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STRATEGIES FOR THE DIFFUSION OF SUSTAINABLE AGRICULTURAL INNOVATION: AN AGENT BASED MODEL FOR THE HORTICULTURAL SECTOR IN PROVINCE OF FOGGIA

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CHAPTER 1

INTRODUCTION

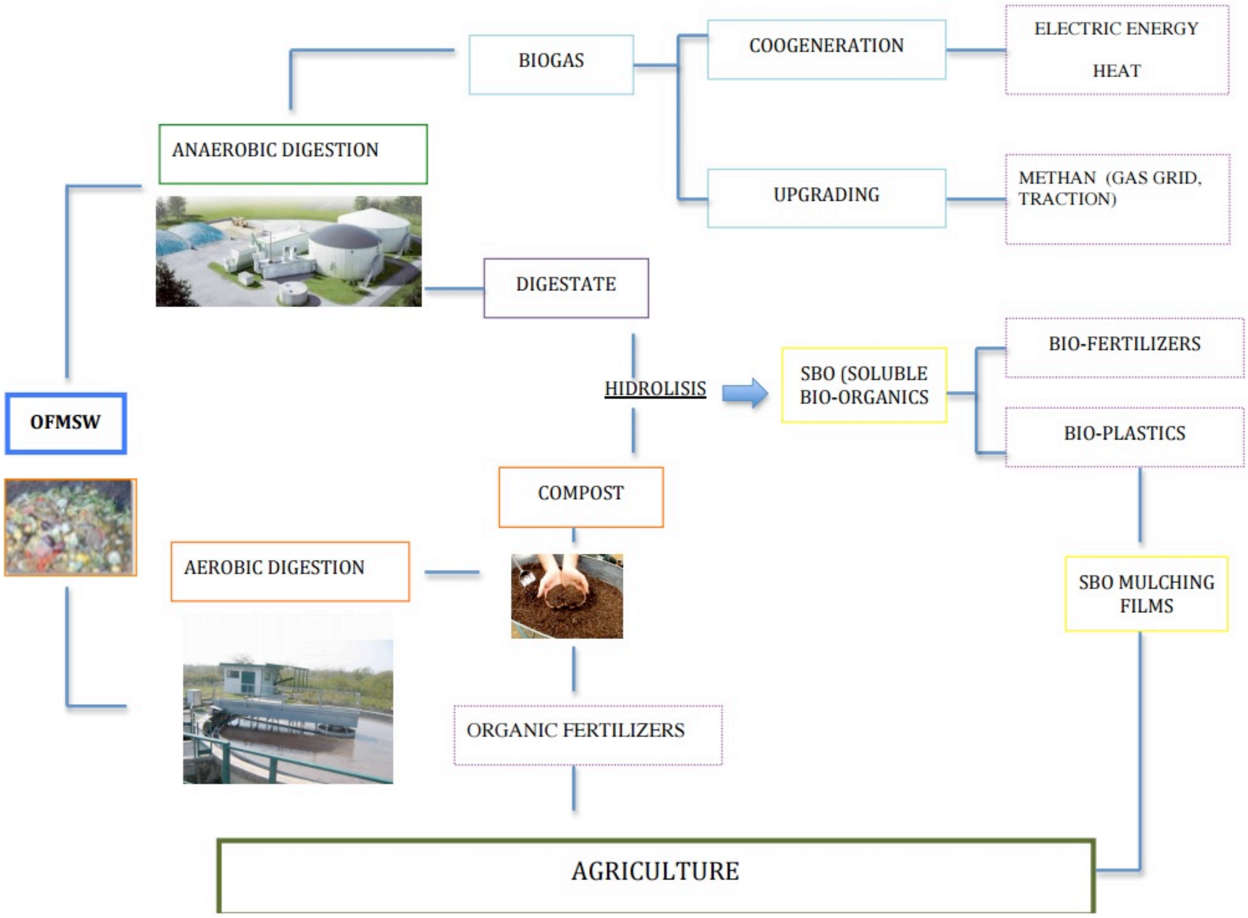
1. Introduction

1.1 Introduction

In the last years the volume of bio-waste has quickly been increasing, therefore the issue of bio-waste valorization has captured the attention of governments, environmental and social organizations, businesses and academics, becoming an increasingly urgent priority. The Organic Fraction of Municipal Solid Wastes (OFMSW) is humid, therefore the decomposition in the landfill generates leaching and fermentation phenomena and production of bad odors. In particular, the leachate from landfills where biodegradable waste is conferred, if not properly managed, can be a source of heavy contamination of groundwater and water bodies. In addition, the methane produced within the body of the landfill, released into the atmosphere, has a climate-changing effect because, as the carbon dioxide absorbs infrared radiation emitted from the "hot" surface of the Planet. There is an abundant literature targeting various aspects associated with bio-waste valorization, like the improvement of bio-waste management, the conversion of bio-waste to synthetic fuels (Dermibas *et al.,*2011); the issue of bio-waste biorefinery (Fava *et al.,* 2015); different valorization pathways (Mirabella *et al.,* 2014 and Galanakis, 2012). Moreover, the ongoing researches are moving on the usability of the organic fraction of municipal waste to produce biodegradable materials. Research carried out at the University of Torino over the last 7 years for instance, has shown that urban and agriculture wastes are source of soluble bio-based substances (SBOs) that can be used for several applications in the fields of chemical and environmental technology, material chemistry, biofuels production, agriculture and animal husbandry (Montoneri et al., 2011). The SBO were studied for their performances in detergent formulations, textile auxiliaries, fuels, plastic, photo-sensitizers, emulsifiers, forming agents, animal husbandry, nanostructured materials. Whereas they were found effective in all cases, the most promising performances were shown in agriculture, in animal husbandry, as modulators of anaerobic fermentation processes, and as reagents for the synthesis biodegradable plastics, that can be used for the production for example of mulching films. The bio plastics (Cioica et al.2008, Pei et al.2011) currently available in the market, or already in the experimental phase, are based on the content of biopolymers isolated from dedicated crop or obtained by fermentation. Most commercial products are blended materials containing synthetic polymers derived from fossil source and polymers of natural origin, the former contributing the mechanical properties and the latter the biodegradability. So far no biodegradable plastics made with bio-based chemicals isolated from bio-wastes are known. So from this point of view SBO represent an additional opportunity for OFMSW management.

Moreover In the agricultural industry, the biodegradable mulching films containing SBO, represents a way to improve the agricultural sustainability[1] (see Figure 3.1).

Figure 3.1 SBO mulching films: an opportunity for OFMSW management and a way to improve agricultural sustainability



Source: my elaboration

As you can see from figure 3.1 the SBO are additional matherials that can be obtained from the OFMSW threatment through aerobic and anaerobic digestion, two processes that are necessary to reduce the environmental impact of OFMSW disposal and to transformate waste

[1] The Food and Agricultural Organisation of the United Nations defines sustainable agriculture as the use of agricultural practices which conserve water and soil and are environmentally non-degrading, technically appropriate, economically viable and socially acceptable.

in useful products for a sustainable agriculture. In particular SBO are obteined from the compost and digestate idrolysis. The first derive from a process accelerated and controlled by the man, predominantly aerobic, that is called composting and leads to the formation of a solid fraction. Compost which is an organic fertilizer that can change and improve the chemical, physical, biological and mechanical properties of the soil with numerous environmental and agronomic benefits. Instead digestate is the result of a process accelerated and controlled by the man, mainly anaerobic, called anaerobic digestion. The digestate is a special waste which is not allowed spreading as such (because of the high salinity and the high concentration of nitrogen), then it can be used as agricultural fertilizer only after being transformed into soil amendment composted by a finishing stage aerobic made in special bio-cells or other systems of composting, mixed with wood chips or other materials used as structuring (straw, vegetable waste, etc.), after reducing the excess water. The compost thus obtained, is defined by the legislative decree 75/2010 as Mixed Composted Soil Conditioner and is able to ensure, in addition to the contribution of humified organic substance a good fertilizing effect too, and an appreciable quantity of magnesium and iron. From the digestate can be produced biogas that can be used for the production of electrical and thermal energy, by means of a cogenerator. A part of the electricity produced can be used for internal purposes; the remaining part can be sold to the grid, and the heat can be used for district heating or to feed the heating of a greenhouse that can be placed in proximity of the biogas plant. The biogas, in addition, can be further purified for the production of bio methane which could be placed in the natural gas grid or used as fuel for automobiles. In fact plastic films for soil mulching used mainly for horticultural cultivation are disposed off through land filling, incineration and recycling while the removal of the plastic is time consuming (about 16h/ha) and, despite the use of machines still requires hand labor. Also because of high transportation cost and landfill tipping fees, farmers consider on-site burning to be economically more favorable (McCraw and Motes, 1991; Kasirajan and Ngouajio, 2012). This common practice produce the release of harmful substances with the associated obviously negative consequences to the environment (Picuno et al.,1994). Therefore the introduction in agriculture of films produced with biodegradable raw materials, such as starch (Bastioli et al. 1998; Lorcks et al., 1998), that can be disposed directly into the soil or into a composting system at the end of their lifetime represents a viable solution to this problem. Taking into account the previous discussion about bio waste valorization and the sustainable agriculture definition I will consider mulching films containing SBO a new Sustainable

Agricultural Practice (SAP) which has a dual function: 1) to broaden the spectrum of OFMSW management, and 2) to improve agricultural sustainability.

1.2 Objectives

The adoption of SAPs has a key role in improving agricultural sustainability (Reimer *et al.,* 2012). Many studies have attempted to understand what are the factors that influence the adoption of SAPs. According to Baumgart-Getz *et al.,* (2012), Tey and Brindal (2012), Prokopy *et al.,* (2008), Knowler and Bradshaw (2007), and Pannell *et al.,* (2006), adoption depends on different factors that can be divided into six dimensions: socio-economic factors; agro-ecological factors; informational factors; psychological factors; institutional factors. The socio-economic dimension includes factors like, gender, age, education levels, and some farm-specific characteristics (farm size, farming experience, access to finance etc.). The second dimension concerns variables like the practice of organic farming, duration of land used and geographical location. Very important are informational and psychological factors too, included in fourth and fifth dimensions, like usefulness of information, intention to adopt, habits and the perceived attributes. The last dimension regards institutional factors, as well as organizational membership, participation in institutional arrangements, participation in certification programs that is farm's presence in different social networks. A social network is the pattern of friendship, advice, communication or support relationships existing among the members of a social community (Knoke and Kuklinski, 1982; Burt and Minor, 1983; Wellman, 1988). There are different works that show, each with a unique theoretical model and distinctive methodological tools, different ways in which networks influence the adoption of an innovation. Coleman and colleagues (1966) founded that some network variables are important predictors of innovativeness; according to Valente (1995) a combination of external influences from cosmopolite sources and the network interconnectedness best explain the medical doctors innovativeness in adopting a medical innovation. Tey *et al.,* (2010) show that social networks are particularly influential on SAPs diffusion. In fact, the diffusion of an innovation, like a new SAP, is the process by which a few members of a social system initially adopt an innovation, then over time more individuals adopt until all (or most) members adopt the new idea (Ryan and Gross, 1943; Rogers, 2003). In this context, agricultural innovations diffusion could be promoted through different links between farmers. The network position of an actor affects the power and influence he can exert on its immediate neighbors and on the collective behavior of the members. This influence can be viewed as a strategic resource for innovation diffusion purpose in a marketing or policy context. Policy maker can induce diffusion choosing specific injection points (members of the network where the novelty is first inoculated) in order to boost adoption speed and adoption level (Diaz-Reiney, 2012) that is various according to the relational profile and location in the network of the injection points chosen. As a consequence, the principal question for policy makers is who are the injection points to recruit to obtain more effective diffusion results. This problem is usually faced heuristically, identifying time after time, through a try and error process, the best injection points. From these observations arises the fundamental research question of this thesis: R1) *does it exist a rational criterion for the choice of the injection points?* Thus, the objective of my thesis is to prove that there are specific network properties belonging to the actors that can be used like rational criteria for the choice of the best injection points. The hypothesis related to these criteria will be tested through an Agent Based Model (ABM) designed to simulate the social interaction mechanisms within a social network composed by different agents.

1.3 Organization of the Thesis

The rest of the work is organized as follows. Chapter 2 depicts the theoretical background of Rogers' theory on innovation diffusion and of policy induced diffusion. Chapter 3 is devoted to introduce the innovation broker's role in the agricultural knowledge infrastructure and to show different methods to efficiently induce diffusion. Moreover this chapter states the fundamental hypotheses of this research. Chapter 4 portrays a review of Agent Based Model for innovation diffusion. In chapter 5, I present the research area, the data collection and the case study. In chapter 6 I describe the model and the simulations setting. In chapter 7 I discuss the results of my research. Finally chapter 8 presents the conclusions of this thesis.

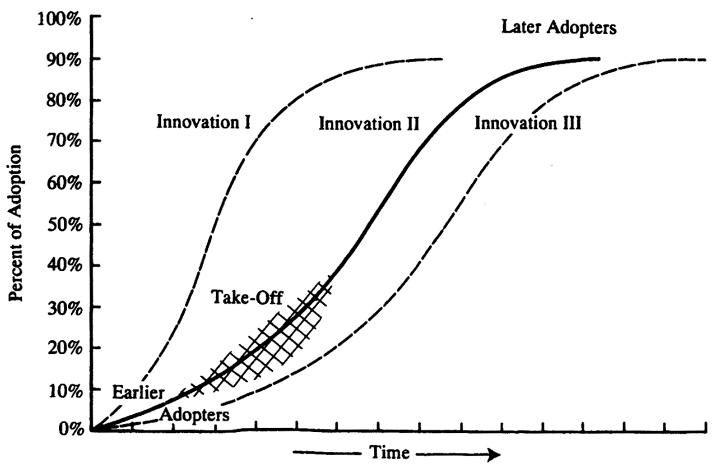
CHAPTER 2

THEORETICAL BACKGROUND

2.1 The Rogers theory of innovation diffusion

Innovation diffusion research seeks to understand how new ideas, products and practices spread throughout a society over time (Rogers 2003). Diffusion research is an interdisciplinary field with roots in anthropology (Wissler 1915), sociology (Tarde 1903), geography (Hägerstrand 1967), political science (Walker 1969), economics (Griliches 1957), and marketing (Arndt 1967). In particular, diffusion of innovations is a theory that seeks to explain how, why, and at what rate new ideas and technology spread through cultures. Everett Rogers, a professor of communication studies, popularized the theory in his book Diffusion of Innovations; the book was first published in 1962, and is now in its fifth edition (2003). Rogers argues that diffusion is the process by which an innovation is communicated through certain channels over time among the participants in a social system. Therefore according to Rogers (2003) innovation is any new idea, practice or object that is intended to be beneficial for the adopter and its diffusion is: "the process by which an innovation is communicated through certain channels over time among the members of a social system", where time is involved in the innovation-diffusion process, innovativeness, and an innovation's rate of adoption. (figure 2.1)

Figure 2.1 The diffusion process



Source: Rogers (2003)

Therefore the four main elements are the 1) innovation, 2) communication channels, 3) time, and 4) the social system. They are identifiable in every diffusion research study, and in every diffusion campaign or program.

2.1.1 The innovation and its characteristics

The S-curve is innovation specic and system-specific, describing the diffusion of a particular new idea among the member units of the specific system. In fact, how Figure 2.1 shows, the diffusion processes is different for each represented innovations (I-II-III), depending on the distinct innovation's characteristics. In particular, Rogers (2003), on the basis of the previous literature on innovation diffusion, found five main attributes that influence adoption decisions and explain the different innovation rates of adoption: 1) relative advantage; 2) compatibility; 3) complexity; 4) trialability; and 5) observability.

1) Relative advantage is the degree to which an innovation is perceived as better than the idea it supersedes. The degree of relative advantage may be measured in economic terms, but social-prestige factors, convenience, and satisfaction are also often important components. It does not matter so much whether an innovation has a great deal of "objective" advantage. What does matter is whether an individual perceives the innovation as advantageous. The greater the perceived relative advantage of an innovation, the more rapid its rate of adoption is going to be.

2) Compatibility is the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters. An idea that is not compatible with the prevalent values and norms of a social system will not be adopted as rapidly as an innovation that is compatible. The adoption of an incompatible innovation often requires the prior adoption of a new value system. An example of an incompatible innovation is the use of contraception in countries where religious beliefs discourage use of birth-control techniques, as in Moslem and Catholic nations.

3) Complexity is the degree to which an innovation is perceived as difficult to understand and use. Some innovations are readily understood by most members of a social system; others are more complicated and will be adopted more slowly. For example, in a study carried out in 1955, Wellin found that the villagers of a Peruvian village, Los Molinos, did not understand germ theory, which the health worker tried to explain to them as a reason for boiling their drinking water. In general, new ideas that are simpler to understand will be adopted more rapidly than innovations that require the adopter to develop new skills and understandings.

4) Trialability is the degree to which an innovation may be experimented with on a limited basis. New ideas that can be tried on the installment plan will generally be adopted more quickly than innovations that are not divisible. Ryan and Gross (1943) found that every one of their Iowa farmer respondents adopted hybrid-seed corn by first trying it on a partial basis.

