reliability, we perform the following steps. First of all reliability is numerically converted according to this scale

- Not reliable=1
- Enough reliable=2
- Very realiable=3

Then we calculate means and variance for adopting and non adopting competitors. This permits the substitution of missing data. In particular missing data for non adopting are substituted with mean of non adopting and the same for adopting.

After all values are normalized on a 0-1 scale, that is:

1 becomes 1/3

2 becomes 2/3

3 becomes 1

M becomes *M*/3

Var becomes *Var*/2

When a contact takes place the agent who contacts is classified according the three categories:

- adopting competitors
- non adopting competitors
- customers

In each case the individual attribute reliability to the contact according to a normal distribution with mean *M* (*M/3*) and variance ~~*var*~~ *Var* (~~*var*~~*Var*/2). Obviously other conversions are possible. The entire procedure looks a bit complicated, but is necessary in order to take into account differences in reliability of information that may induce different effects on updating of agent's variables. Weights are obtained by standardisation to 1.

Let us consider the updating mechanism applied to the interaction between a NOT ADOPTING firm *i (contacting agent)*, which consider links with adopting competitors enough reliable , and an ADOPTING firm j *(contacted agent)*.

For the i-th agent we have:

$$CN = i$$
$$S = 0$$
$$PE = a_i$$
$$EX\_NCOM = b_i$$
$$EX\_NCUS = c_i$$
$$SE = d_i$$

Similarly for j:

$$CN = j$$
$$S = 1$$
$$PE = a_j$$
$$EX\_NCOM = b_j$$
$$EX\_NCUS = c_j$$
$$SE = d_j$$

After the contact the profile of the agent *i* becomes:

$$CN = i$$
$$S = 0$$
$$i \quad \begin{array}{c} PE = p_i \; ?a_j + (1 - p_i)\; ?a_i \\ EX\_NCOM = p_i \; ?b_j + (1 - p_i)\; ?b_i \\ EX\_NCUS = p_i \; ?c_j + (1 - p_i)\; ?c_i \end{array} \quad ?$$
$$SE = d_i$$

where p_i is the reliability parameter for the category of adopting competitors held by agent i.

Only the~~agent *i* s~~ variables of agent *i* have been changed because *i* agent is activating his social link and is looking for information about new technology. The contacted agent does not change his mind. In further versions of the model we could consider a balanced updating situation.

4.3 Updating rule in contacts with customers

When a contact with a customer happens there is no modification in contacting agent s structural variables. The only effect of this kind of social link is the introduction of a *service variable*, labelled SCUS, in the agent profile. If the contacted customer is an adopter we have

$$SCUS=1$$

while if he is a non adopter:

$$SCUS=0$$

This happens because customers do not have to choose about e-selling and therefore do not have expectations about this technology that can communicate during the interaction. The only relevant information they can offer deals with their utilisation of Internet for purchasing. With reference to our previous example, if *i* comes into contact with a customer who makes e-procurement, its array of state variables becomes:

$$\begin{gathered} CN = i \\ S = 0 \\ PE = a_i \\ EX\_NCOM = b_i \\ EX\_NCUS = c_i \\ SE = d_i \\ SCUS = 1 \end{gathered}$$

It is important to observe that in this case SCUS will have the same weight of SCOM in the decision of adoption. If we want to avoid this (because we think that adoption by a customer is less relevant than adoption by a competitor) we can take into account at least

the results of three other contacts with customers that our agent has had in previous steps of the simulation. So it isn t relevant only the last single customer s contribution.
According to this second solution every agent has memory of the state of the last three contacted customers. These data are collected in suitable state variables.
Now it is possible to apply an exponential smoothing mechanism which attributes higher weights to more recent contacts.

4.4 Zero contact agents

Some firms that answered the questionnaire (especially non-adopters) indicated that they didn t look for information about e-commerce. They declared to have no contacts with other subjects in the competitive system. Transposing this in our simulation model, we observe that these firms don t take part in the interaction mechanism. They can change their state (for instance becoming adopters) only because of network externality effect.
We can accept this and consider these firms as latecomers [17] or explore other possible solutions. For instance we can suppose that then an agent has a contact, before updating his variables checks if his partner is a zero contact subject. If this is true also contacted agent s variables are updated according the above described rules. In this case we would have another problem: people with zero contacts didn t indicate reliability so we can t determine the weights. We can solve this problem modelling for these agents a high resistance to opinion change by using very low weights, for instance 0,1.
Another possibility consists in assuming that firms who maintained not to collect information about e-commerce really had very few contacts. We could choose a very low contact probability for these individuals.

5. The adoption function

[17] Roger (1983)

Each agent weights up the opportunity of changing his attitude about e-selling according to a decisional rule or *adoption function*, which is evaluated after having had a contact with competitors or customers.

We assume that this function is the same for all agents. Clearly this restricting hypothesis can be removed, like the assumption on homogeneity of updating rules, in order to study the impact on diffusion of further sources of heterogeneity.

The adoption function allows the agent to modify the value of his state variable S, so for its co-dominion there are two possible solutions.

It may be the set

$$\{ 0,1 \}$$

if $F=1$ the agent changes his state, if $F=0$ the agent does not modify his situation.

This methodology is difficult to follow because the definition of such a function is quite complex; moreover in this way we give no importance to the presence of ~~histeresis~~ hysteresis in the system[18]: since the probability (PRS) of state change is equal for non-adopting and adopting agents:

$$PRS = Pr(F=1)$$

This is quite unrealistic: a firm, which has chosen to adopt the new technology, has sustained the corresponding costs for its implementation (think to the construction of the e-selling web site). So the probability for such a firm to return back to the initial position is lower: it will switch back only after a careful evaluation of the disadvantages caused by Internet trading.

For overcoming these limitations we can imagine that co-dominion is the interval

$$[0,1]$$

This is equivalent to F as the probability that a change in state occurs.

In order to capture ~~histeresis~~ hysteresis effect we assume that:

- when S=0 the Agent changes his state (S becomes equal to one) if F > 0,5
- when S=1 the Agent changes his state (S becomes equal to zero) if F < 0,2

The dominion of the adoption function is formed by two parts:

- the result of the evaluation of the structural variables (indicated by *R*)

- the network externality effect (indicated by *NE*)

These two elements can have different or equal weight in agents decision. As a first version of the model we assume equal importance obtaining:

$$F = \frac{1}{2} ?R + \frac{1}{2} ?NE$$

Let us now define *R* and *NE*.

5.1 Evaluation of structural variables

Social contacts modify agent s profile according to the kind of social link that has been activated. After each contact with a competitor the agent evaluates if his state and the services variables satisfy some given conditions and then applies a *majority criterion*. Roughly speaking, the agent checks if state variables are above or below a certain threshold. However, data indicate that adopting firms expectations about price and security are more moderate then the non adopters ones. For an explanation of this effect we can make reference to Rosenberg[19]. According to him, expected technology improvements slow down the diffusion process, so this negative correlation between state of adoption and expectations on performance can be explained. It can be also clarified invoking better knowledge of the new technology by adopters. In particular, the main differences regard expectation about data security and integrity and they are statistical different from zero[20]. We can argue that probably e-sellers explored these solutions, had not problems to find the satisfactory solution and so do not expect further improvements in the field of security. Therefore for PE and SE we don t define a threshold by a tolerance range. Let us consider this array where each element is the threshold or the interval for the corresponding state variable:

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[18] Hardin R. (1971)
[19] Rosenberg N. (1976)
[20] Bonaccorsi A., Rossi C. (2001)

$$TRI_i = \begin{matrix} I_{PE} \\ TR_{EX\_NCOM} \\ TR_{EX\_NCUS} \\ I_{SE} \end{matrix}$$

Given these values, the decisional algorithm of the individual is the following:

If (SCOM=1) he says YES ~~then~~ else he says NO.