If the new seed could not have been sampled experimentally, its rate of adoption would have been much slower. An innovation that is trialable represents less uncertainty to the individual who is considering it for adoption, as it is possible to learn.

5) Observability is the degree to which the results of an innovation are visible to others. The easier it is for individuals to see the results of an innovation, the more likely they are to adopt. Such visibility stimulates peer discussion of a new idea, as friends and neighbors of an adopter ask him or her for innovation-evaluation information about it. Solar panels on a household's roof are highly observable, and a California survey found that the typical solar adopter showed his equipment to about six of his peers (Rogers et al, 1979). Other consumer innovations like home computers or videotape recorders are relatively less observable, and thus may diffuse more slowly.

Generally, innovations that are perceived by receivers as having greater relative advantage, compatibility, trialability, observability, and less complexity will be adopted more rapidly than other innovations (Rogers 2003) (Figure 2.2).

2.1.2 The innovation diffusion process

According to Rogers: “The innovation-decision process is the process through which an individual (or other decision-making unit) passes from first knowledge of an innovation to forming an attitude toward the innovation, to a decision to adopt or reject, to implementation of the new idea, and to confirmation of this decision”.

The Rogers innovation decision process consists of five stages:

1. *Knowledge* occurs when an individual (or other decision making unit) is exposed to the innovation's existence and gains some understanding of how it functions.

2. *Persuasion* occurs when an individual (or other decision making unit) forms a favorable or unfavorable attitude toward the innovation.

3. *Decision* occurs when an individual (or other decision-making unit) engages in activities that lead to a choice to adopt or reject the innovation.

4. *Implementation* occurs when an individual (or other decision making unit) puts an innovation into use.

5. *Confirmation* occurs when an individual (or other decision making unit) seeks reinforcement of an innovation-decision already made, but he or she may reverse this previous decision if exposed to conflicting messages about the innovation.

The innovation-decision process involves time in the sense that the five steps usually occur in a time-ordered sequence of knowledge, persuasion, decision, implementation, and confirmation. The *innovation- decision period* is the length of time required to pass through the innovation-decision process.

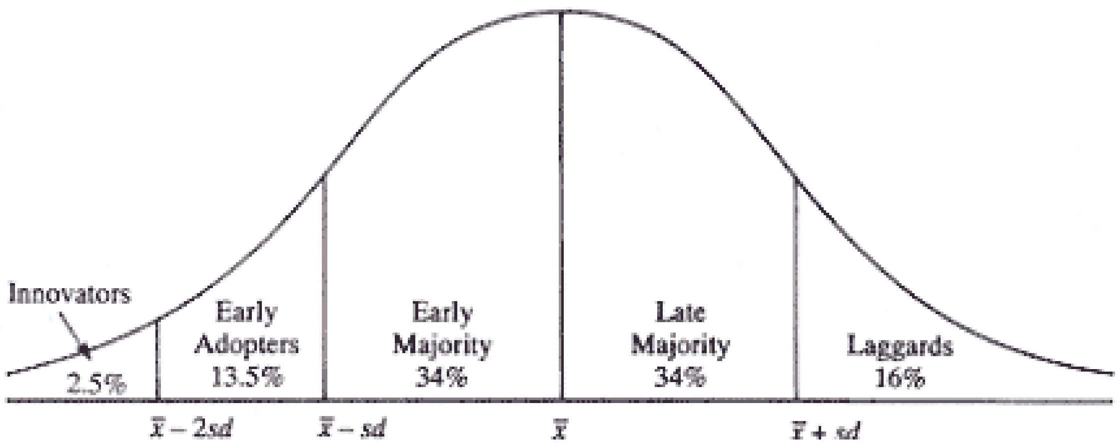
2.1.3 Innovativeness and adopters categories

According to Rogers, adopter distributions follow a bell-shaped curve over time and approach normality, because of the cumulatively increasing degree of influence upon an individual to adopt or reject an innovation, resulting from the activation of peer networks about the innovation in the social system. This influence results from the increasing rate of knowledge and adoption or rejection of the innovation in the system. Adoption of a new idea is the result of human interaction through interpersonal networks. If the first adopter of the «innovation discusses it with two other members of a social system, and each of these two adopters passes the new idea along to two peers, the resulting distribution follows a binomial expansion, a mathematical function that follows a normal shape when plotted over a series of successive generations. The process is similar to that of an unchecked infectious epidemic (Bailey, 1957). Evidence supporting this statement comes from investigations of agricultural, consumer, and other innovations in a variety of social systems, in the United States, India, and other nations (Rogers, 1958; Bose, 1964; Ryan, 1948; Beal and Rogers, 1960; Dimit 1954; and Hamblin et al, 1973). All these researches show that S-shaped diffusion curves are essentially normal, a conclusion that is very useful for classifying adopter categories (Rogers 2003). In particular, Rogers established five adopter categories that describe and explain impacts of heterogeneity on adoption decisions (Mahajan et al.1990). These five categories are distinguished by adoption timing that measures the adopter innovativeness (see Fig.2.1). The innovativeness dimension is continuous and it is characterized by a normal distribution that has several characteristics that are useful in classifying adopters. One of these characteristics or parameters is the mean *(x),* or average, of the sample. Another parameter of a distribution is the standard deviation *(sd),* a measure of dispersion about the mean.

These two statistics, the mean *(x)* and the standard deviation *(sd),* can be used to divide a normal adopter distribution into categories. If vertical lines are drawn to mark off the standard deviations on either side of the mean, the curve is divided into categories in a way that results in a standardized percentage of respondents in each category (Figure 2.2).

The area lying to the left of the mean time of adoption minus two standard deviations includes the first 2.5 percent of the individuals to adopt an innovation—the *innovators*. The next 13.5 percent to adopt the new idea are included in the area between the mean minus one standard deviation and the mean minus two standard deviations; they are labeled *early adopters*. The next 34 percent of the adopters, called *early majority,* are included in the area between the mean date of adoption and minus one standard deviation. Between the mean and one standard deviation to the right of the mean are located the next 34 percent to adopt the new idea, the *late majority*. The last 16 percent are called *laggards*. (Rogers 2003)

Figure 2.2. Adopter categorization on the basis of innovativness



Source: Rogers 2003

Adopters in each category differ in several characteristics, for instance in their use of communication channels, readiness to assume risk, and social affiliation (Rogers 2003).

2.1.4 Rate of adoption

There is a third specific way in which the time dimension is involved in the diffusion of innovations. *Rate of adoption* is the relative speed with which an innovation is adopted by members of a social system. When the number of individuals adopting a new idea is plotted on a cumulative frequency basis over time, the resulting distribution is an s-shaped curve (see figure 2.1). At first, only a few individuals adopt the innovation in each time period (such as a year or a month, for example); these are the innovators. But soon the diffusion curve begins to climb, as more and more individuals adopt. Then the trajectory of the rate of adoption begins to level off, as fewer and fewer individuals remain who have not yet adopted. Finally, the s-shaped curve reaches its asymptote, and the diffusion process is finished. Most innovations have an s-shaped rate of adoption. But there is variation in the slope of the "s" from innovation to innovation (see figure 2.1); some new ideas diffuse relatively rapidly and the s-curve is quite steep. Another innovation may have a slower rate of adoption, and its s-curve will be more gradual, with a slope that is relatively lazy. One issue addressed by diffusion research is why some innovations have a rapid rate of adoption, and why others are adopted more slowly (Figure 2.1). The rate of adoption is usually measured by the length of time required for a certain percentage of the members of a system to adopt an innovation. Therefore, we see that rate of adoption is measured using an innovation or a system, rather than an individual, as the unit of analysis. Innovations that are perceived by individuals as possessing greater relative advantage, compatibility, and the like, have a more rapid rate of adoption (as I pointed out previously in the section 2.1.2).

There are also differences in the rate of adoption for the same innovation in different social systems. Clearly, there are aspects of diffusion that cannot be explained only by the nature of individual behavior. The system has a direct effect on diffusion, and also an in direct influence through its individual members.

2.1.5 The social system: social and communication structure

Innovation decision process cannot be explained as a result of individual and innovations characteristics alone, but it is also fundamentally a social process (Rogers 2003). According to Deroian, 2002 the structure of a social system can facilitate or impede the diffusion of innovations in the system. The impact of the social structure on diffusion is of special interest to sociologists and social psychologists, and the way in which the communication structure of a system affects diffusion is a particularly interesting topic for communication scholars (Rogers 2003). Katz (1961) remarked, "It is as unthinkable to study diffusion without some knowledge of the social structures in which potential adopters are located as it is to study blood circulation without adequate knowledge of the structure of veins and arteries."

Rogers define *structure* as the patterned arrangements of the units in a system. This structure gives regularity and stability to human behavior in a social system; it allows one to predict behavior with some degree of accuracy. Thus, structure represents one type of information in that it decreases uncertainty. Perhaps we see an illustration of this predictability that is provided by structure in a bureaucratic organization like a government agency where there is a well-developed social structure consisting of hierarchical positions, giving officials in higher ranked positions the right to issue orders to individuals of lower rank. Their orders are expected to be carried out. Such patterned social relationships among the members of a system constitute *social* structure, one type of structure.

An individual's position and connectedness within a social system is important for adoption behavior (Valente 1995). Individuals who have more direct ties to other actors are more innovative, receive more information, and are less dependent on other individuals (Wasserman and Faust 1994; Valente 1995). Individuals who have dense networks are considered not to receive much information from outside. In a dense personal network, most members are connected to each other and are thought to hear of an innovation later (Valente 1995).

In addition to social structure among, Rogers define another type of structure, the *communication structure,* that exists in the interpersonal networks linking a system's members, determining who interacts with whom to create and share information with one another in order to reach a mutual understanding (Rogers 2003).

The *interpersonal channels,* involve a face-to-face exchange between two or more individuals, and are important in persuading an individual to adopt an innovation.

The information diffuses through Mass media channels too (radio, television, newspapers and so on) that are often the most rapid and efficient means to inform an audience of potential adopters about the existence of an innovation (Kats and Lazarsfeld 1955; Lazarsfeld et al. 1944; Lazarsfeld and Menzel, 1963) that is, to create awareness-knowledge (Rogers 2003).

The importance of interpersonal and mass media channels in the innovation-decision process was investigated in a series of researches with farmers, and then largely confirmed in studies of other types of respondents. For example, Sill and Copp (1958) found that if the probability of adoption were to be maximized, communication channels must be used in an ideal time sequence, progressing from mass media to interpersonal channels. A farmer upsetting this sequence in any way prejudices progress at some point in the adoption process." The greatest thrust out from the knowledge stage was provided by the use of the mass media, while interpersonal channels were salient in moving individuals out of the persuasion stage.

Beal and Rogers (1960) obtained data on the relative importance of interpersonal and mass-media channels at each function in the adoption of 2,4-D weed spray from 148 Iowa farmers.

On the basis of these studies Rogers, referring to his model of the innovation-decision process[2] argues that: " *Mass media channels are relatively more important at the knowledge* *stage and interpersonal channels are relatively more important at the persuasion stage in the innovation decision process"*.

So mass communication channels are primarily knowledge creators, whereas interpersonal networks are more important in persuading individuals to adopt or reject.

In literature can be identified several innovation diffusion models based on the relevance of social networks' role in diffusion of innovations and on the assumption that people adopt an innovation when sufficient information has reached them. One of the first diffusion investigation based on these assumptions was the classic study of a new drug's spread among doctors carried out by Professor James Coleman and his colleagues in 1966. In particular they included various indicators of network communication behavior among their independent variables of study; they found these network variables to be the most important predictors of innovativeness. Moreover they proceeded to study the way in which interpersonal networks explained the very nature of the diffusion process. This methodological advance allowed Coleman et al to gain important understandings into the S-shaped diffusion curve.

Their work stands out as a model for gaining in-depth insight into the nature of diffusion, and their approach has attracted the later attention of various other diffusion scholars who have probed the dynamics of diffusion networks, like for example Rogers and Kincaid (1981). They conducted personal interviews with the sixty-nine married women in a Korean village in order to determine the role of interpersonal networks in the diffusion of family-planning innovations. Each respondent was asked which other women she talked with about contraceptive methods. Spatial location of each respondent's home was a very important predictor of who talked with whom, even though the village was extremely small (only about two typical city blocks in diameter). But space was by no means a complete explanation of diffusion networks links; in fact some women talked with a peer on the opposite side of the village. Physically lengthy links were especially characteristic of opinion leaders, which suggested that one of the important roles of such leaders was to interconnect the spatially related cliques in the village, and thus to increase the connectedness of the village's communication structure. Social similarity also helped to explain who was linked to whom; women of similar social status and age were more likely to interact with each other.

A general conclusion from who-to-whom studies is that space and social distance (that is, heterophily/homophily) are the main determinants of who talks to whom in diffusion networks. Homophily is the degree to which pairs of individuals who interact are similar in certain attributes, such as beliefs, education, social status, and the like. Although a conceptual label— homophily—was assigned to this phenomenon only in fairly recent years by Lazarsfeld and Merton (1964), the existence of homophilous behavior was noted a half-century ago by Tarde (1903): "Social relations, I repeat, are much closer between individual who resemble each other in occupation and education." Heterophily is the degree to which pairs of individuals who interact are different in certain attributes. So Heterophily is the opposite of homophily.

When two individuals share common meanings, beliefs, and a mutual language, communication between them is more likely to be effective. Most individuals enjoy the comfort of interacting with others who are quite similar.

Homophily and effective communication breed each other, instead heterophilous communication may cause cognitive dissonance because an individual is exposed to messages that go unheeded becouse they are inconsistent with existing beliefs, causing an uncomfortable psychological state. But heterophilous communication has a special informational potential, even though it may be realized only rarely. These interpersonal links are especially important in carrying information about innovations, as is implied in Granovetter's (1973) theory of "the-strength-of-weak-ties," so homophilous communication may be frequent and easy but may not be so crucial as the less frequent heterophilous communication in diffusing innovations.

Extended models include that information about the innovation is assessed towards an individual threshold[3] that can change over time and depending on the adoption rate within the personal network of the decision-maker. Granovetter (1978) postulated that individuals were heterogeneous in the extent to which their social system influences on them. In fact, individuals have varying thresholds for adoption of an innovation. According to threshold models, individuals make decisions based on the proportion of others that have already done so (Granovetter 1978; Markus, 1987). In particular, a threshold is reached when an individual s convinced to adopt as the result to knowing that some minimum number of other individuals in the individual’s personal communication network have adopted and are satisfied with innovation (Rogers 2003).

A social-psychological theory with direct applicability to diffusion networks is social learning theory (Bandura 1977). The central idea of social learning theory is that an

[3] A threshold is the number of other individuals who must be engaged in an activity before a given individual will join the activity (Granovetter, 1978; Markus, 1987)

individual learns from another by means of observational modeling; that is, one observes what another person is doing, and then does something similar. But not exactly the same thing. That would be simple imitation or blind mimicry. But social modeling permits the observer to extract the essential elements from an observed behavior pattern in order to create a similar behavior.

The basic perspective of social learning theory is that the individual can learn from observation of other people's activities, so the individual does not actually need to experience a verbal exchange of information in order for the individual's behavior to be influenced by the model. Thus, nonverbal communication is considered important in behavior change (as well as verbal communication). Therefore according to this theory, the potential adopter decision, whether or not to buy the new product, is based not only on his own preferences but on the decisions of his neighbors in the social network, hence the adoption behaviour of one member influences the adoption decision of another member (Rogers 1995;Valente 1995).