If ($PE \in I_{PE}$) he says YES ~~then~~ else he says NO.

If (EX_NCOM> TR_{EX_NCOM}) he says YES ~~then~~ else he says NO.

If (EX_NCUS> TR_{EX_NCUS}) he says YES ~~then~~ else he says NO.

If ($SE \in I_{SE}$) he says YES ~~then~~ else he says NO.

If number of YES is greater then number of NO (#YES>#NO) then he puts R=1 ~~then~~ else he punts R=0[21]

If at least three of the five variables satisfy the requirement, R assumes value 1.

There is now the problem of choosing thresholds and intervals.

For the two thresholds there are not much problems, since they are obtained directly from the questionnaire[22]. For EX_NCOM, EX_ NCUS there is heterogeneity in thresholds, since each firm has its idiosincratic value.

The question is a little more complex for PE and SE: we have to define arbitrarily a appropriate interval for these variables. A possible solution is using adopters average as its central value (M_PE_A=? and M_PE_S=?) and then deciding upon interval s width. We can define a fix width, so that all agents have the same interval.

If we want to avoid this we can assign to each subject a different width simply extracting it from normal distributions with means M_PE_A and M_SE_A (respectively) and variance equal to variables variance.

[21] Another possible solution is abandoning the majority criterion and assuming that R is equal to number of YES divided by number of considered variables. That is R=#YES/5. In such way we have: $R \in (0,1)$. It is one if YES=5 and it is zero is YES=0.

[22] In the questionnaire there are two questions about percentage of competitors and percentage of customers who have to adopt in order to induce firm to use e-commerce. See Appendix II for further information.

In the definition of the R variable the aim is to permit that agents have memories of the past contacts.

In order to do this R is the result of an exponential smoothing weighted on time.

We take trace of the past values of R, using an appropriate data structure, while allowing the memory going to zero if the weight falls under a given threshold.

5.2 Network externality effect

Besides the evaluation of the structural variables, we insert in the adoption function network externality effects, *NE*. Because of this phenomenon the benefits of new technology adoption increase with the number of other agents that already employ it. .Most authors assume that this grow happens at a decreasing rate. So we consider that:

$$NE'(n) > 0 \quad NE''(n) < 0$$

Since F must be defined between 0 and 1, a typical function that satisfies the previous conditions is the following:

$$\sqrt{\frac{n_A(t)}{N}}$$

where $n_A(t)$ is the number of agents using the e-commerce at the time t.

In brief the adoption function is the following:

$$F = \frac{1}{2} ?R + \frac{1}{2} ?\sqrt{\frac{n_A(t)}{N}}$$

6. The epidemiological model as a benchmark

We develop a benchmark epidemiological model to have a comparison with our model. It is based on the following assumptions:

Homogeneity of the agents: We simply ignore the characteristics of individual agents.
Non perfect information: The agents receive information when thy are contacted by an adopter agent. The agents reached by information on the technology adopt with a given probability.
Word of mouth: Potential users adopt the new technology, when they hear about it. We let the technology diffusion to depend only on the information that agents receive about it.

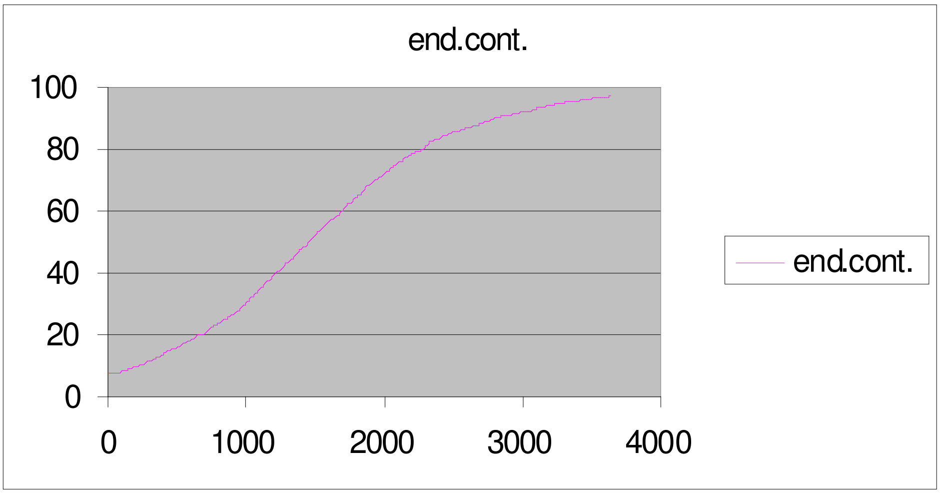
The diffusion source is represented by adopters who meet non adopters with probability $\alpha(t_i)$ with $\alpha(t_i) = \frac{y(t_{i-1})}{N}$ where N is the number of the agents and $y(t_{i-1})$ is the number of adopters at the previous time step t_i-1. Initially it is $y(0) = 8$.
When an adopter meets a non adopter the last one will convert to the new technology with a probability $beta = \frac{1}{10}$. This parameter can be changed in future versions. With respect to the epidemic models discussed in section 1 of this paper, β here depends on time. It will be:

$$\beta(t_i) = \alpha(t_i) ?beta$$

Therefore we will have:

$$\Delta y(t) = \beta(t) y(t) ?[N - y(t)]?\Delta t$$

The diffusion curve has an S-shape as shown in figure. It is the result of a simulation obtained with our software.



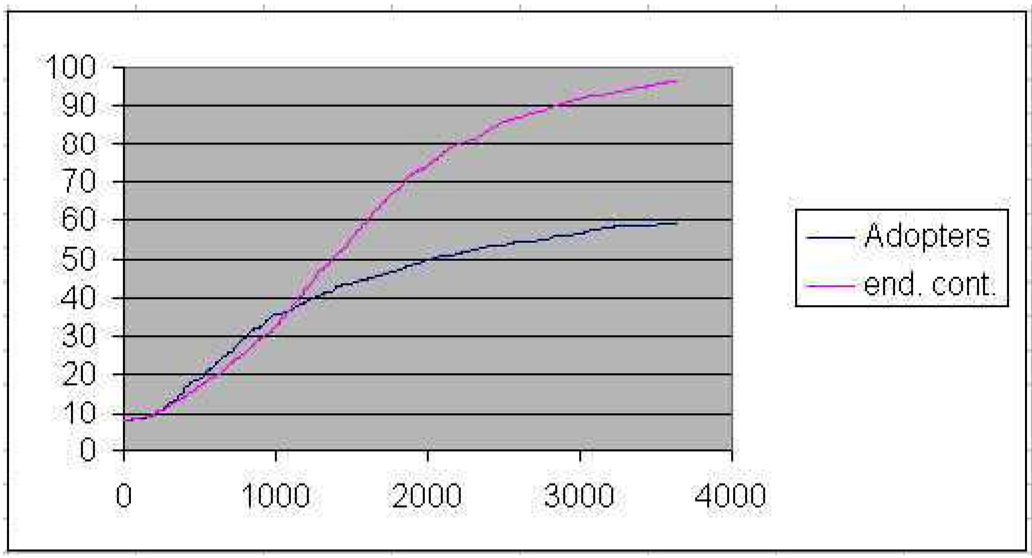
7.Main results

As shown in table 7.1 we classified our simulation in 7 groups. The A group consider all the parameters as active. The B group doesn't take care of the performances of the technology. The C group doesn't take care of the diffusion. The D group does not take care of the network externality. The E F and G groups consider respectively network externality, diffusion and performances. The Alfa parameter has been set to 0.25 0.5 0.75 in the A B and C groups. Alfa is zero when only network externality occurs and one when it is not considered.

	A			B			C			D	E	F	G
Alfa	0.25	0.5	0.75	0.25	0.5	0.75	0.25	0.5	0.75				
Performances (Pe & Se)	X	X	X	-	-		X	X	X	X	-	-	X
Diffusion (ConNum & CliNum)	X	X	X	X	X	X	-	-	-	X	-	X	-
Network externality	X	X	X	X	X	X	X	X	X	-	X	-	-
										Alfa = 1	Alfa = 0	Alfa = 1	Alfa = 1

Table 7.1

We ran 10 simulations for each sub-group in the table and then , using the output files obtained from AS we calculated the average.



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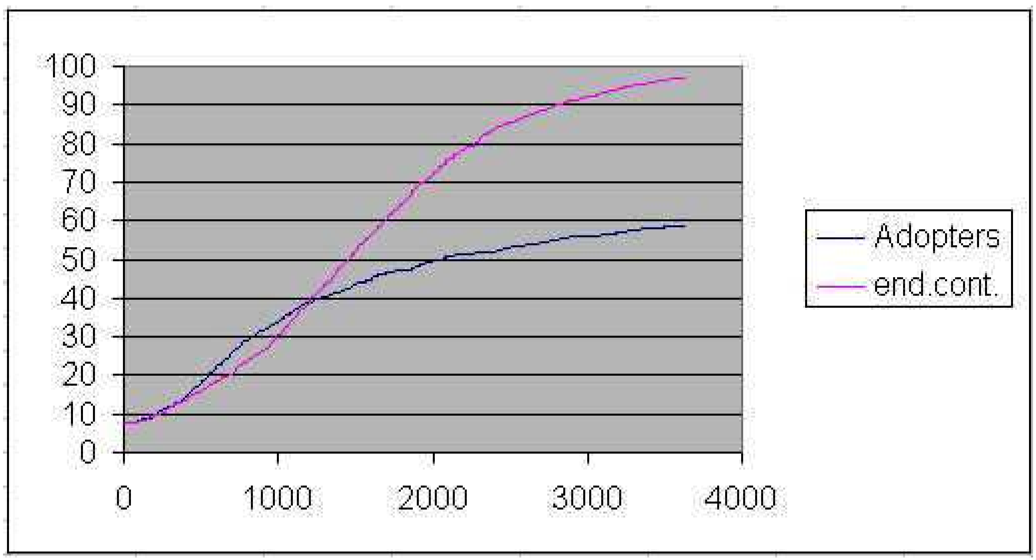