2.1.6 The role of opinion leaders in a diffusion network

In diffusion networks an important role is played by Opinion Leaders. Opinion leadership is the degree to which an individual is able informally to influence other individuals' attitudes or overt behavior in a desired way with relative frequency . So opinion leaders are individuals who lead in influencing others' opinions about innovations. Various studies have attempted to understand the attributes and roles of opinion leaders (Weimann, Tustin, Vuuren, and Joubert, 2007). Besides their central position (Berelson and Steiner, 1964; Czepiel, 1974; Valente, 1996) other characteristics of opinion leaders, such as interpersonal influence and innovativeness, may significantly affect their influence. Two main types of interpersonal influence exist: informational and normative influence (Deutsch and Gerrard, 1955). Informational influence refers to the tendency to accept information from others as evidence of reality. For example, opinion leaders directly influence other consumers by giving them advice and verbal directions about their search for, purchase of, and use of a product (Flynn, Goldsmith, and Eastman, 1994). Normative influence, on the other hand, entails the tendency to conform to the expectations of others (Burnkrant and Cousineau, 1975). Hence, normative opinion leaders exert social pressure and social support and thereby influence decision-making pro- cesses of the influenced consumers (Glock and Nicosia, 1964). Since people aim to create and maintain meaningful social relationships, they often engage in behaviors approved by others, such as adopting a product to appeal to other product adopters (Cialdini and Goldstein, 2004). The product and situation determine which type of influence is more important (Grewal, Mehta, and Kardes 2000). Privately consumed goods prioritize the informational influence, whereas for publicly consumed goods both types of influence are critical. Opinion leaders can accelerate the diffusion of innovation and are potentially interesting for political issues (Deroian, 2002). Valente and Davis (1999) investigate how the diffusion of innovations can be accelerated through opinion leader recruitment. They use homogeneous agents that adopt once 15% of their neighbors have adopted. The formal description of the underlying model is sketchy and the network model used, which randomly allocates seven ties per agent, does not appear to resemble most real-world social network structures very closely. Nevertheless, simulation results demonstrate that diffusion occurs faster when initiated by opinion leaders rather than by random or marginal agents and that targeting opinion leaders may therefore accelerate diffusion. Similar to Valente and Davis (1999), Delre et al. (2010) also investigate the effectiveness of opinion leader recruitment. Results suggest that the most important function of highly interconnected hubs is to inform others about the new products, but that their effect on the decision making of consumers can be often overestimated. They also find that in markets in which such hubs do not exist, diffusion is less likely to occur. For such markets, direct to consumer advertising could be an alternative strategy to stimulate the spreading of the new product in different areas of the network. Finally, van Eck et al. (2011) also study the role of opinion leaders, but take into account not only their central network position, but also the influence of personality traits and knowledge among influential consumers. Hence all these works show that the opinion leader can be recruited by policy makers to speed diffusion in a network of potential adopters and to reach higher level of diffusion, in other words to induce diffusion. Induced diffusion is a recent research area that study how regulatory interventions accelerate the adoption process (speed) and how they increase the long term penetration rate (level). In the following section I present a brief literature review on this new theoretical field and on patterns of diffusion when it is induced, that are different from the conventional patterns observed when diffusion is unaffected by policy interventions.

2.2 Induced diffusion

The origins of the concept of induced diffusion can be traced back to Hicks (1932) "induced innovation" hypothesis, according to which a change in the relative prices of the factors of production would by itself engender invention or innovation to economize the use of a factor which has become relatively expensive. A considerable literature has been developed using the induced innovation hypothesis within and beyond Hicks' original macroeconomic focus on the effects of wage rises on labor saving inventions (P. Funk, 2002; D. Popp, 2002). In particular, mounting concerns about climate change and environmental decay have led in recent years to the development of a literature exploring the possibility of price-induced innovation (A.B. Jaffe et al. 2002). For instance, Popp 2002 using patent data explores the effect of rising energy prices on innovation in energy technologies, whilst Newell et al., 1999 investigate the effects of rising energy costs on improvements in the energy efficiency of goods.

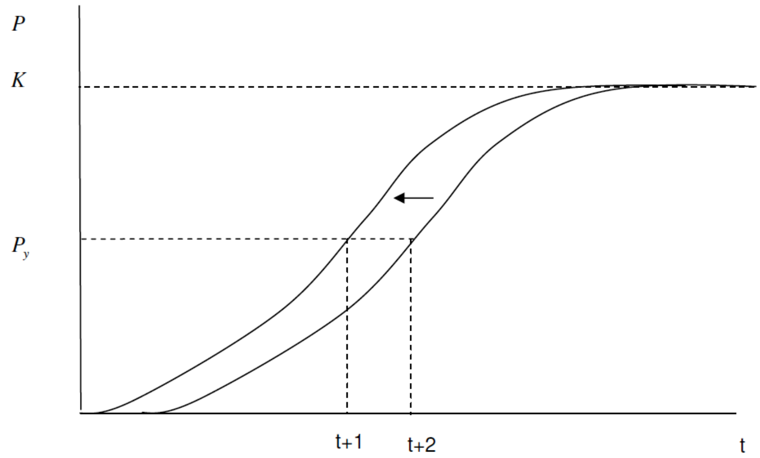
Research in this context has explored not just invention and innovation but also diffusion. Accordingly two related concepts to induced innovation are induced adoption and induced diffusion. The term 'induced adoption' appears to have first been employed by Antonelli (1990) in an examination of the territorial distribution of fax machines and modems and shows that their adoption is highly uneven geographically, favoring regions with higher levels of fixed and human capital and where there are positive network externalities, such as business clusters of service industries. These results highlight the importance of regional and socioeconomic differences as the broader context with which to engender the adoption of innovations. The most prominent use of the term induced diffusion was by Jaffe et al. (2002). In fact in their widely cited review of work on environmental policy and technological change, they explain the concern with induced diffusion, as distinct from induced innovation, when they observe that:

"While the induced innovation literature focuses on the potential for environmental policy to bring forth new technology through innovation, there is also a widely-held view that significant reductions in environmental impacts could be achieved through more widespread diffusion of existing economically-attractive technologies."

Following from this, Diaz-Rainey in their induced diffusion literature included in a work of 2009, suggests a more formal definition of induced diffusion. In particular they define it as: "Any intervention that aims to alter the speed and/or total level of adoption of an innovation by directly or indirectly internalizing positive and/or negative externalities".

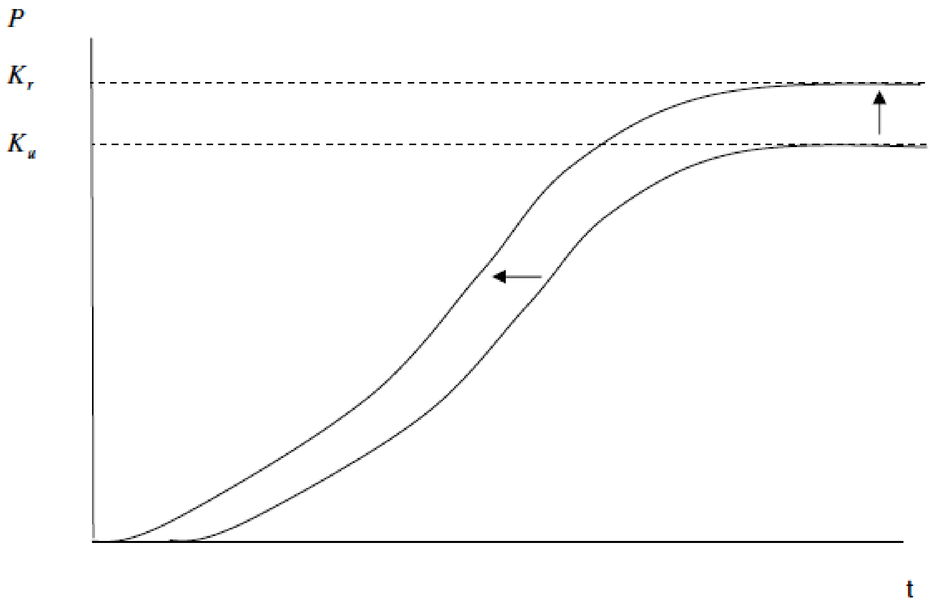
Following this definition Diaz-Rainey represent the desired impact of induced diffusion on diffusion speed (acceleration effect) (figure 2.3) and on diffusion level (increased saturation effect) (figure 2.4). Depicted in both panels are cumulative normal 's' shaped diffusion curves.

Figure 2.3 Induced diffusion: acceleration



Source: Diaz-Rainey 2009

Figure 2.4 Induced diffusion: acceleration effect and increased saturation effect



Key: *P* **=** cumulative market penetration of an innovation; t = time; K = saturation

Source: Diaz-Rainey 2009

In Figure 2.2.1a policy interventions succeed in accelerating diffusion for a given level of cumulative adoption P_y from t+2 to t+1. In other words the diffusion curve shifts to the left. Under this scenario, however, both curves ultimately reach the same market saturation point. In the second panel is diffusion also accelerated, however, in this case the policy interventions also results in a higher 'realistic' saturation point, K_r rather K_u.

Diaz-Rainey (2009), in his work, after showing graphically the effect of policy maker intervention on speed and on level of diffusion, introduced some empirical evidence on the efficacy of some tools available to policymakers with which induce diffusion, as well as: trading mechanisms (Kerr and Newell, 2003); price and taxes (Baker *et al.,* 1989; Lafferty *et al*. 2001; Jaffe *et al*. 2002; Greene 1990; Hassett and Metcalf 1995; Jaffe and Stavins 1995; Rose and Joskow 1990; Stoneman and Battisti 1998; Brown 2001; Golove and Eto 1996; Sanstad and Howarth 1994; Sorrell *et al*. 2004); subsidies (Hassett and Metcalf 1995; Jaffe and Stavins 1995; Soderholm and Klaassen 2007; Koefoed and Buckley 2008); command and control instruments (Cutler and McClellan 1996; Battisti and Stoneman, 1998; Stoneman and Battisti, 1998; Gray and Shadbegian, 1998; Stoneman and Battisti, 2000; Baker 2001; Snyder *et al*., 2003; Battisiti, 2008; Mickwitz *et al*. 2008; Luken and Van Rompaey, 2008; Koefoed and Buckley, 2008); information policy (Morgenstern and Al-Jurf, 1999; Howarth *et al*. 2000; Anderson and Newell, 2004). Since Diaz-Rainey (2009), the research in the emerging area of induced diffusion has grown a lot. For instance, Cantono and Silverberg (2009) explore through Agent Based Simulation the alternative policy approaches to 'kick-start' the diffusion of eco-innovations using a mixed probit and epidemic model. Further, Higgins et al. (2011) explore various policy options for reducing the greenhouse gas emissions from the housing stock using a decision support diffusion model applied to a case study in Australia. Finally Rixen and Weigand (2014) simulate through an Agent Based model the effect of different policy intervention on speed and level of Smart Meter adoption in Germany. The previous consideration about the importance of innovation networks (knowledge transfers among innovation potential adopters), included in the first section of this chapter and the consideration that innovation diffusion can be induced by policy makers, support the point of view adopted in this work and lead to the following question: how public policy could promote this knowledge transfer (word of mouth) in the agriculture sector both beetween research and the farmers worlds and between these last? A solution to this problem could be the innovation broker, a new figure contemplated by EIP (European Innovation Partnership), described in the following chapter.

Chapter 3

The innovation broker

3.1 The innovation broker's role in the agricultural knowledge infrastructure

EIP has been established by the Commission's proposal for a post-2013 rural development policy (COM 2012 79) with the aim of building a bridge and achieving synergies through fostering exchange between research and practice. Its implementation will be channeled through the Operational Groups (OG), as key acting entities involving different actors, such as farmers, advisors, researchers, NGOs, enterprises, etc. (ENRD, 2013b). The agricultural EIP adopts the interactive multi-actor model of knowledge exchange (European Commission, 2013; World Bank, 2006; Hall et al., 2006; Knickel et. Al., 2009; Mosley, 2000; Labarthe & Laurent, 2013; Latruffe, 2010), in order to promote end user focused solutions or developing new opportunities (ENRD, 2013a).

In the context of the agricultural EIP, the main task of the innovation broker is to help the setting up of operational groups around concrete innovation projects through collecting information, animating bottom-up initiatives, helping to refine innovative ideas, providing support for finding partners and funding, as well as for preparing the project proposal work plan.

These functions are not exhaustive of the possible activities that the innovation broker can play in view of smoothing the innovation process (Cristiano and Proietti, 2011). In fact, the literature describes a variety of functions performed by innovation brokers, that will be explained in the following paragraph.

According to Klerkx and Leeuwis (2009) the formation and functioning of innovation networks and systems can be problematic due to the existence of several gaps between actors. In this context, there is the need for subjects whose main function is to fill these gaps by connecting different players so as to facilitate knowledge exchange across the boundaries between them. This task will be performed by the "innovation broker" (Herman et al.,2012; Perèz et al., 2010; EU SCAR, 2012), meaning " an agent or broker in any aspect of the innovation process between two or more parties", whose activities include helping to provide information about potential collaborators, brokering a transaction between two or more parties, acting as a mediator or go-between bodies or organizations that are already collaborating, helping find advice, funding and support for the innovation outcomes of such collaborations (Howell, 2006). As Howell observes, organizations can provide intermediary functions as their primary or exclusive role, but also as jointly activities of research and technical services. The role of the innovation broker is very usual in the Netherlands, since it has emerged following the privatization of the research and extension system and a paradigmatic shift in the agricultural and rural fields, as well as in innovation pathways. Klerkx and Leeuwis (2009) give examples of the seven distinct types of agricultural innovation brokers that can currently operate in the Netherlands:

- innovation consultants are organizations focused either on the individual farmer (type 1), or ona collective of farmers (type 2) with a common interest, who wish to jointly develop or implement an innovation;
- peer network brokers (type 3) are organizations involved in the setting up of peer networks (generally with a sub-sectorial focus) concerned with informal knowledge exchange among the farmers;
- systemic brokers (type 4) go beyond individual firms, or networks of firms, addressing higher level innovation architectures that involve complex constellations of business, government and societal actors, dealing with complex problems and radical innovations;
- internet portals (type 5) connect farmers with relevant information sources;
- research councils with innovation agency (type 6) are aimed at connecting relevant actors in the agriculture value chain in order to facilitate farmer-driven research planning mechanisms;
- education brokers (type 7) link education establishments with the aim of positioning the agricultural schools in view of responding to innovation queries from the agricultural sector.

Howell (2006) describes a detailed set of functions concerning innovation brokerage that are primarily targeted at assisting individual firms in innovation processes, through articulating their innovation needs and composing the network (e.g. knowledge processing, selection of collaborative partners and network brokerage, gate-keeping and knowledge brokering, etc.). Besides, Smits and Kuhlmann (2004) describe other functions with a more systemic focus, aimed at interfacing with different actors and animating groups, such management of interfaces, building and organizing (innovation) systems, stimulating demand articulation, and so on. Klerkx and Leeuwis (2009) summarize the last functions as innovation process management, which includes a host of facilitation tasks that ensure that networks are sustained and become productive, e.g. through the building of trust, establishing working procedures, fostering learning, managing conflict and intellectual property management (Leeuwis, 2004). In the context of the agricultural EIP innovation process management is not an expected function, as the broker's core objective is to help the group in the elaboration of a well-designed project plan. However, in case the project gets funded, the innovation broker could also be involved in its implementation, as a facilitator, and even in the dissemination of results. Despite the potential role of innovation brokers in facilitating partnerships and linkage among different innovation players, several risks have been identified with particular regard to their neutral position and possible function ambiguity, as well as, to funding problems (Klerkx et al., 2009). Concerning neutrality, innovation brokers can reveal possible dependence from shareholders, who may exercise pressure to compose and manage network in order to satisfy their own interests. Therefore, there is a concrete risk that innovation intermediaries may be used as a vehicle for realizing other parties' objectives and expectations. Neutrality issues seem to be particularly relevant with regard to network brokerage roles performed by traditional research and extension providers. In these cases, it is possible that the articulation of needs and the selection of cooperation partners may be influenced in favor of the needs of the provider rather than those of the client. Besides, function ambiguity tensions may arise as a consequence both of a new, and not completely clear, mission of innovation brokers and of an overlap with intermediary functions from research and extension services. Innovation brokers acting with insufficiently differentiation from the role of advisory and research providers may be seen by these latter as direct competitors. At the same time, farmers who are not aware of what they can expect from the innovation broker, cannot have the indispensable confidence in her/his functions. Moreover, farmers' representatives can see the innovation broker as a threat due to a possible role of opinion leader in performing 'animation' functions. According to Klerkx et al. (2009), specialized innovation brokers may be an option to prevent neutrality tension and to act as innovation catalysts more freely, but, on the other hand, they bear their own tensions with regard to neutrality, function overlap and funding. A further drawback can be related to the difficulty of recognizing the value of intermediating role among the variety of tasks performed by a multi-actor network. This may lead innovation brokerage activities to be economically non-self-sufficient and, thus, impossible to exist without public funding schemes. Cristiano and Proietti (2014), in a study that aim to profile the innovation brokerage model applied in Italy, synthesize the functions described by the European Commission and those described by the literature in eight tasks:

- Discovering innovative ideas, identifying and articulating farmers' needs;
- Connecting partners, identifying suitable partners from different knowledge fields;
- Supporting partners to refine the idea, articulating their demands and expectations;
- Identifying funding;
- Preparing the project proposal;
- Coordinating/ facilitating, leading the dialogue and the learning process;

- Running innovation, playing a role in initiating, developing and testing an innovation;
- Communicating results, carrying out effective dissemination activities addressed to transfer knowledge on the innovations.

Moreover Cristiano and Proietti (2014) in their work show that the implementation of measure 124 of RDPs in Italy has driven a variety of actors belonging to AKIS (Agricultural Knowledge and Innovation System) , innovation center, university and research centre, farmers, LAGs, Producer Organization (PO), cooperatives, consortiums, local administration, to self-organize themselves and establish partnerships for the specific purpose of developing, through cooperation, innovation projects and demonstrate that the involvement, as innovation brokers, of actors who are already part of the system and who also play a role in the implementation of the project, lets the innovation process be more sustainable, avoiding the risk of projects that do not necessarily address the real needs of change of the farmers or the group, and promotes a collaborative learning environment.

Regarding to the last task described by Cristiano and Proietti (2014), how the innovation broker should implant useful information into a farmer's networks about a new technology so that it reach the maximum number of individuals? The logic answer to this question is that the innovation broker to pass information about the novelty to the maximum number of potential adopters and to obtain the highest diffusion level should choice as injection points the most influent actors in the farmers' network. In social network literature have been described different algorithms to identify influential spreaders in networks, among which there is a recent algorithm developed by Morone and Makse (2015) that are discussed in the following paragraph.

3.2 Different methods for the innovation broker to carry out effective dissemination activities

Localizing in a network the optimal (minimal), set of structural nodes, called influencers, which, if activated, would cause the spread of information to the whole network (Domingos et al. 2002) is one of the most important problems in network science (Kempe et al. 2003, Newman 2010).

This problem has been heuristically adressed as (like) a problem that leads to the identification of the nodes suitable for the optimal network's fragmentation.

Heuristic methods quantify node's importance in a network (Newman 2010; Kleinberg 1999), on the basis of individual's node attributes such as: 1) Closeness Centrality; 2) Betweenness centrality (BC); 3) Eigenvector Centrality (EC); 5) High-Degree (HD).

1) Closeness Centrality (CC) (Bavelas 1950) measures how close a vertex is to all other vertices in the graph. More precisely CC at node i is the inverse of the average distance to all other nodes. Nodes are ranked according to their CC from the highest to the lowest score, and removed accordingly. A property of CC is that it tends to give high scores to individuals who are near the center of local clusters (i.e. network communities), and hence it over-allocates spreaders (or immunized nodes) next to each other. Moreover, it comes with a high computational cost that prevents the application to large networks.

2) Betweenness centrality (BC) (Freeman, 1977). Betweenness centrality of node i is the sum of the fraction of all-pairs shortest paths that pass through i. BC is a very popular tool for network analysis, which has applications in different fields, from community detection to the human brain. However, it comes with a high computational cost that prevents the examination of large graphs of interest. The best algorithm for BC computations has O(NM) time complexity for unweighted networks with N nodes and M vertices. It is not fast enough, for example, to handle our 10+ million people network. It does not outperform other centralities.

3) Eigenvector Centrality (EC). It is an alghoritm introduced by Straffin in a work of 1980 and it corresponds to the largest eigenvalue of the adjacency matrix. Node rank is the corresponding entry of the eigenvector. Nodes are removed starting from the highest rank. This method is not very powerful, especially for the case of SF networks, where most of the weight may be carried by few nodes (hubs), while the others have vanishingly small weights, and thus they are not properly ranked.

4) PageRank (PR) (Brin and Page 1998). It is the famous algorithm used by Google for ranking websites. It consists in condensing every page in the World Wide Web into a single number, its PageRank. PageRank is a global ranking of all web pages, regardless of their content, based solely on their location in the Web's graph structure. PR can be thought of as the most successful rank, ever. At its heart, it is another eigenvector centrality. It computes the probability that, if someone follows links on the web at random, performing a random walk of clicks, he/she eventually hits your website. The higher this chance, the higher the PR of the website. Therefore, sites that get linked more are considered reputable, and, linking to other websites, they pass that reputation along. Thus, the shortcoming with PR comes from the fact that PR takes node's score into account when calculating other's scores. In other words, a high-PR site may confer a much higher score to otherwise unpopular sites it happens to link. Notice that in our algorithm using the non-backtracking operator this problem is cured nicely, since the infuence is computed by "ignoring" the node you come from.

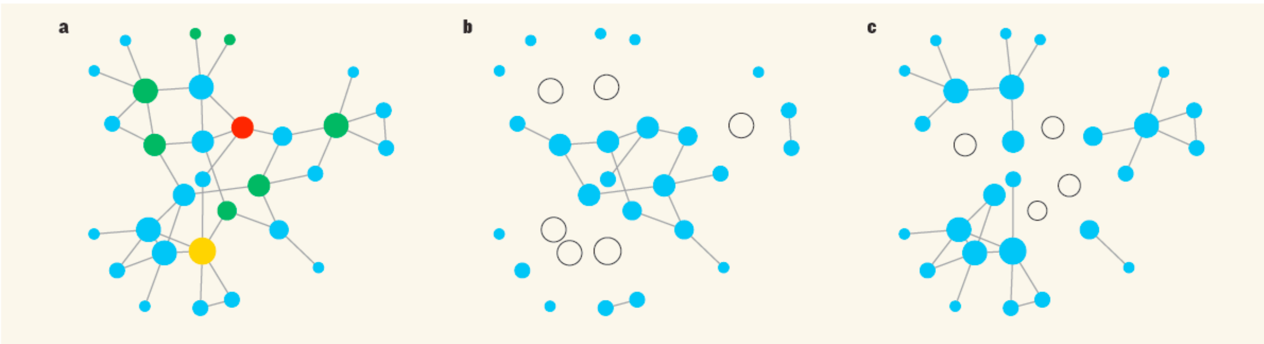
5) High-Degree (HD) (Pastor-Satorras et al. 2001, Albert et al. 2000, Cohen et al.2001). According to this method nodes are ranked by degree, and sequentially removed starting from the node of highest degree. One of the limitations of this method is the fact that hubs may form tightly-knit groups called\rich-clubs" (Colizza et al. 2006, Wasserman 1994). Strategies based on high-degree will highly rank these rich-club hubs. On the other hand, an optimized scheme will target only one of them to avoid overlap between the already attacked areas in the network. High Degree Adaptive (HDA) is the adaptive version where the degree of the remaining nodes is recomputed after each node removal.

All these methods based on individual node ranking consider the influencers as isolated entities and not the interaction with each other, so they not optmize an objective global function of influence, this means that the removal of some nodes, based on one of the heuristic methods described previously, doesn’t guarantee the maximum distruption on a network. Morone and Makse (2015) face this problem by mapping the integrity of a tree-like random network into optimal percolation (Hashimoto 1989; Karrer et al.2014) theory. From this, they derive an energy function with a minimum that corresponds to the set of nodes that need to be eliminated, to yield a network whose largest cluster is as small as possible. To do this, Morone and Makse (2015) introduced the concept of *collective influence*, an algorithm that allows them to efficiently dismantle networks. They define the collective influence of a network node as the product of its reduced degree (the number of its nearest connections, *k*, minus one), and the total reduced degree of all nodes at distance *d* from it (defined as the number of steps from it).

$$CI(i) = (k_i - 1) \Sigma (k_j - 1) \qquad (3.1)$$

Collective influence describes how many other nodes can be reached from a given node, assuming that nodes of high collective influence have a crucial role in the network. The collective-influence-based algorithm then sequentially removes nodes, starting with those that have the highest collective influence (known as influencers) and recalculating the collective influence of the rest following each operation. The authors show that, for large networks, removing the set of influencers identified by this algorithm is more effective in fragmenting a network than removing the hubs, or than removing nodes that are identified through other algorithms, such as degree or closeness centrality. The set of influencers identified by the authors contains many nodes with few connections. This highlights the fact that the importance of a node in ensuring a network's integrity is determined not only by the number of direct links it has to other nodes, but also by which other nodes it is connected to. Morone and Makse concluded in their work that the influencers founded by collective influence are more effective in destroying a network than nodes selected by other methods, like for example the high degree method. Kovacs and Barabasi, 2015 showed an example of this optimal network disaggregation (see Fig. 2.4.1).

Figure 3.3.1 - Optimal network demolition



Source: Kovacs and Barabasi, 2015

In the network showed in figure a), for d = 2, the red node with k = 4 has the highest collective influence, because the total reduced degree of the nodes at d = 2 from it (green and yellow circles) is 21. This yields a collective influence of 3 • 21 = 63. The most connected hub, with k = 6 (yellow circle), has a collective influence of 60. Figure b), show what happens if the 6 nodes with the highest k (white circles) are removed. This one causes considerable damage to the network, but leaves a sub-network that contains 12 nodes unperturbed. In figure c, by contrast, the removal of four influencer nodes (white circles) chosen according to their collective influence lead to a fragmented network in which the largest connected cluster that remains has only ten nodes. The major finding of the contribution of Morone and Makse (2015) is the elaboration of an algorithm that allows identifying the members of the network having the most capillary influence on the rest of the web (influencers). In this thesis I stress that the disconnection of these influencers leads to the optimal fragmentation of the web, regardless the overall characteristics of the network, that is the optimal disconnection is reached both in sparse and cohesive network with many or few members. On the basis of these observations, I expect that i) also in very dense networks the injection points characteristics are not indifferent to the final rate of adoption; ii) the final rate of adoption is higher if the injection points are chosen according to the CI algorithm rather than the other centrality measures; iii) and the maximum number of adoption is reached earlier.

From these derives the fundamental hypothesis of the present work:

Hypothesis 1: The diffusion rate reached during the diffusion campaigns is not invariant with respect to the role and the position of the injection points chosen, even in very dense networks.

Hypothesis 2: the diffusion rate reached in the diffusion campaigns realized using as injection points the agents with the greater CI is higher than those reached in the diffusion campaign realized using as injection points the actors with higher traditional network centrality (e.g. degree centrality).

Hypothesis 3: the time taken to reach the maximum number of adopters in the dissemination campaigns realized using as injection points the agents with the higher collective influence, is less than the time taken to reach the maximum number of adopters in the diffusion campaigns realized using as injection points the agents with the higher traditional network centrality (e.g. degree centrality).

These hypothesis are tested basically comparing the diffusion performances, in the network identified by the case study, obtained choosing the injection points with different criteria. In particular, the first hypothesis is tested comparing the diffusion performances obtained with CI and Degree Centrality (DC) vs. random.

Following Morone and Makse (2015) that developed their line of research comparing CI and DC, the second and the third hypothesis are tested comparing the performance of the CI with those of the DC. This comparison was made not on real data that do not exist on the innovation diffusion studied in this work, but on the results of an Agent Based Model calibrated on real world data resulting from a survey and an interviews specifically realized.

The model will be presented in the fifth chapter following, in the next chapter, the literature review of the models that are more used to analyze the innovation diffusion.

CHAPTER 4

DIFFERENT MODELS TO STUDY DIFFUSION OF INNOVATIONS

4.1 Introduction

Adoption and diffusion of a new technology have been widely studied from different perspectives. Many studies in adoption and diffusion of innovation are rooted in the work of Bass, who formalized the aggregate level of penetration of a new product emphasizing two processes of communication: external influence via mass media and internal influence via word-of-mouth (Bass, 1969). The decision is described as the probability of adopting a new product and is assumed to be linearly dependent on these two communication processes and fits very well with the real data for durable goods. While the Bass model is very useful for forecasting the initial adoption of a product, the model assumes an homogeneous consumer group as it does not specify micro-level decision-making. It also assumes perfect mixing in which all consumers have the same probability of connecting with other consumers without specifying how consumers communicate and influence each other. Social and behavioural research, meanwhile, has focused on the micro-level drivers of adoption, which contribute to the understanding of micro-level factors determining the adoption by individual consumers (e.g., Rogers, 2003). These studies emphasize that technical features do not entirely explain the diffusion dynamics of new technologies and highlight the relevance of the human factor. Furthermore, other studies have indicated that not only agent heterogeneity (Andrews and DeVault, 2009; Delre et al., 2007) but also social influence and network configuration (Kuandykov and Sokolov, 2010; Bohlmann et al., 2010; Delre et al., 2010) affect diffusion of innovation. Consequently, both social and psychological factors need to be considered when describing and predicting the behaviour of consumers.

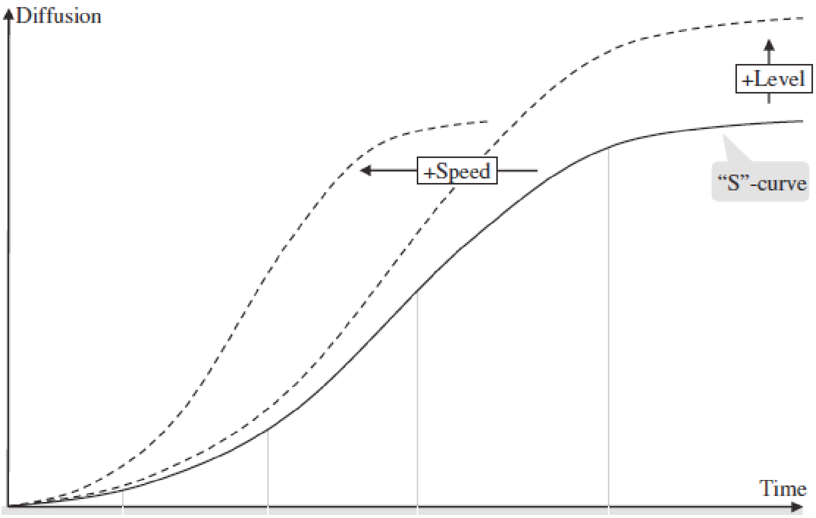
ABM, which is typically a bottom-up approach, in the sense that the system features emerge as the result of the interaction of its components, is capable of capturing those factors. It starts from modelling consumer's decision-making and simulates the diffusion as an aggregate process of individual adoption decisions. This is a suitable approach when information exchange in a social network and individual heterogeneity play a role (Rahmandad and Sterman, 2008). Despite its capability, ABM has mostly been applied as an experimentation tool to demonstrate diffusion patterns resulting from simple decision rules followed by different artificial agents in the system (e.g., Janssen and Jager, 2002; Andrews and DeVault, 2009; Delre et al., 2007, 2010).

So we can group the diffusion models essentially into two categories: the aggregate models of innovation diffusion and the individual level models of innovation diffusion, among which there are ABMs.

4.1 Aggregate models of innovation diffusion

In 1969, Bass published a seminal paper on the adoption of innovations (Bass 1969). His model was based on generalizations of empirical diffusion data for consumer durables, such as fridges, TVs, tumble driers, and air conditioners. The General Bass Model describes cumulative adoption as an “S”-curve. For a given innovation in general, initially there are only a few adopters, called innovators. Others learn from the innovation from various sources, including from the innovators, and occasionally adopt. The s-shaped adopter distribution rises slowly at first when there are few adopters in each time period. It then accelerates to a maximum until half of the individuals in the system have adopted. It then increases at a gradually slower rate as the few remaining individuals finally adopt (see Figure 4.1). Two indicators measure the performance in Bass's model: Speed and level of adoption.

Figure 4.1 – Cumulative adoption as an S-curve



Source: adapted from Rixen and Weigand 2013

Consumer durables with short product lifecycles, high risk to be imitated, and/or huge development effort rely on fast speed. Therefore, quickly attaining a critical mass of adopters is crucial. A sufficient number of individuals needs to adopt the new product to induce a self-sustaining continued adoption (Rogers 2003). Especially high-tech companies rely on fast spread of their products. Level describes the innovation's penetration rate (also referred to as saturation).

Following Rogers (1962) diffusion of innovations theory, Bass characterizes the diffusion of an innovation as a contagious process driven by external influence (e.g. advertising, mass media) and internal influence (e.g. word-of-mouth).

Based on this original formulation, a number of efforts have been made to extend and refine the Bass framework to reflect the complexity of new product growth. One of the advantages of this modelling paradigm is that it provides a parsimonious and analytically tractable way to look at the whole market and interpret its behaviour. A related advantage is that these models make use of market level data to forecast sales, which is typically more readily available than individual-level data. Assuming that sufficient data points are available, the model can be fitted to early sales data to obtain parameter estimates for new products. For the Bass model, the well-researched estimation literature covers a number of estimation methods, including ordinary least squares (Bass 1969), maximum likelihood (Schmittlein and Mahajan 1982), nonlinear least squares (Srinivasan and Mason 1986) and genetic algorithms (Venkatesan et al. 2004). The Bass model fits many historic data on completed diffusion processes well (cf. Sultan et al. 1990) and is excellent at backcasting.

Aggregate models are typically based on a formulation of differential equations that specify the flow(s) between mutually exclusive and collectively exhaustive subgroups such as adopters and non adopters (Chatterjee and Eliashberg 1990). This modeling paradigm has produced a rich stream of literature which has been reviewed by numerous authors. Mahajan and Muller (1979) review early contributions, Mahajan et al. (1990, 1995, 2000) provide an overview of the Bass model, its extensions and applications, Sultan et al. (1990) meta-analyse 213 estimates of innovation and imitation parameters of the Bass model, and Parker (1994) reviews theoretical origins, specifications, data requirements, estimation procedures and pre-launch calibration possibilities for aggregate models. More recently, Meade and Islam (2006) review the wealth of literature from a forecasting perspective and conclude that few research questions have been finally resolved.

Although diffusion modelling has become a vibrant research tradition, most reported works has consisted of refinements and extensions of the Bass diffusion model without alteration of its basic premises (Mahajan et al. 1990; Bemmaor 1994). Most models therefore still show the structure of the basic epidemic model introduced by Bass.

Traditional aggregate models are not behaviourally based (Goldenberg et al. 2000). It is therefore not surprising that these models do not reproduce the complexity of real-world diffusion patterns.

Also, while the two coefficients of Bass-type models have appealing interpretations (internal and external influence, respectively), it is not clear whether they truly reflect the underlying diffusion mechanisms. Hohnisch et al. (2008) therefore refer to these models as “phenomenological” and thus underline that they provide empirical generalizations and do not aim to explain the mechanisms that cause diffusion processes.