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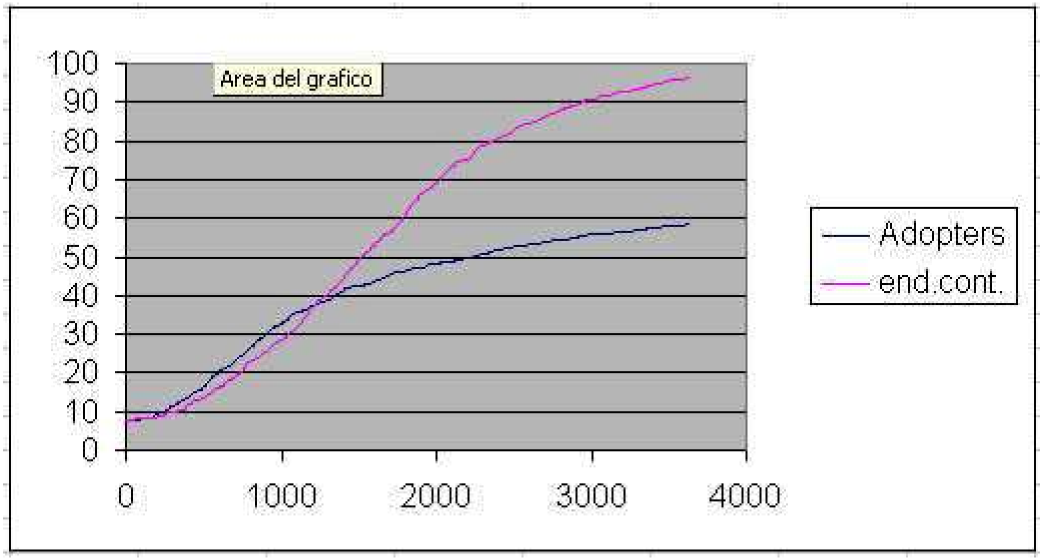
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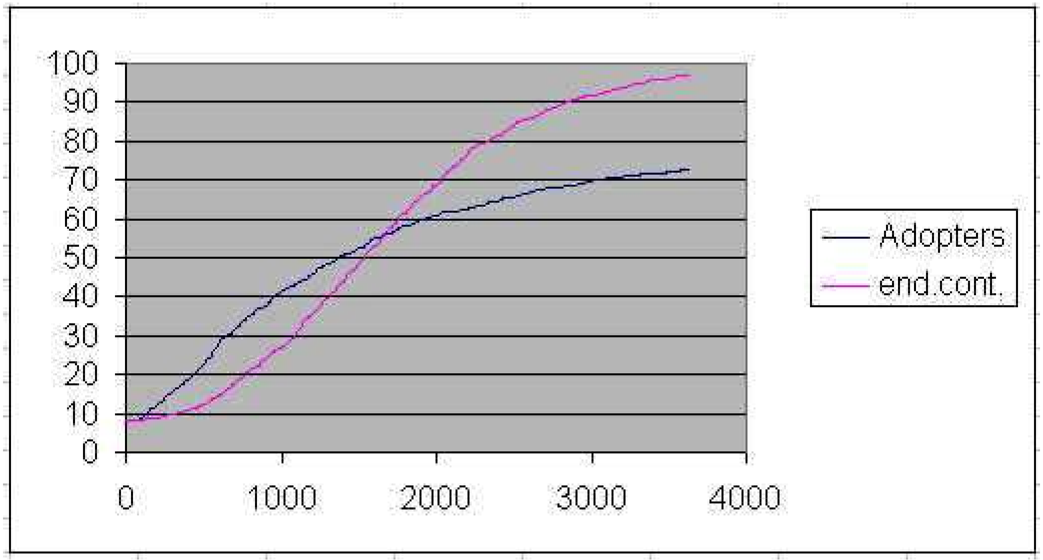
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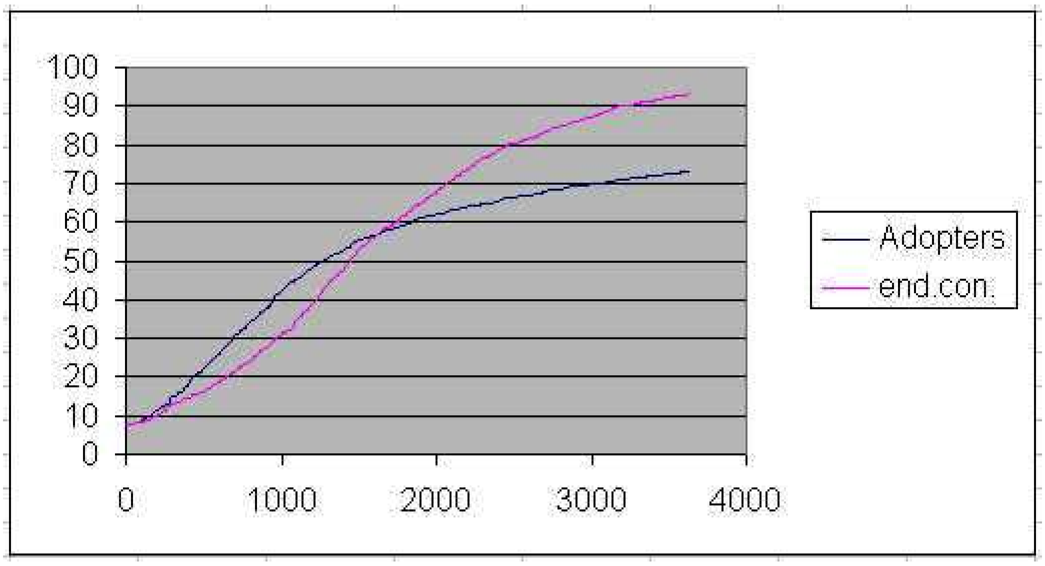
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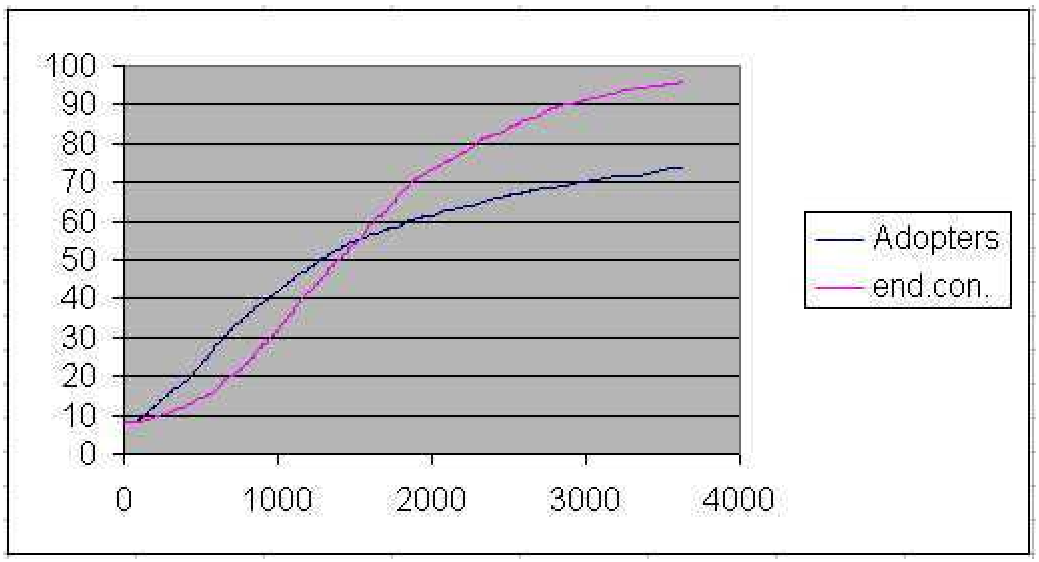
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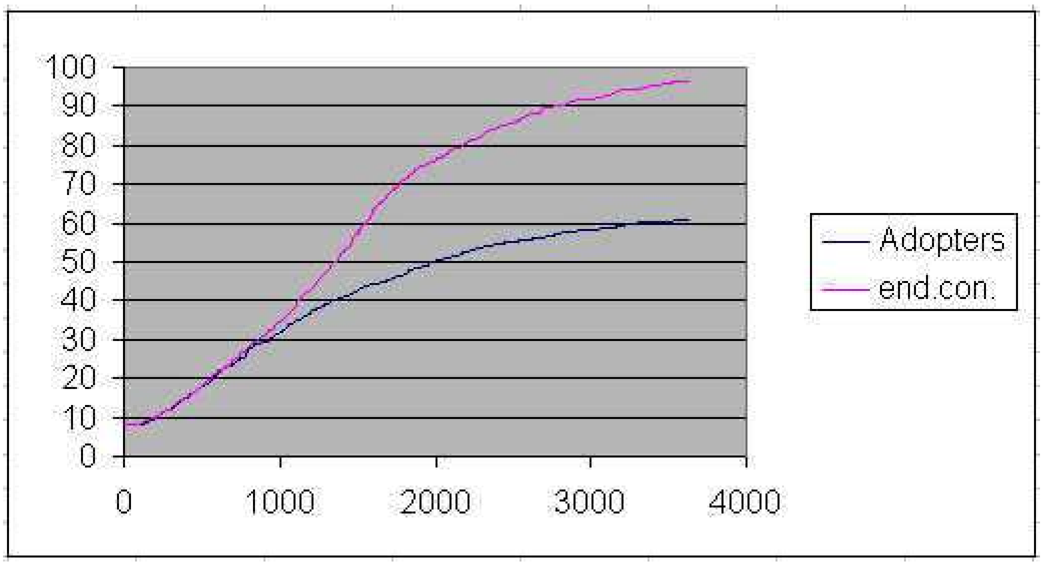
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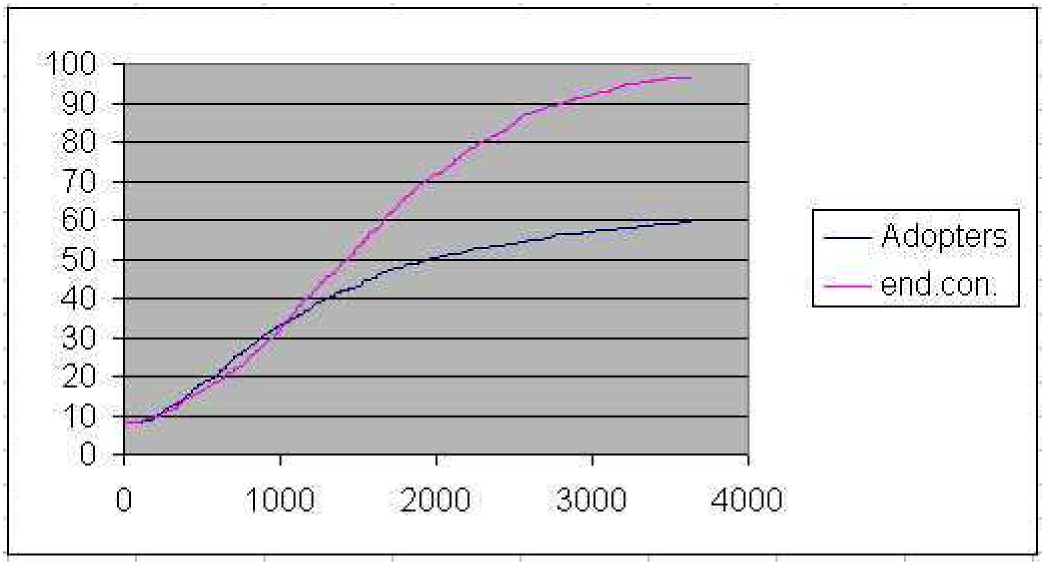
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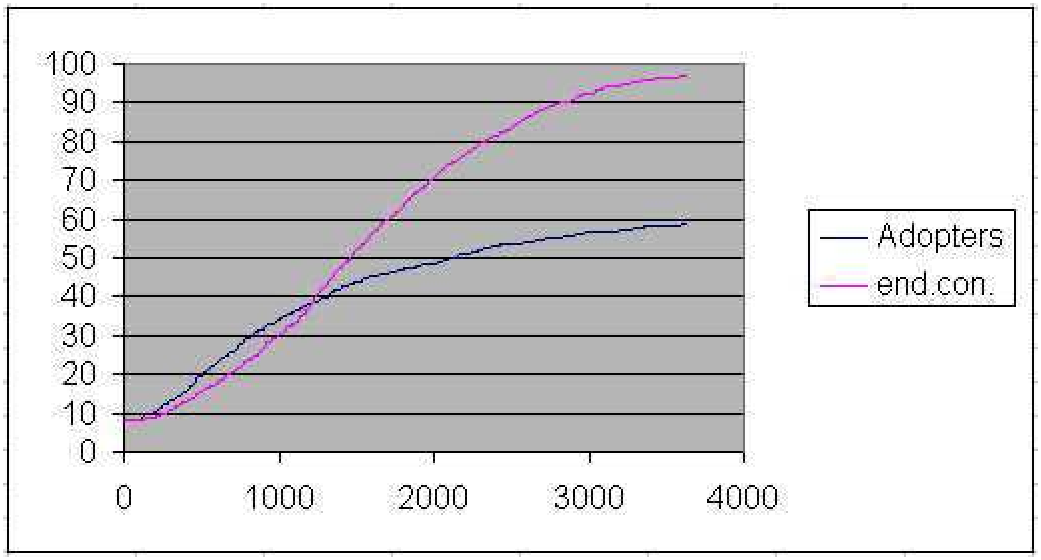