The mathematical form of the Bass model requires the assumption that the potential adopter population is homogeneous (Tanny and Derzko 1988; Chatterjee and Eliashberg 1990; Bemmaor 1994; Van den Bulte and Stremersch 2004), which may be considered a gross simplification since potential adopters are typically heterogeneous in economic factors such as income, in their individual preferences, the information they have etc., and consequently in their propensity to adopt. The heterogeneous population argument was already used by Rogers (1962), who defined five adopter categories based on propensity to adopt.

To consider heterogeneity in traditional diffusion models, compartmental approaches were developed that aggregate the population into a relatively small number of states such as unaware, aware, in the market, adopters etc. (e.g., Urban et al. 1990). However, compartment models still assume homogeneity and perfect mixing within compartments and do not consider heterogeneity in individual attributes and in the network structure of interactions (Rahmandad and Sterman 2008).

Due to the parsimonious structure of aggregate models, it is also not possible to distinguish effects of different social processes on diffusion. In the Bass model, for example, the internal influence parameter p is often interpreted as word-of-mouth (hereafter WoM). However, it can also capture imitation effects such as social learning, social pressures, or network effects (Van den Bulte and Stremersch 2004). Furthermore, Bass-type models make very specific assumptions about the structure of social interactions. The formulation implies a fully connected social network in which everyone in the target population is directly connected to everyone else, and can potentially influence all others (Shaikh et al. 2006). It also presumes that the influence of adopters on non-adopters is a linear function of the number of adopters throughout the diffusion periods. Because of these simplifying assumptions, the coefficient of imitation cannot be expected to directly reflect the underlying social mechanisms that shape diffusion processes.

Managers planning the introduction of a new product are interested in predicting the effects of the decision variables at their disposal, most notably the marketing mix factors product, price, promotion, and distribution, none of which were initially considered explicitly in early diffusion models.

This issue has been recognized and various authors have included marketing mix variables into aggregate diffusion models in order to better describe reality and potentially provide directions for how to alter the diffusion process by manipulating those variables (Ruiz-Conde et al. 2006). In particular, marketing mix variables considered include price (Robinson and Lakhani 1975; Bass 1980; Feichtinger 1982; Jain and Rao 1990; Bass et al. 1994, 2000), distribution and supply restrictions (Jones and Ritz 1991; Jain et al. 1991), and promotion and advertising (Dodson and Muller 1978; Horsky and Simon 1983; Simon and Sebastian 1987; Dockner and Jorgensen 1988; Bass et al. 1994).

Many of the issues and limitations outlined here can be overcome through an individual-based modelling approach, which will be discussed in the following section.

4.3 Individual level models of innovation diffusion

One of the first micro models of innovation diffusion was introduced by Chatterjee and Eliashberg (1990), who propose an analytic method to aggregate individual-level behavior based on specific heterogeneity assumptions. They consider perception of the innovation, personal preference, and the perceived reliability of information as individual-level determinants of adoption. They also provide a closed formulation of the interface between individual and aggregate level to link individual decision-making and aggregate dynamics. However, the analytical tractability of the model hinges on limited analysis of aggregated variables and consumer characteristics (Delre 2007).

The framework also cannot incorporate heterogeneity related to linkages in the social network (Bohlmann et al. 2010). Chatterjee and Eliashberg'smodel generated much interest on the impact of heterogeneity in diffusion models. This question has been a matter of discussion in innovation diffusion research for a long time (cf. Rogers 1976), but due to the limitations of aggregate models, it remained largely untackled until the advent of ABMs.

ABMs differs fundamentally from both aggregate differential equation and aggregate simulation approaches such as system dynamics (cf. Milling 1996; Maier 1998; Milling 2002). Unlike both, it is a bottom-up, disaggregate approach and thus not limited in its capacity to account for heterogeneity and social structure. The elementary modelling unit is not the (complex) system, but rather the individual. In ABMs agents' state, interaction, internal processing, and behaviour, by contrast, tends to be more complex. and ABMs can be based on arbitrary local interaction structures. Moreover key characteristics of agents include autonomous behaviour, interdependency, simple rules, and adaptive behaviour (cf. Macy and Willer 2002).

Finally, ABMs differ from differential equation models not only in terms of modelling granularity, but also fundamentally in how the results are obtained. Rather than describing the whole system directly and "phenomenologically", macro-scale dynamics in ABMs are emergent phenomena that arise from micro-level interactions between agents when the model is executed.

4.4 Agent based modelling of innovation diffusion

A pivotal element of agent-based diffusion models is the explicit representation of consumers' decision making processes, most importantly those related to the decision to adopt an innovation (or to reject it, which, however, is not considered explicitly in most models). A number of both deterministic and stochastic approaches have been developed to model these decisions, ranging from simple decision rules to sophisticated psychological models.

The most common approach to incorporate consumers' heterogeneity is to specify it in terms of an intrinsic "propensity to adopt", typically through heterogeneous adoption thresholds drawn from a distribution. One of the first micro-simulation studies to investigate heterogeneity in this manner was conducted by Goldenberg et al. (2000). They propose a cellular automata model in which cells are characterized by an adoption threshold that is randomly drawn between zero and one and interpreted as a "quality expectation". The spread of an innovation with a certain fixed "product quality" is modelled spatially on a lattice in which cells decide whether or not to adopt once a sufficient number of neighbouring cells have adopted. Simulation results exhibit strong fluctuations in sales and suggest that heterogeneity may have a strong influence on innovation diffusion.

Delre et al. (2007a,b, 2010) also use heterogeneous adoption thresholds in their models. They interpret these thresholds as "utility aspiration levels" and specify them as weighted sums (with heterogeneous weighting factors) of two separate threshold functions: (1) a social utility threshold, i.e., a minimum fraction of adopters in the social neighbourhood, and (2) a utility threshold function based on agents' heterogeneous "quality expectation". They find that increasing heterogeneity accelerates diffusion because the critical mass is reached sooner than in homogeneous populations (Delre et al. 2007b). In addition to an adoption ("exposure") threshold, Alkemade and Castaldi (2005) introduce an "over-exposure" threshold to incorporate the idea that innovations tend to be considered no longer "fashionable" once their user base becomes too large. Each agent adopts when the proportion of adopters in their neighbourhood exceeds its exposure threshold, but remains below its over-exposure threshold. Heterogeneity in both thresholds is introduced by drawing the exposure threshold from a uniform distribution and adding a fixed value to obtain the over-exposure threshold. While heterogeneity is incorporated in the model, the effect of varying degrees of heterogeneity are not analysed in the paper.

A conceptually different, but structurally very similar approach is to model heterogeneity in terms of varying individual reservation prices. Cantono and Silverberg (2009) follow this approach and investigate the path of diffusion of a new energy technology when some consumers are willing to pay more for goods that are perceived as “green”.

Agents adopt once any of their neighbours has adopted *and* the price falls below their individual reservation price drawn from a lognormal distribution. Learning economies reduce the price as a function of the extent of previous adoption, which may lead to delayed adoption for a certain range of initial conditions. Results indicate that a limited subsidy policy can trigger diffusion that would otherwise not happen when reservation prices are heterogeneous, learning economies are in a certain range, and initial price levels are high. Hohnisch et al. (2008) also model heterogeneous reservation prices, but draw them uniformly and independently. Agents adopt once the price falls below their reservation price, which is interpreted as a subjective “individual valuation”. The authors also formulate an extended model in which these “individual valuations” are time-dependent. They explain the empirical finding of a delayed “take-off” of a new product by a drift of the percolation dynamics from a non-percolating regime to a percolating regime which occurs because the probability of buying increases over time with the cumulative number of buyers. Heterogeneity in reservation prices plays a critical role in this process and determines whether diffusion takes place or fails.

In a comparison of agent-based and differential equation-based diffusion models, Rahmandad and Sterman (2008) investigate the impact of heterogeneity in terms of contact frequency. They model the spread of a contagious disease and therefore do not incorporate deliberate adoption decisions, but rather model adoption as state changes triggered by a stochastic processes. Nevertheless, they stress that results extend beyond epidemiology to innovation adoption. With respect to heterogeneity in individual contact rates, they find that it causes slightly earlier mean peak times as high-contact individuals rapidly seed the epidemic, followed by lower diffusion levels as the high-contact individuals are removed, leaving those with lower average transmission probability and a smaller reproduction rate. Note, however, that although the authors emphasize the transferability of results, caution is required when translating these findings to an innovation diffusion context.

A more empirically-oriented approach to represent heterogeneity in propensity to adopt is to link it directly to individuals' sociodemographic characteristics. While such an approach compromises explanatory power, it has the advantage that empirical data (if available) can be used more easily. Dugundji and Gulyás (2008) follow this approach in investigating the impact of heterogeneity on the adoption of transportation mode alternatives and use empirical pseudo-panel micro data to parameterize their model. They consider both observed heterogeneity (in terms of sociodemographic characteristics, individual-specific attributes of the choice alternatives, and the availability of alternatives) and unobserved heterogeneity (in terms of common unobserved attributes of the choice alternatives in the error structure of their econometric estimation model). They find that heterogeneity has a dramatic impact on the magnitude of the transportation mode shares, on the speed of the transition to a steady state, and very fundamentally on the number of possible observable steady-state solutions and conclude that *"heterogeneity cannot be ignored in any true empirical application"*. In all of the papers referred to above, heterogeneity is found to affect the diffusion of innovations considerably. It may cause fluctuations in sales, delay take-off, result in irregular diffusion patterns that deviate significantly from the typical s-shaped curve, and explain diffusion failure, all of which are phenomena that are frequently observed in the diffusion of real products.

ABMs offer researchers the opportunity to explicitly model the interactions that exert social influence, and thereby allow them to take the structure of social interactions into account.

Social influence is a generic concept that can operate on multiple levels:

- *Micro-level social influence* is transmitted locally through pairwise communication links. WoM is arguably the most relevant form of micro-level social influence. Evidence of its powerful role in the diffusion of innovations is well documented in both industry market research and scholarly research (e.g., Arndt 1967; Reingen and Kernan 1986; Brown and Reingen 1987; Mahajan et al. 1990; Herr et al. 1991; Buttle 1998). Many of the reviewed models incorporate positive WoM mechanisms, and few of them (Moldovan and Goldenberg 2004; Goldenberg et al. 2001; Deffuant et al. 2005) also consider negative WoM, which evidence suggests has a much stronger effect than positive WoM (Richins 1983).
- *Meso-level social influence* is the influence that stems collectively from an agent's immediate social environment (i.e., neighborhood in the social network). Concepts associated with

meso-level social influence include group conformism, social comparison, herding behaviour, local network externalities, and conspicuous consumption, which holds that the intrinsic value of a products may be less important than the social meaning (Veblen 1899).

- *Macro-level social influence* can be considered as the global interactions at the level of society as a whole. Examples for this type of influence include influence of the aggregate network-level opinion (e.g., Deroïan 2002) or macroeconomic feedbacks (externalities) such as learning effects, which are based on cumulative sales (e.g., Hohnisch et al. 2008).

In order to model micro- and meso-level social influence, it is necessary to define the topology of interactions between agents. Consumer agents and the links they have with each other form a graph that represents the social network in which interactions take place. Whereas the Bass model formulation implies a fully-connected social network, ABMs may use more realistic interaction topologies that resemble real-world social networks relying on generative algorithms to systematically create graphs that reproduce characteristic features of real-world social networks.

One of the first and most generic generative graph algorithms is the random graph model introduced by Gilbert (1959) and, more commonly acknowledged, by Erdos and Rényi (1960). This graph model is used prevalently in diffusion models and often serves as a baseline for comparisons with other network structures. The diameter of the resulting random graphs tends to be small, i.e., the largest number of links on the shortest path between any two nodes is small, which is a characteristic the generated graphs share with most real-world social networks (Travers and Milgram 1969). In reality, however, social networks tend to be highly clustered, which means that the probabilities of nodes being connected are not independent, but triadic closures are likely. More precisely, there are higher conditional probabilities that an arbitrary pair of nodes are linked, provided both are linked to a third node. In a social context, this means that networks tend to be "cliquish", i.e., *A* being linked to *B* as well as to *C*implies a strong likelihood that *C* is also linked to *B*. Networks that have a small diameter and are also highly clustered are called small world networks and can be generated by means of a generative algorithm developed by Watts and Strogatz (1998), which interpolates between random and regular networks.

Finally, a notable characteristic of many social networks is the relatively high number of nodes with a degree that greatly exceeds the average (where "degree" refers to a node's number of links). This corresponds to the notion that some people have a much larger number of acquaintances than others and serve as "hubs" in the network. More specifically, many (but not all) social networks exhibit the scale-freeness property, i.e., the probability *P(k)* that a node in the network is connected to *k* other nodes decays as a power law (Barabási and Bonabeau 2003). A network model that captures this characteristic was proposed by Barabási and Albert (1999). It starts with a few nodes linked to each other; nodes are added one by one and attached to existing nodes with probabilities according to the degree of the target node. Therefore, the more connected a node is, the more likely it is to receive new links. More works incorporate social influence either as the spread of awareness of an innovation, positive or negative WoM, or by considering the share of adopters in the agent's network neighbourhood when making adoption decisions. Thiriot and Kant (2008) propose an entirely different approach which allows them to study social representations of innovations. They formalize beliefs and messages as associative networks that consist of directed associations between concepts. Consumer agents embody a belief base, a list of currently salient social objects, and are linked to an agent profile which contains the default exposure to mass channels, background knowledge, and subjective production of knowledge. Agents communicate and exchange messages, which contain transmissible associative networks that may cause them to revise their beliefs.

Advances in network modelling and the development of generative algorithms for small-world (Watts and Strogatz 1998) and scale-free (Barabási and Albert 1999) networks have strongly stimulated research in this area. A number of authors (Alkemade and Castaldi 2005; Delre et al. 2007b; Kocsis and Kun 2008; Martins et al. 2009; Choi et al. 2010) have analysed diffusion in small-world networks with varying degrees of randomness.

Alkemade and Castaldi (2005) compare diffusion in regular, random, and small-world networks and vary network density as well as "exposure" thresholds (i.e., minimum proportion of adopters in the neighbourhood) and "over-exposure" thresholds (i.e., maximum proportion of adopters in the neighbourhood). The latter thresholds inhibit adoption if the proportion of adopters in the social neighbourhood is already too large for it to still be "fashionable". Results indicate that in a sparse network cascades occur even when consumers' exposure threshold is high. As the network density increases, cascades become more unlikely and the critical exposure threshold becomes smaller. The authors find that the critical exposure thresholds are similar for small-world and regular networks. On the random network, no cascades occur if the density is sufficiently low, because the network becomes disconnected.

Delre et al. (2007b) also compare various interpolations between regular and random networks, but base their model on different assumptions. They do not consider "overexposure" and model agents' decision making by means of a threshold function that consists of an individual utility part (obtained if the quality of the innovation exceeds a threshold) and a social utility part (obtained if the fraction of adopters in the agent's social neighborhood exceeds a threshold). Results indicate that innovations diffuse faster in more regular (i.e., clustered) networks than in random networks because individuals are exposed to more social influence and may therefore decide to adopt sooner. As a unique contribution among all reviewed papers, the authors also investigate how the dimension of personal networks affects the diffusion and conclude that bigger personal networks are associated with slower diffusion, particularly in random networks.

A different modelling approach is taken by Kocsis and Kun (2008), who focus on the diffusion of telecommunications technology, an industry characterized by strong positive network externalities. They develop an opinion dynamics model in which adoption decisions depend on a cost minimization procedure that is based on the number of agents in the personal network that decide to adopt or reject a technology. The proposed model constructs a small-world type network starting from a square lattice topology with periodic boundary conditions and randomly rewiring edges. The authors vary the share of rewired edges and find that in the presence of network externalities, rewired edges (i.e., increasing randomness) can facilitate but can also hinder diffusion, depending on how advantageous the advanced technologies are in comparison with the lower level ones.

In many of the reviewed models, agents' decision to adopt is considered a signal in favour of an innovation by neighbouring agents. An interesting approach is to also interpret neighbours' refusal to adopt as evidence against the product. Martins et al. (2009) formulate a model that incorporates this idea by means of a Bayesian system. To examine the impact of small-world effects, they conduct experiments with a regular square lattice topology and varying degrees of random rewiring. Results show that more rewiring (i.e., a higher degree of randomness) is associated with faster diffusion and an increased final proportion of adopters, which contradicts results by Kocsis and Kun (2008). This can be explained by the differing modelling assumptions.

Whereas Kocsis and Kun (2008) model only positive feedback effects due to externalities, Martins et al. (2009) also implicitly model a "diffusion of rejection", which may spread faster in more clustered networks. The authors also study the influence of the location of early adopters, comparing instances of clustered versus randomly scattered "seed" adopters (1% of the population) and find that the process of innovation diffusion from an initial cluster is much slower than in the case of randomly spread adopters.

Motivated by the question why diffusion sometimes propagates throughout the whole population and why at other times it halts in its interim process, Choi et al. (2010) study the diffusion of network products in random and small-world networks. They specify the consumers' willingness to adopt as a function of the product's intrinsic value perceived by each consumer (normally distributed constant) and the benefit due to local network effects based on the proportion of adopters in the agent's neighbourhood. In line with results of Kocsis and Kun (2008), they find that network structure plays a moderator role for the link between network effects (i.e., positive externalities of adoption) and innovation diffusion. Results also suggest that a new product is less likely to reach full diffusion in random networks than in cliquish networks because randomness in the topology makes it harder for an innovation to build up network benefits at the initial stage. However, once the diffusion process reaches a critical mass, diffusion is faster in a random network.

Scale-free network topologies (Barabási and Albert 1999) have also attracted considerable interest, although somewhat less than small-world networks, which appear to be more appropriate interaction models for many (but not all) markets. A paper that focuses exclusively on comparing the diffusion in scale-free and random networks was put forth by Kuandykov and Sokolov (2010). In their model, consumers adopt with a probability that is determined by the fraction of adopters in the neighbourhood and two fitting parameters that control time to adoption start and S-curve steepness, respectively. System behaviour and the resulting shape of the diffusion curve are a direct consequence of the choice of these two aggregate-level parameters. Based on (only) a single replication per condition analysed in the paper, the authors observe faster adoption for a random network compared to a scale-free network with the same number of nodes. However, time to full adoption in the random network tends to grow with the number of links. Results also indicate that innovation spreads remarkably faster through what the authors refer to as a "clustered random network" (a network in which agents are distributed among three clusters that are then connected sequentially) than through one uniform cluster with the same total population and the same number of initial adopters.

Few authors have compared all three of the most common network topologies so far. The first paper to compare the effect of small-world and scale-free networks on market dynamics was put forth by Janssen and Jager (2003). They model agents' behaviour from a social psychology perspective and adopt the "consumat" approach (Jager et al. 2000), which incorporates alternative assumptions on behavioural rules. The proposed model simulates market dynamics that emerge from agents' choice between multiple products which are replaced as soon as they become unprofitable. It is not a dedicated diffusion model, but results relate to innovation diffusion nonetheless. Findings indicate that a scale-free network leads to a market dominated by far fewer products as opposed to a small-world network.

Results also show that in scale-free networks, a small proportion of consumers (hubs, or early adopters) may have an exceptional influence on the consumptive behaviour of others. Rahmandad and Sterman (2008), while primarily concerned with comparing stochastic agent-based and deterministic differential equation models, also study the impact of different network structures. In particular, they compare fully connected, random, small-world, scale-free and lattice networks. In line with previous research, they find that higher clustering slows diffusion to other regions, because it increases the overlap in contacts among neighbours. In the small-world and regular lattice networks, this leads, on average, to lower peak prevalence and higher peak times. Because the model is concerned with the spread of contagious diseases, one should be cautious when interpreting results from an innovation diffusion perspective.

One of the most comprehensive studies on the impact of social network topology to date was conducted by Bohlmann et al. (2010), who compare diffusion in cellular (Moore neighbourhood), random, small-world, and scale-free networks. Furthermore, they also study how the strength of communication links between two market segments—an innovator segment and a follower segment—affects diffusion. They formulate a model with probabilistic adoption (p = 0.5) when a threshold (proportion of adopting neighbours) is reached. By varying this adoption threshold, the authors find that it affects the likelihood of diffusion cascades differently among the various network structures: diffusion appears more likely in clustered networks under high adoption

thresholds. The random network exhibits more consistent peak adoption across threshold levels. Moreover, the effect of network structure becomes more significant when agents' adoption threshold increases. For the two-segment model with varying link strength between innovator and follower market segments, results unsurprisingly indicate that an early emphasis on innovator adoptions rather than innovator-to-follower communications can speed market adoption when follower communications are weak.

The authors conclude that network topologies are a key factor in determining an innovation diffusion process and its pattern and that in particular highly clustered networks can have substantially different diffusion patterns than more randomly connected networks.

In order to model the effect of social hubs in the diffusion process, Delre et al. (2010) test the impact of the number of contacts as well as degree and direction to which social influences determine individual's choice to adopt. Like in previous work (Delre et al. 2007a,b), agents' decision making is based on heterogeneous utility thresholds defined as the sum of social and individual utility parts. However, unlike in prior contributions, the authors use "broad-scale" networks (Amaral et al. 2000), i.e., scale-free networks with a cut-off parameter (faster decay of the number of links) to structure interactions and motivate this with constraints people often have in building links with other people. Furthermore, their approach differs from prior work in that connections can be directed and weighted. In particular, they assume that the influence of a neighbour is proportional to the number of links it has and that the probability of directing the link from i to j depends on the number of links that i and j have. Results demonstrate that social influences can have a positive effect on the diffusion of the innovation if a given critical mass is reached, but also can have a negative effect otherwise. Social influence may decrease the chances for the diffusion to spread significantly if the innovation is of lower quality (i.e., induces less individual utility) and thus hardly reaches the critical mass. Uncertainty about the innovation success therefore increases in more socially susceptible markets. These results dissent with the common intuition that fashionable markets are easy to penetrate because consumers tend to copy each other. When the weights are stronger for those neighbours that have more relationships, the innovation reaches higher degrees of penetration. However, this effect is relatively small compared to other network factors. The direction of the relationships among consumers does not substantially affect the final market penetration. Finally, results indicate that innovations have, on average, fewer chances to spread in markets with high social influence.

Adopting Granovetter's "strength of weak ties" theory (Granovetter 1973), Goldenberg et al. (2001) break down the personal communication between closer and stronger communications that are within an individual's own personal group (strong ties) and weaker and less personal communications that an individual has with a wide set of other acquaintances and colleagues (weak ties). They formulate a cellular automata model that does not explicitly represent agents' adoption decision processes, but rather models the spread of information about an innovation by means of probabilistic state changes of passive cells. The probability of an individual cell becoming informed is based on probabilities of becoming informed via weak-tie WoM, strong-tie WoM and exposure to marketing efforts. In their full factorial experimental design the authors systematically vary these three probabilities as well as the size of each individual's personal network and the number of weak tie contacts. Results indicate that the influence of weak ties on information dissemination is at least as strong as the influence of strong ties and that the process is dominated by WoM rather than by advertising.

Summarizing results of the reviewed studies, it can be concluded that the topology of the social network involved in consumers' decision making is consistently found to have a large impact on innovation diffusion. Random networks, as opposed to more regular or more clustered ones, tend to favour the spread of information and they are therefore frequently associated with faster diffusion and an increased share of adopters at the end of the diffusion process. However, in markets in which positive externalities of adoption or strong meso-level social influence (e.g., group conformism, herding behaviour etc.) exist, diffusion appears to be both more likely and faster in more clustered networks. Social influences can have a positive or negative effect in these markets, depending on whether a given critical mass is reached. These markets are therefore more uncertain concerning the final success of the innovation.

From a theory-building standpoint, the strong impact of network topologies implies that researchers must be careful when selecting a network structure for diffusion research. One of the concept associated with meso-level social influence is those of networks externalities. The source of these externalities may be global or local, i.e., the utility of the innovation may depend on the proportion of adopters in the entire social system or in the local social neighbourhood (Goldenberg et al. 2010a).

Kocsis and Kun (2008) model local network effects in their opinion dynamics model of telecommunications technology. However, they do not use network externalities as an explanatory variable. Choi et al. (2010) also model the diffusion of network products, but they focus on the role of network structure and do not study the impact of network externalities in detail.

Goldenberg et al. (2010a), by contrast, focus specifically on the effect of network externalities and seek to analyse their absolute impact. To this end, they formulate both an agent-based and an aggregate model. In the ABM, consumers consider adoption only if the proportion of adopters in the population exceeds an agent-specific threshold drawn from a truncated normal distribution (this part of the formulation incorporates global network externalities). Once this threshold is exceeded, an agent adopts with a probability determined by two parameters, one of which controls the influence of the fraction of adopters in the agent's (Moore) neighbourhood on a two-dimensional lattice (incorporates local network externalities), and the other controls the influence of "external factors" such as advertising. The authors perform simulations with varying adoption threshold distributions and influence parameters and demonstrate that network externalities consistently have a "chilling" effect on the profitability of new products. They substantiate this claim by formulating an aggregate model to which they fit empirical diffusion data on six network products and, thus, are able to confirm the "chilling" effect of externalities.

Real-world social networks, unlike their idealized representations in most diffusion models, are not static, but evolve over time. This may not be relevant if the speed of diffusion is faster than changes in the social network structure and the structure of the social network is not influenced by the innovation itself, but it may be highly relevant for certain types of innovations. In a policy-oriented study, Deroïan (2002) therefore model the social network as a set of relationships generated by the agents themselves. The authors thereby endogenize the evolution of the social network as a step-by-step process based on the assumption that two individuals are more confident in each other if they share a common opinion (i.e., homophily). The simulation captures the emergence of a collective evaluation of an innovation and explains diffusion failure as the formation of a negative collective evaluation. Unlike most other models reviewed, Deroïan uses a directed influence graph that incorporates both positive and negative (inhibitive) influence. Drawing on ideas from the opinion dynamics literature, the authors model adoption decisions based on individual opinions (i.e., continuous propensities to adopt). The formation of these opinions, as a cumulative process, gradually increases the pressure of the whole community on individual opinions. The authors examine the impact of receptivity and network size on opinion and diffusion dynamics.

Results confirm that the diffusion of an innovation can be affected by the state of the influence network in the demand side and that irreversible dynamics occur in the system. ABMs of innovation diffusion offer the potential to explicitly incorporate marketing variables, thus allowing decision-makers to compare different scenarios and test various strategies in what-if experiments. Promotion is by far the most widely studied marketing variable in the agent-based innovation diffusion literature (Goldenberg et al. 2001; Moldovan and Goldenberg 2004; Moldovan and Goldenberg 2004; Alkemade and Castaldi 2005; Goldenberg et al. 2007;; Delre et al. 2007a)

An interesting promotional strategy is to leverage the important role of highly connected individuals (i.e., "hubs" or "opinion leaders") and use it as a marketing instrument. In a pioneering, predominantly conceptual contribution, Valente and Davis (1999) investigate how the diffusion of innovations can be accelerated through opinion leader recruitment. They use homogeneous agents that adopt once 15% of their neighbours have adopted. The formal description of the underlying model is sketchy and the network model used, which randomly allocates seven ties per agent, does

not appear to resemble most real-world social network structures very closely. Nevertheless, simulation results demonstrate that diffusion occurs faster when initiated by opinion leaders rather than by random or marginal agents and that targeting opinion leaders may therefore accelerate diffusion. Similar to Valente and Davis (1999), Delre et al. (2010) also investigate the effectiveness of opinion leader recruitment. Results suggest that the most important function of highly interconnected hubs is to inform others about the new products, but that their effect on the decision making of consumers can be often overestimated. They also find that in markets in which such hubs do not exist, diffusion is less likely to occur. For such markets, direct-to-consumer advertising could be an alternative strategy to stimulate the spreading of the new product in different areas of the network. Finally, van Eck et al. (2011) also study the role of opinion leaders, but take into account not only their central network position, but also the influence of personality traits and knowledge among influential consumers. To this end, they extend the model developed by Delre et al. (2007a). Like in the original model, agents' adoption decisions are based on a utility threshold function that includes individual preference and social influence parts. Social pressure, however, is not modelled as a threshold, but rather as a continuum (i.e., if more neighbours adopt the product, normative influence in favour of the product increases). Furthermore, the small-world network used in the original model is replaced with a scale-free network to better account for the central position of opinion leaders. The authors test critical assumptions by means of an online survey on the WoM behaviour of children in the context of the diffusion of free Internet games. The empirical data supports the hypotheses that opinion leaders (i) are better at judging product quality, although they do not know more about the product, (ii) are more innovative than followers, (iii) take more central positions in the network, and (iv) are less susceptible to normative influence than followers. The authors parameterize the model accordingly and find significant differences between networks that contain opinion leaders and those that do not. In particular, opinion leaders increase the speed of the spread of information, the adoption process itself, and the maximum adoption percentage. The results indicate that targeting opinion leaders is a valuable marketing strategy not only because of their central position, but also because of their influential power.

Overall, we can conclude that advertising can be an important driver for diffusion success, particularly in the initial stages of information dissemination. Advertising strategies directed at highly connected individuals can be effective in accelerating diffusion.

In the presence of negative WoM, however, too much advertising might even have an adverse impact on innovation success. To mitigate the destructive effect of negative WoM, firms should aim to activate opinion leaders in advance. While absence of promotional support may lead to failure of product diffusion, optimal timing and targeting of distant, small, and cohesive groups of consumers may accelerate diffusion. Nevertheless, the most important role of advertising is to spread initial awareness. Adoption itself is mostly driven by WoM, in particular after take off, rather than directly being influenced by advertising.

Besides advertising, policy interventions too can encourage the diffusion of environmental innovations, in other words can induce diffusion.

CHAPTER 5

RESEARCH AREA, DATA COLLECTION AND CASE STUDY

5. Research area, data collection and case study

5.1 Description of Research Area

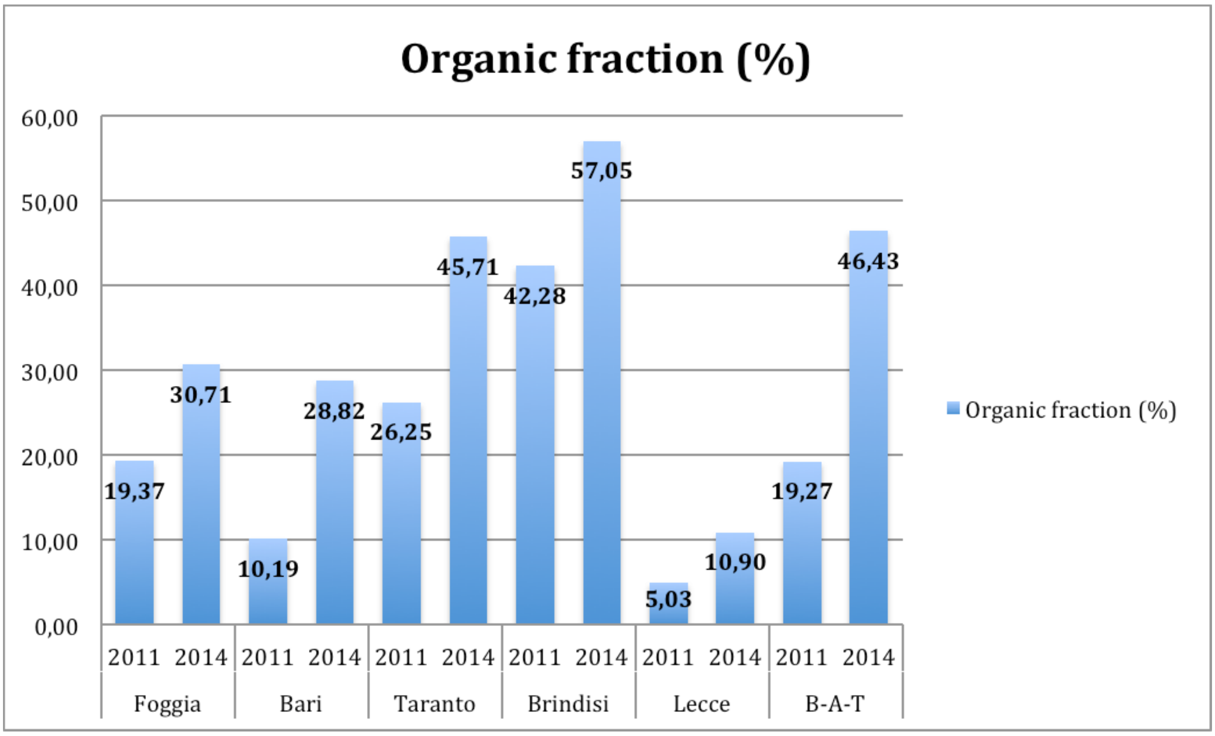
The geographic field of application for my research is the Province of Foggia (Apulia Region, Italy) that extends for 6,966.17 square kilometres with a population of 638,041 inhabitants; it is the second largest province in Italy. According to the OECD methodology (based on the parameter of the density of the population), the Province of Foggia is classified as “predominantly rural”. Furthermore, this area is divided into five macro homogeneous zones: an urban centre that coincides with the Capital Town, two low-lying rural areas with specialized intensive agriculture (Alto and Basso Tavoliere), and two rural areas with development problems (Subappennino Dauno and Gargano) characterized by medium mountain (MiPAAF 2007). The interest in this area lies in three reasons.

The province of Foggia is one of the most extended agricultural area in Italy, with 495,111.10 hectares of utilized agricultural area (UAA) (3.9 per cent of national UAA) and with 48,149 firms (3% of national total) (ISTAT, 2010) and it is a land clearly intended to crops (99.9% of the total companies) (ISTAT, 2010). Hence in this area the agricultural firms prevail compared to the industrial and other sectors. The legal status is mostly represented by individual ownership with a percentage of 98.4% of total enterprises accounting for 90.9% of the UAA. Looking at the data collected by national census (ISTAT, 2010) winter cereals are widespread with 23,775 farms and 254,693.74 UAA. On the other hand, in recent years the provincial horticultural productions have been developing in a similar shape. Indeed, the most significant data refers to processed tomato crop with 4% of the total UAA and 1901 farms, summing up about 19,140 hectares, which confirms its leadership at the national level (ISTAT 2010).