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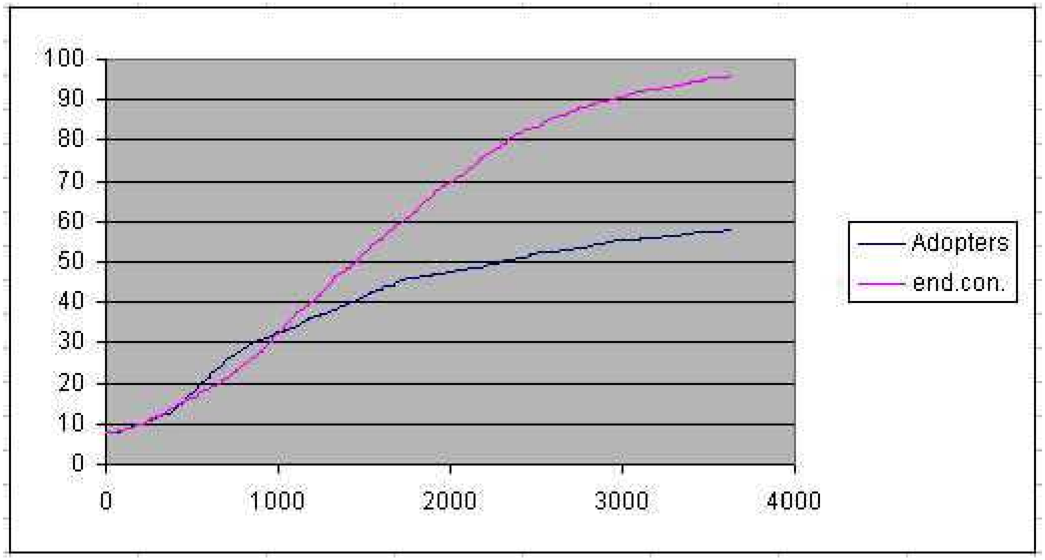