Moreover it is one of five areas in Italy, where it has the highest rate of pollution resulting from the incineration of agricultural waste (ISPRA 2013), in fact, this area has issued 10,254 Mg of carbon monoxide (CO), 473 Mg of nitrogen oxides (NO_X) and 488 Mg of methane (CH_4) (ISPRA, 2013). So this is an area where it is necessary to improve the agricultural sustainability.

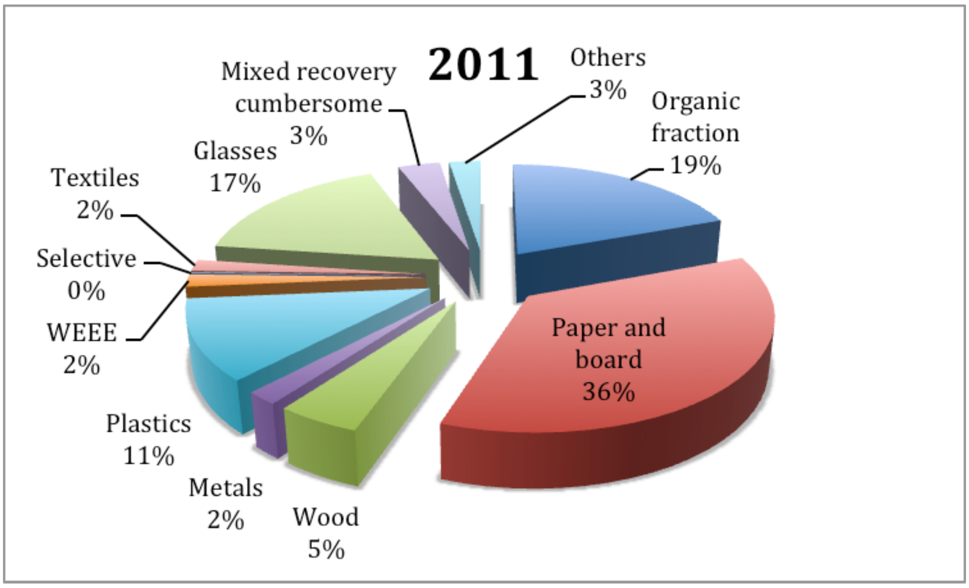
The last reason but not the least is that, regarding the organic fraction of municipal solid waste (MSW) collecting in the last years, in particular between 2011 and 2014, there were, an increase of about 500 thousand tons (+ 9.7%) of separate collection of organic (wet + green), like in the other Apulia province (see Figure 3.2; Figure 3.3).

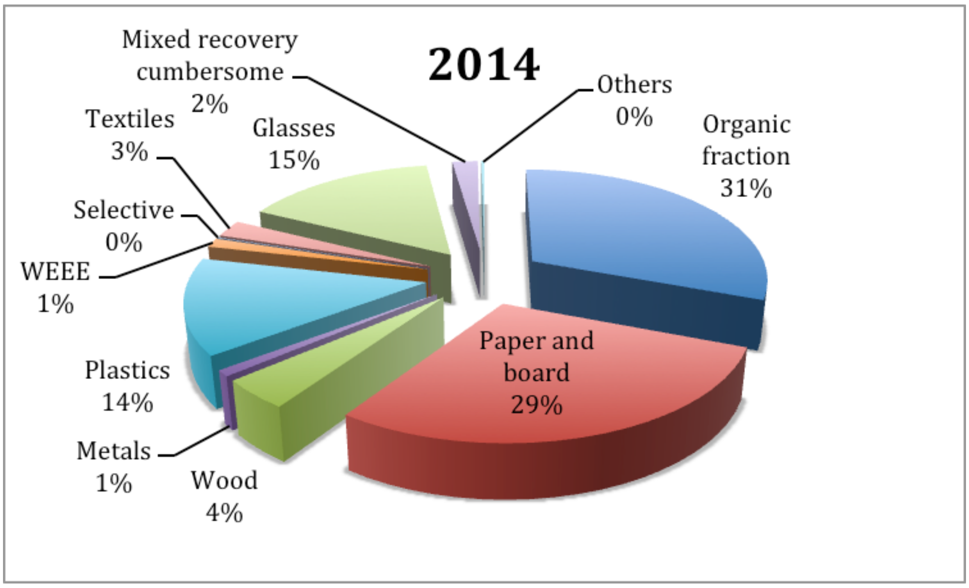
Figure 5.1 - Evolution of organic fraction at provincial level, years 2011/2014



Source: ISPRA Waste Report 2015

Figure 5.2 – Comparison between MSW recycling rates in Province of Foggia, years 2011-2014





Source: ISPRA Waste Report 2015

This means that in this Province too, like in the other of Italy, we face more and more the problem of how to ménage this organic fraction derived from MSW, therefore the production of SBO from the hidrolisis of the digestate and the compost derived from OFMSW threatment represent an additional opportunity for OFMSW management .

5.2 Data collection

To calibrate the Agent Based Model that will be described in the following chapter, I use, a dataset of 107 farmers producing vegetable crops in the area of Foggia Province (South Italy), therefore potentially interested in the use of a SAP represented by a SBO mulching film. This dataset derived from a face to face survey carried out during the month of May 2014 by SAFE department of University of Foggia, to study the diffusion of mulching technique. Sample involved farmers who already apply mulching technique, both biodegradable and conventional films, as well as those farmers who currently do not apply. The interviews were based on a structured questionnaire of four sections. In the objective of the first section was to collect information about farmers' socio-economic characteristics such as farms features (e.g. legal status, management type, land tenure, number of workers and type of crops), environmental concern, risk propensity, social networks and information channels. The collection of this data is necessary to examine farmers' behaviour and their attitudes towards the agricultural innovations (Birol *et al.,* 2007; Prokopy *et al.,* 2008; Bakopoulou *et al.,* 2010; Blazy *et al*., 2011; Pei-Chun, L. and Yi-Hsuan, H. 2012).

The aim of the second section was to inform respondents about potential economic and environmental benefits of biodegradable films and to grasp farmers' adoption attitude. The initial question of this question is: "*Have you never utilized or are you using mulch films?*" (Question 24) to distinguish between users of mulching technique from potential adopters. Then the potential adopters were asked their general willingness to adopt the mulching technique (Question 25), and their specific willingness to adopt biodegradable films (Question 32). At the same time, from those who already adopt mulches films (biodegradable or not) were collected information about the application rate, colour, market price of used films as well as current procedure for the disposal. Finally, all current users and all respondents who are willing to adopt biodegradable films were asked their preferences towards organic waste derived films (Question 34).

The third section was devoted to collect information about preferences for films properties, such as *Strength* (mechanical resistance during the stretch out of the film in the field), *Integrity* (compared to the crop duration), *Mechanical harvesting* (possibility of mechanical harvesting of crops), *Transparency* and *Disposal* (minor operations for the removal and disposal of the film at the end of cycle) and to test the potential adopters willing to pay through an auction simulation. The questionnaire ended with some minor personal information.

Then to build the interpersonal network of each agents, following the participatory social network approach (Edwards, G. 2010), that is based on the involvement of actors directly implicated in the network investigated, by means of workshops or deep interviews to co-produce a representation of that network, I had directly interviewed a local expert, who usually observed interactions among the farmers within the network, to detect information about the presence of links between the potential adopters. So I presented a list of farmers clustered into four groups according to their geographical position to the local expert who, basing on the relationships observed, identifying two types of connections: professional (farmers that work in the same cooperative) or social reasons (farmers that are friends or acquaintance) Specifically, the case study area was divided into four geographical areas localized in the Province of Foggia (see Figure 1): Northwest, Northeast, Southwest, Southeast. In the North-West zone are clustered farms located in the municipalities of Serra Capriola, Torremaggiore, Lucera, Apricena and Foggia. Farms located in the municipalities of Manfredonia, San Giovanni Rotondo, San Marco in Lamis are grouped in the Northeast area. Farmers located in the municipalities of Orsara, Troia and Foggia are included in the South- West area. Finally, farms located in Stornara, Cerignola, Ortanova, Ordona, Trinitapoli, Ascoli Satriano and Foggia are grouped in the South-East macroarea.

Figure 5.3 – Geographical partition of the case study area

North-West North-East

South-West South-East

Source: My elaboration

To the expert I initially submitted the following two questions: *1) For this area, what are the farmers who are members of the same cooperative? 2) In this group, what are the farmers who have known each other?* Then I have reported the answers to these questions in a dichotomous matrix that takes the value one in the presence of one of two types of recognized relationships and value 0 in the absence of such relations.

Finally, I investigated the existence of opinion leaders for each area. The opinion leadership is the degree to which an individual is able informally to influence other individuals' attitudes or overt behavior in a desired way with relative frequency. Opinion leaders are individuals who lead in influencing others' opinions about innovations. The behavior of opinion leaders is important in determining the rate of adoption of an innovation in a social system (Rogers, 2005). In order to identify the opinion leader in the farmers networks I asked to the expert: *" Who are the leaders in this social system? Is there any farmer who others turn to ask for information or advice?".*

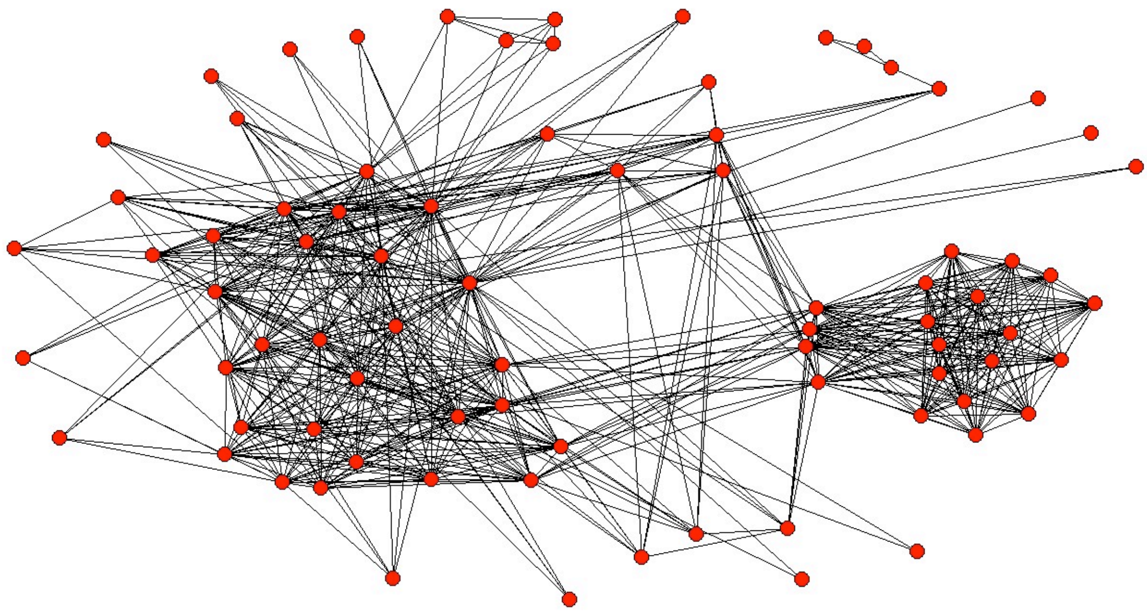
The demographic data have been employed in the calibration of the model settings. The relational data, obtained through the interview to the local expert have been used to build the network of firms, that will be showed in the following section, representing the interaction arrangement of the agents.

5.3 Case study

Following the research question and objective of my thesis (see chapter 1), as case study, I will investigate how the intervention of the Innovation Broker (see chapter 3) could increase the speed and level of SBO mulching films diffusion in a farmers network located in province of Foggia. In particular in the context of the EIP (European Innovation Partnership), and with reference to the last task of the innovation broker identified by Cristiano and Proietti (2014) (see chapter 3), I suppose in my work that an Operational Group (OG), involving different farmers located in the Province of Foggia and the University of Torino, after creating mulching films derived from SBOs and implementing it among the farmers partners of the OG, would like to have a larger base of early adopters in Province of Foggia who might further spread the innovation. The OG will do this through the help of the innovation broker (a LAG in the province of Foggia) that has already help it in the previous OG's setting up phases.

Therefore I focus my work on the last function of the innovation broker described by Cristiano and Proietti (2014). In this phase the objective of the innovation broker is to transfer knowledge, on the innovation existence and implementation by OG's farmers, to others farmers of Province of Foggia, to form a favourable attitude towards the mulching film derived from SBOs (innovation) and persuade them to adopt it (Rogers 2003). Following Rogers' theory (Rogers 2003) according which the information about the innovation diffuses through the agents connections, I felt was necessary to build the relationships' network among these farmers on the basis of real relational data obtained through the interview depicted in the previous section. Moreover since I needed a complete connected network to calibrate my model, I used the greatest component of the network detected, formed of 80 farms. The resulting network is reported in figure 5.4.

Figure 5.4 – The farmers network



Source: my elaboration

This network covers the 2% of the entire population of horticultural farms in the area. Of course, the aim here is not to produce statistical results with inference aims, but to provide real world data in order to calibrate the model. Each link is bidirectional and allows each agent to receive/send information and influence from/to its neighbors. To provide the useful context to the interpretation of the results of my work, are provided below the results of a network analysis carried out on the above mentioned farmers, obtained with the implementation of the software Ucinet. The key network features of this web are reported in the table 5.1. As shown in the table, we deal with a network formed of a unique component (3), not fragmented (5) characterized by a high density (2), where nodes have 16 relations with others in mean (3). The average distance (6) of two random chosen nodes is low, while the maximum distance revealed (7) is six. On the whole, the network is very dense and cauterized (8).

Table 5.1 – Network Cohesion

Network Measures	
1 Average Degree	16.2
2 Density	0.205
3 Components	1
4 Connectedness	1
5 Fragmentation	0
6 Average Distance	2.415
7 Diameter	6
8 Overall Clustering Coefficent	0.78

Source: our elaboration

This network context represents the information basis to properly interpreter the model findings. Moreover, since the objective of this work is to find the actors able to act as effective spreaders of a SAP within a network based on their centrality and position, following Morone and Makse (2015), I calculated several SNA measures of the farmers. The measures adopted are:

1) the Degree Centrality, that is defined as the number of links of the single. The degree can be conceived as the immediate potential of a node for influencing the information flowing through the network;
2) the betweenness, that measures the number of times a node acts as a bridge along the shortest path between two other nodes. It can be and indicator of the influence of an agent on the communication between other agents. The betweenness of node *i* is calculated as the proportion of the shortest paths of others passing through *i*;
3) the Closeness, that is the reciprocal of the farness of a node. The farness is the sum of the distances of a node from all other nodes. Thus, the more close a node is the lower its total distance from all other nodes;
4) the local Clustering Coefficient, that measures how close is the neighbours of a node to being a completely connected.

Table 5.2 reports the descriptive analysis of these measures. And panels A-D in figure 4 shows the frequency distribution of each index.

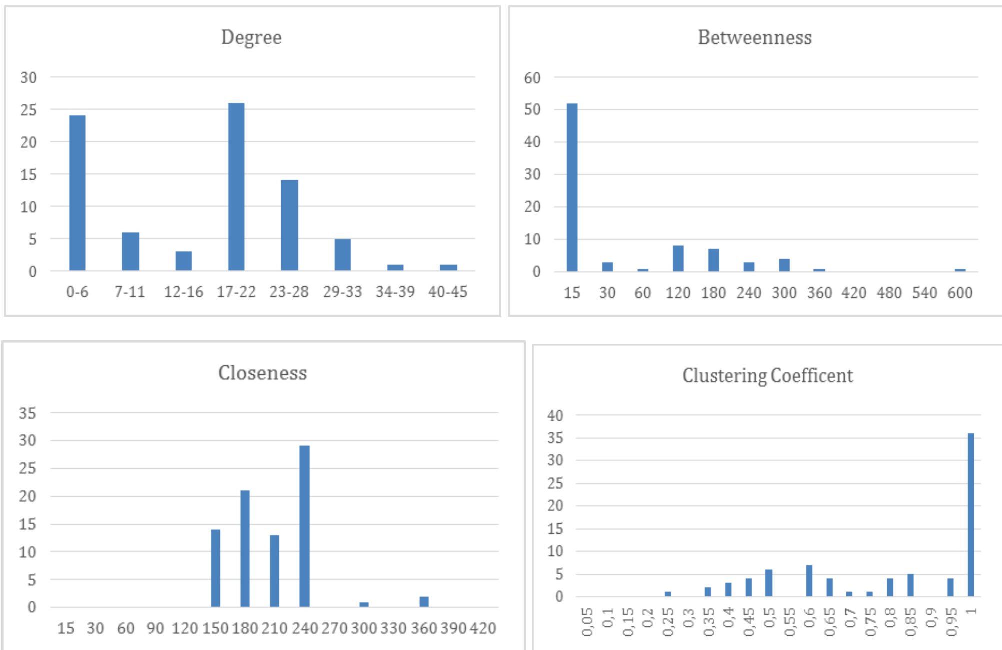
Table 5.2 – SNA measures

Network Measure	mean	st.dev	Min	max
1 Degree Centrality	16,20	10,10	1,00	45,00
2 Betweenness	55,87	98,27	0,00	554,08
3 Closeness	190,75	42,27	132,00	359,00
4 Local Clustering Coefficient	0,78	0,24	0,25	1,00

Source: my elaboration

The table shows that, in mean, the node as 16 ties with neighbors (1), intercept 56 shortest path length among others (2), are close each others (3), and are very clustered (4). The frequency distribution of these measures (fig. 4), confirms that the most part of nodes have a high degree (panel A). On the contrary, the high average value of the betweenness is due to few actors with high values, but the most part falls in the first class, thus the norm is a value of 15 or less (panel B). The measures of closeness are grouped around medium values (panel C), while the clustering coefficient is the maximum for 36 actors, with some other actors with various levels (panel D).