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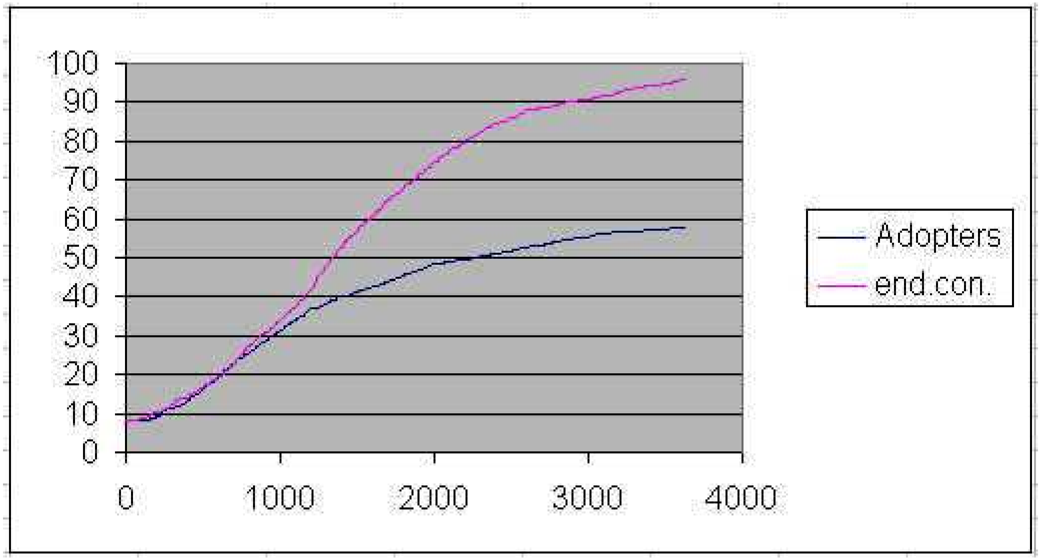
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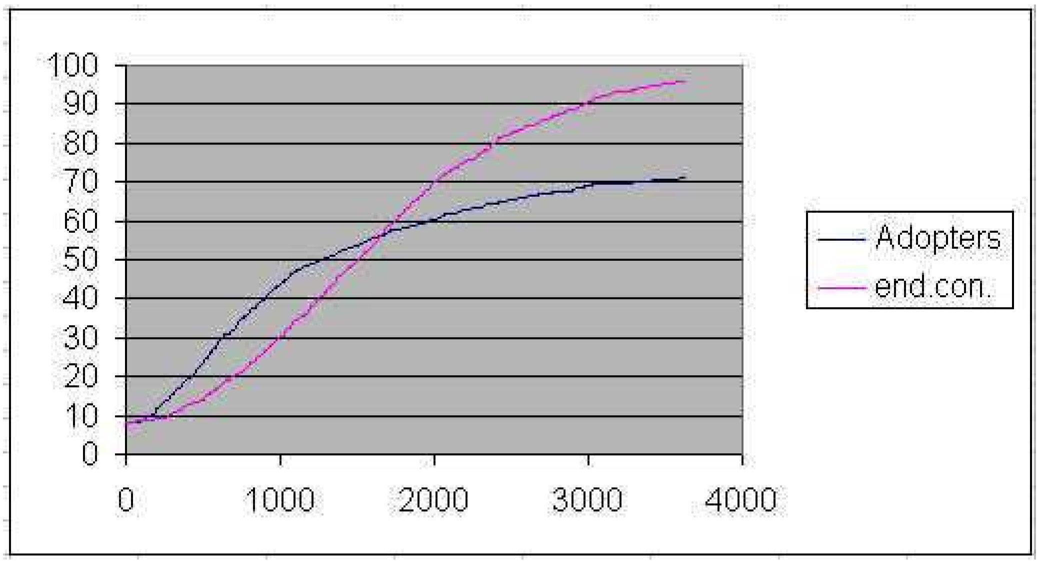
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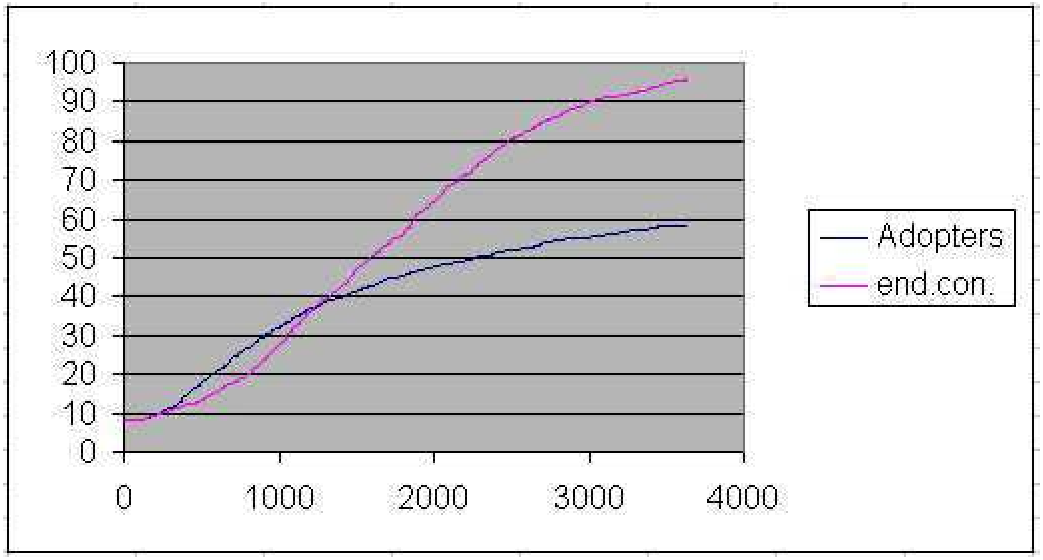

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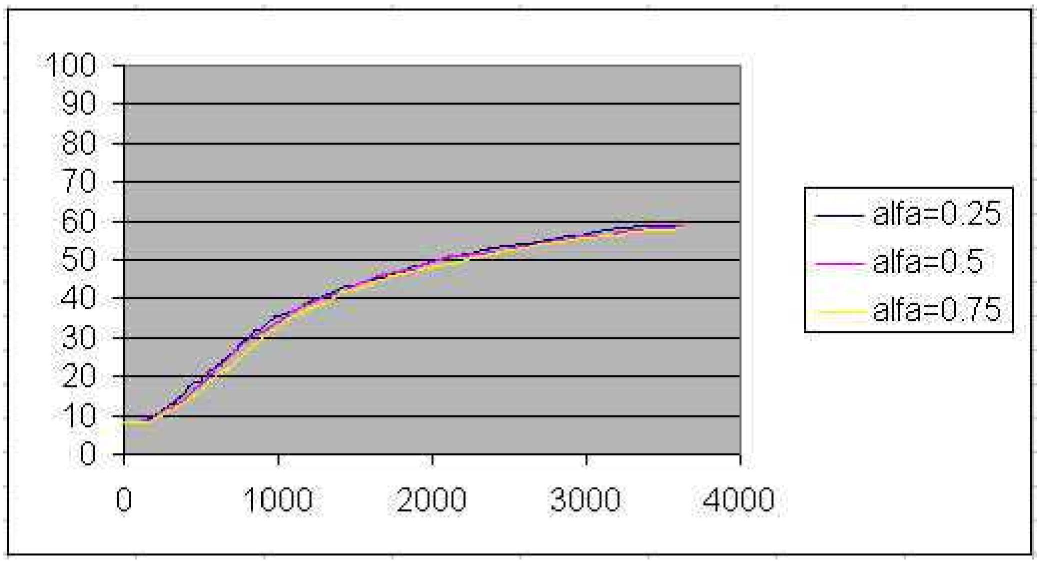

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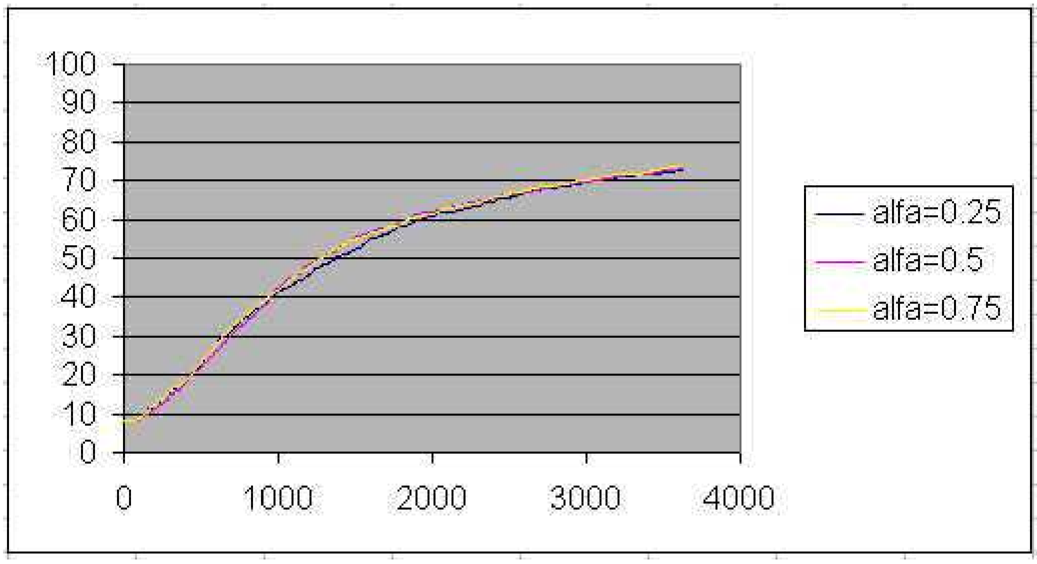

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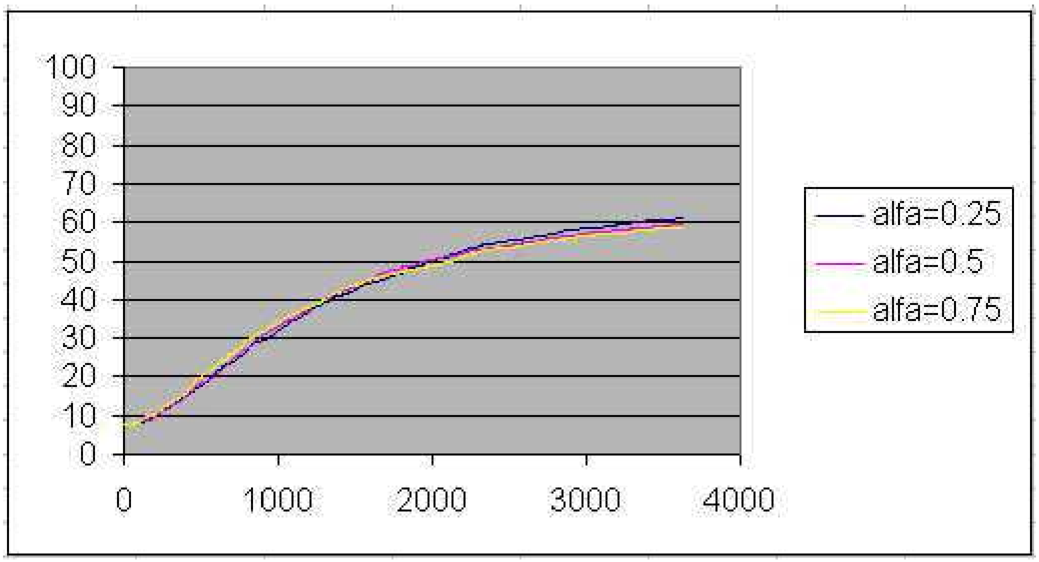

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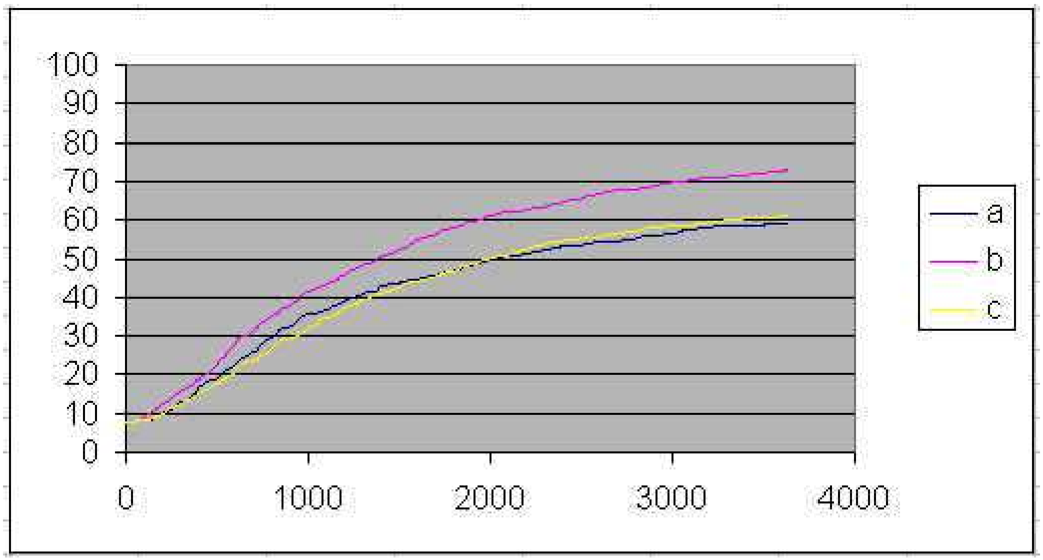

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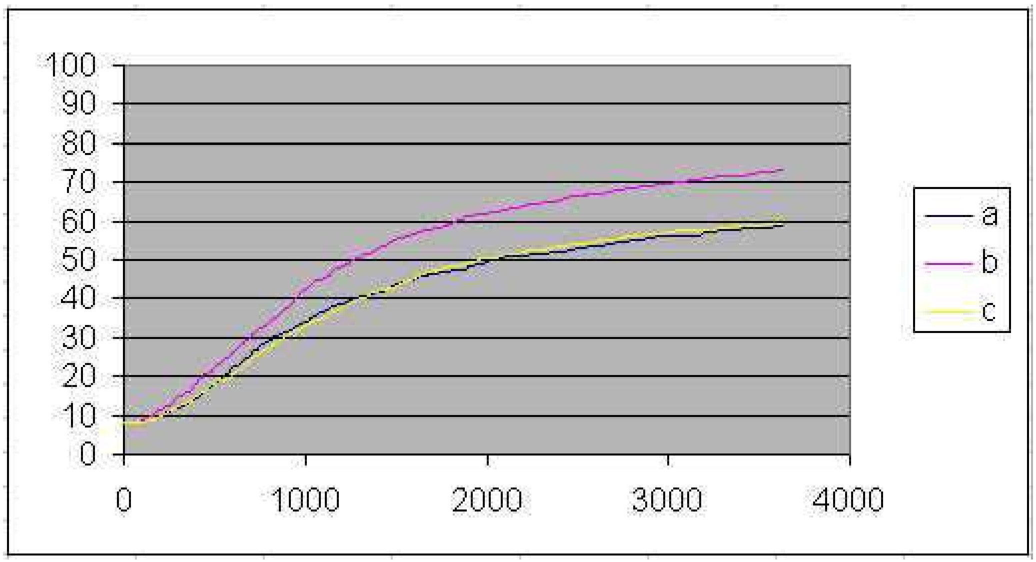

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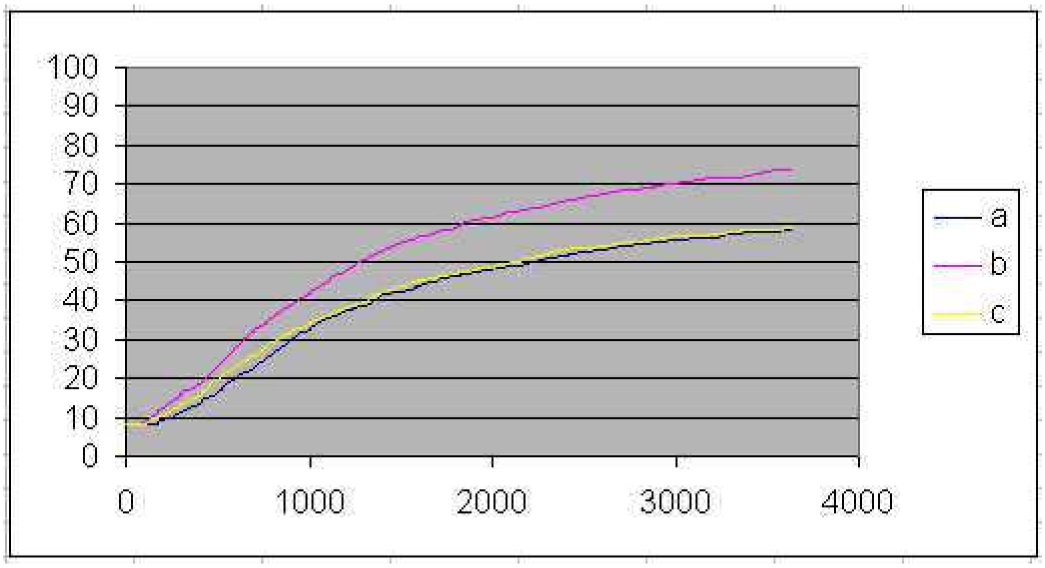

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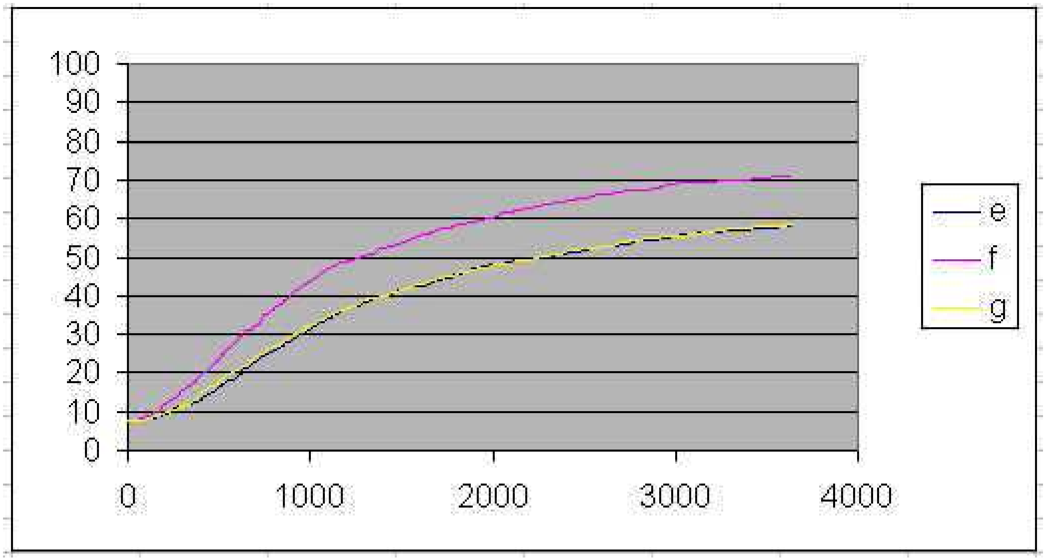

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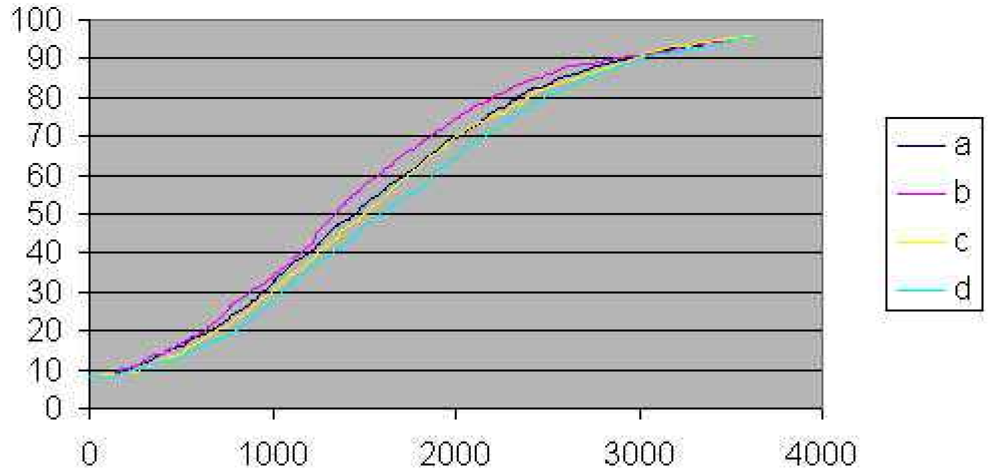
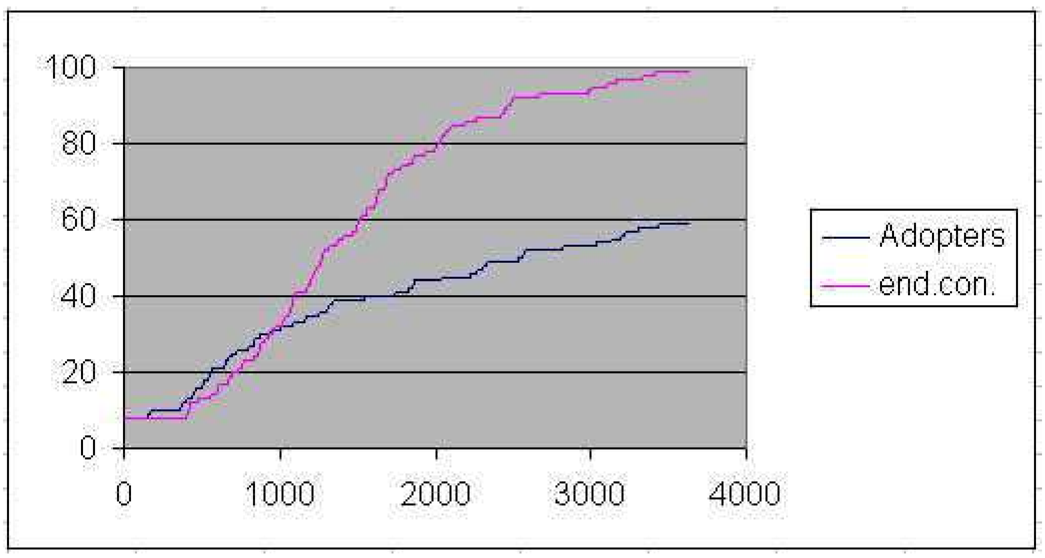


endemic curves



a025 simple simulation example

In all the simulations the theoretic curve, the one obtained with endemic contagion, has the typical S shape. This is a comforting result and the S shape has been used as benchmark with all results obtained from our model.
One common thing to all the curves resulting from the base of our model is that *saturation is never reached*. There is always a group of subjects (between the 20% and the 40%) which don't adopt b2b e-commerce technology. This is an important result, which is innovative with respect to existing literature on diffusion.
In addition to this the curves obtained from the basic simulation model (the one which considers both the expectation the diffusion and the performances of the technology) *don't show the classical S shape* but they grow faster then the S shaped curve in the beginning. This is due to the heterogeneity effect, since the initial group is formed by optimistic agents with a strong social activity. After this the diffusion phenomena is heavily slower and the S shaped curve runs quickly to saturation. This is a further remarkable result, which goes directly against much literature on diffusion based on assumptions of homogeneity. This also confirms the prediction of the model proposed by Manfredi and Bonaccorsi (2000).
A purely qualitative observation of the shapes show that the diffusion expectations on the technology (like the ones on the number of customers and competitors who will adopt e-commerce) if considered alone let the diffusion process to grow quick while the expectations on the performances of the technology (the price expectation and the expectation on the reliability of the net) make the diffusion process to grow slower. Considering both the effects (diffusion and performances expectations) together we observe *the effect of the expectation on the performances prevails*, especially regarding the saturation. This is a third interesting result.
The shapes obtained from the model using only network externality is similar to the shapes obtained when externality effect is not present and there are not expectations on customers and competitors. This fact seem to explain the reason why the shapes don't change much when we change the alfa parameter value.

An useful progress could be the study of the characteristics of the agents which usually don't adopt. The model we have been working to is still preliminary and will be modified in further extensions.