Figure 5.5 – Frequency distribution of the network measures



A B C D

Source: my elaboration

In this kind of network, very dense and clustered for diffusion purposes, is not primarily important how connected is the injection point and how high is its immediate influence, but how close he is to the rest of the web by means of secondary and thirdly links. For this reason in the model simulation that will be described in the following chapter, it will be considered, as injection point selection criterion, the Collective Influence too, an algorithm (Morone and Makse work of 2015), that, taking into account of these types of links, let to find the set of node in a network more effective in fragmenting this last than removing nodes that are identified through other algorithms.

CHAPTER 6

METHODOLOGY

6.1 Model's objective and assumptions

The model implemented in the present work is set to depict a population of economic agents connected through social relationships used as medium for information and opinions exchange. More specifically, it belongs to the Word of Mouth (W-o-M) models category (see chapter 5). The agents' network reproduce those that emerges from the relational data obtained through the interview described in the previous chapter. Hence, it is a static representation of the reality. The model characteristic is the presence of an activation threshold from which depends the single agent's decision to adopt or reject the innovation. The six basic assumption of this model are based on the innovation diffusion theory elaborated by Rogers (2003). The "innovation–decision process" described by Rogers is "fundamentally an information-seeking and information-processing activity in which each agent is motivated to reduce uncertainty about advantages and disadvantages of an innovation" (Rogers 2003, p.14). This process starts with the information that an innovation exist. Thus, the first assumption is that:

A1: *To form a positive attitude toward the innovation, a potential adopter should first become aware of its existence, in other words should have knowledge about the innovation.*

The fact that an individual knows a certain innovation does not mean that he will adopt it. In fact, each agent has a personal idea about the innovation based on his personal beliefs. In particular although he has awareness-knowledge about the innovation is not said that he decide to adopt it, since he could consider the new technology not relevant or useful to his business.

A2*: For the adoption to occur the agent should form a positive attitude toward the innovation, so that persuasion can take place. At the persuasion stage, the individual becomes more psychologically involved with the innovation.*

This phase of the innovation decision process is characterized by a particular phenomenon: the single agent need social reinforcement from his neighbors toward the innovation to reduce uncertainty and to be adequately informed. This means that he takes into account the opinion of his near peers based on their personal experience with the adoption of the novelty. In this phase, in fact, potential adopters want to know the answer to the question: what are the innovation's advantages and disadvantages in my situation? While this type of information is completely available in codified form for technical and scientific insiders, it is difficult to understand for economic actors and is often available from peers whose subjective evaluation is more usable for them. On the basis of these considerations, the third assumption is:

A3*: the neighbors opinions about the novelty have a relevant role in influencing the potential adopter persuasion process.*

Among all the possible communication flows between the single agents which are the most effective ones in terms of persuasion to adopt? According to an important principle of human communication, the exchange of ideas occurs most frequently between individuals who are alike, or homophilous. Moreover, communication between agents is more effective when they are homophilous, that is they share common meanings, beliefs and mutual understandings. These considerations lead to the formulation of the following sub-assumption:

A3.1: *The more homiphilous the neighbors are, the more likely the communication will be influent on the agent's decision.*

Moreover, according to Rogers, homophily occurs when two individuals are similar in certain attributes, such as education, socioeconomic status and preferences. From this, the second sub-assumption relative to neighbors influence is elaborated:

A3.2*: The homophily degree between two agents is represented by the overlap of certain socioeconomic farmer's attributes, like, age, farm size, employees' number, distance between them.*

From the previous discussion, the fourth assumption is derived:

A4*: the agent form its preference for the new technology on the basis of his personal opinion (A2) and on the ones of his neighbors (A3).*

This preference could be positive or negative. A positive preference for the innovation not necessary lead to adoption decision. In fact, it is crucial for the potential adopter to try the innovation or consider the number of other peers that have adopted and are satisfied with the innovation. This means that each potential adopter has a certain resistance to innovate represented by his personal threshold for adoption. Each agent in a system has a specific adoption threshold. The existence of such a threshold one explanation for the occurrence of the S-shaped diffusion curve. The innovators that first adopt have a very low threshold for adoption, due to their high degree of venturesomeness. Later adopters have higher thresholds (that is stronger resistance to the innovation), which are reached only when many other individuals in their personal network have adopted.

The fifth assumption arises from this consideration:

A5*: Each agent has a resistance to innovate, represented by a personal adoption threshold.*

The threshold models (Granovetter, 1978; Macy. 1991) basic hypothesis is that the individual decision to adopt an innovation depends on the number of other individuals in the system who have already adopted the novelty. On the basis of this hypothesis derives the last assumption of the model:

A6*: The agent's decision on the adoption is determined by the comparison between the agent preference for innovation (A4) and his personal innovation threshold (A6). In particular the* *individual decide to adopt if his preference (A4) is enough to let him to overcome his resistance to innovate (A6)*.

The following section describes as the model embeds these six assumptions.

6.2 Model description

According to the above discussed assumptions the model used depicts a network of farmers linked by professionals and social relationships. Fig. 1 depicts the model dynamics. In the figure, a node represents the single farmer, that is the decision-making unit, and the edges represent the relations linking the farmer with its neighbors. Each link is bidirectional and allows to receive/send information and influence from/to its ends. The process of novelty diffusion can be unpacked in four consecutive phases.

1) An initial set of agents is endowed with the novelty. These agents are conceived as the injection points (or spreaders) where the novelty is inoculated. The injection points are not only informed of the new technology but are persuaded to use it, as their preference of the novelty become high (panel A);

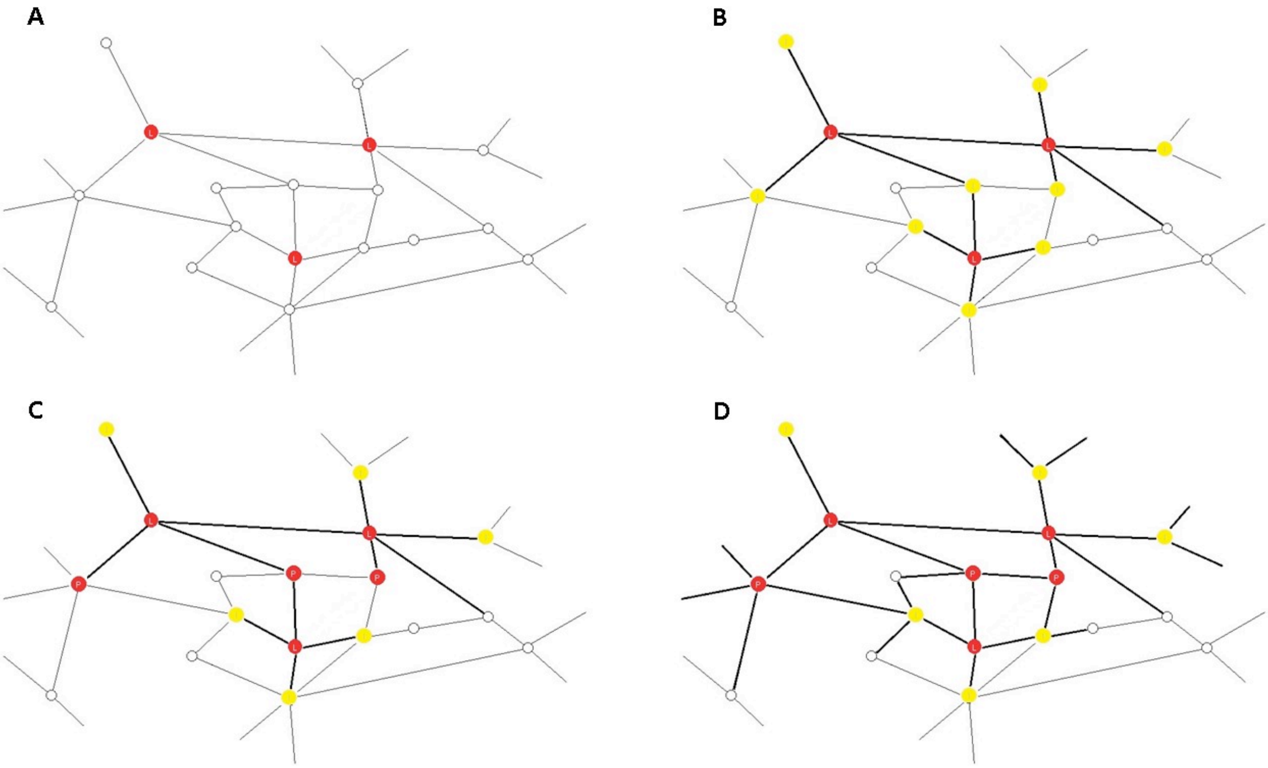
2) the injection points pass the information about the novelty and about their preferences toward it to their neighbors who became aware and form their own preferences in turn (panel B);

3) the agents informed decide whether to adopt the novelty comparing the level of their preferences with their innovation threshold (panel C);

4) in each subsequent period, the agents form or reconsider their preferences on the basis of the information received from its neighbors (panel D).

The process described in points 3 and 4 repeats until T periods of information passing.

Figure 6.1 – The diffusion model



A) The injection points are endowed with the novelty (red circles). B) The injection points pass the information to their neighbors (yellow circles) who became aware and form their own preferences. C) The agents informed decide whether to adopt the novelty. D) The agents informed pass the information to their neighbors in turn.

Following Delre et. Al 2007, the single agent informed about the existence of the innovation forms its preference toward the new technology on the basis of its personal opinion and observing his neighbors behaviors. In particular, the algorithm to calculate the preference of the agent *i* at time *t* (P_{it}) is:

$$P_{it} = P_{it-1} + \left(\sum \frac{P_{jt-1} w_{ji}}{n}\right) C \quad with\ C = \frac{E_i}{maxE} \qquad [1]$$

Where P_{it-1} represents the preference of the agent *i* at time *t*-1. If the agent is not an IP, at t_0 the preference level of agent *i* is set on *0*. It can increase up to 1 depending on its interaction with its neighbors; P_{jt-1} is the preference of the neighbor *j*; w_{ij} is the weight of the social tie that links agent *i* with its neighbor *j*; *n* is the number of agent *i* neighbor; E_i is the years of education of the agent *i*; and *maxE* is the number of years of a complete course of education.

After having formed a preference about the innovation, the agent compares it with its persuasion threshold θ_i. At each time step each agents decide to adopt or not on the basis of the fallowing decision rule:

$$Adoption\ (Ad_i) = \begin{cases} true\ if\ P_{it} > \theta_i \\ false\ if\ P_{it} < \theta_i \end{cases} \qquad [2]$$

Each variable of the model has been calibrated on the basis of empirical data derived from the two surveys described in the previous chapter.

6.3 Model calibration

The model above described contains several functional parameters. This section contains a description of the calibration process of these parameters that can be divided in three categories i) Global attributes; ii) Links attributes; and iii) Agents attributes (see table 6.1). The parameters were calibrated based on real world data and simulation dynamics.

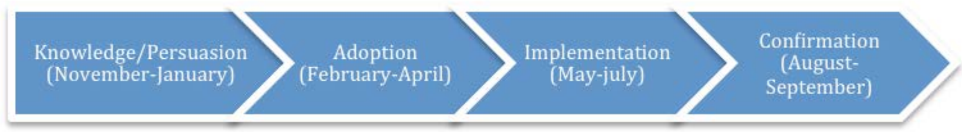
Table 6.1 – Parameter identification

Parameter	Symbol	Description	Value
Globals			
Number of agents	N	It is the number of agents interacting in the model	80
Time	T	It is the number of steps considered in the simulation model	100
Links attributes			
Homophily	w_{ji}	It represents the level of homophily of the link's ends	Various [0,1]
Agents attributes			
Threshold	θ_i	It is the innovation threshold	Discrete
Injection Point status	IP_i	It is a logic value: true if the agent is an injection point	Boolean
Education	E_i	It represents the year of education of the agent	Discrete
Adoption	Ad_i	It is a logic value: true if the agents adopt the novelty	Boolean

Source: my elaboration

The global attributes are the *number of the agents* (N) interacting in the model, the *timeframe* (T) of the model, and the . The former was set at 80, since I considered the greatest component of the network investigated in the case study (see chapter 5). The latter was set at 100 time-steps, corresponding to a 25-year time span. Each time step corresponds to three months. As suggested by the experts interviewed three months seems a good time proxy for a step. In fact, in the practice, usually, a farmer evaluates what kind of mulching film to adopt in the period from November to January. In this period, he collects information about the characteristics of the different mulching films on the market. After deciding what kind of mulching film to adopt, the farmer starts to buy it in February and to implement it on the soil in May. In July he starts the harvest, therefore, from August to October he has the opportunity to evaluate the results of the mulching film implementation. This means that every three months the potential adopter pass from one phase of the Rogers "innovation decision process" to another as showed in figure 6.2.

Figure 6.2 – Time frame description



Source: my elaboration

The links have only one attribute, the weight (w_{ij}) that represents the strength of the tie between the agent *i* and its neighbor *j*. It catches the homophily level between theme, and was calibrated on the basis of four socioeconomic variables identified by the first and the fourth section of the questionnaire. The use of four variables in this calibration, provides a more robust approach in modeling homophiles' relationships across the network than using any one characteristic as the basis for all homophiles' ties (Centola 2011). The statistics of the variables used are showed in table 6.2.

Table 6.2 - Homophily's variables

Variable	Mean	Standard Deviation	Min	Max
Age (years)	45.74	11.6	24	72
Farm size (hectares)	76.96	203.71	4	1805
Employees	13.94	16.76	1	112
Distances between farmers (Kilometers)	59.77	40.92	0	198.42

Source: my elaboration

The firm size is calculated ad the sum of the hectares dedicated to vegetable crops (tomatoes, potatoes, eggplant, peppers etc) on which potentially can be used SBO mulching films. The total number of farm's employees is given by the total of permanent workers, seasonal employees and family labor. The distances between the municipality where farms are localized, were calculated with the support of GIS (Geographic Information System) software obtaining the distance matrix reported in Appendix A. In particular w_{ij} has a value ranging from 0 to 1, and for each ordered couple of agents *i* and *j*, it is calculated as the average of the following four indexes:

1) Age (a)

$$\min a_{ij} / \max a_{ij}$$

where *min* a_{ij} and *max* a_{ij} represent respectively the minimum and the maximum age of the couple of agents *i* and *j*, and its ends;

2) Farm size (Fs)

$$\min Fs_{ij} / \max Fs_{ij}$$

where min Fs_{ij} and max Fs_{ij} represent respectively the minimum and the maximum firm size of the couple of agents *i* and *j*, and its ends;

3) Number of employees (Em)

$$\min Es_{ij} \Big/ \max Es_{ij}$$

where min Em_{ij} Emij and max Em_{ij} Emij represent respectively the minimum and the maximum number of employees of the couple of agents *i* and *j*, and its ends;

4) Location (L)

$$(\max \mathrm{dij} - \mathrm{dij}) \Big/ \max \mathrm{dij}$$

where d_{ij} represent the distance between the couple of agents *i* and *j*, and its ends.

The Agents attributes are the *innovation threshold* (θ_i), the *injection points* status (Ip_i), the *level of education* (E_i) and the *status of adoption* (Ad_i).

To calibrate the innovation threshold (θ_i) for each potential adopters I used the persuasion score, assigned on the basis of the farmers answers to the second part of the questionnaire, described in the previous chapter. In particular farmers have been divided into six level of persuasion, according to how far they are from adopting the SBO mulching film technique (1 most adverse – 6 most favorable). Each level has a persuasion score to which corresponds a certain threshold (See table 6.3).

Table 6.3 – The farmers innovation threshold

Preference Level	**Frequency**	**Frequency %**	**Persuasion Score**	**Threshold (θ_i)**
1) Adverse to mulching films	13	16,25	-1	0,2
2) Willing to adopt mulching technique (conventional) but adverse to adopt SBO films	2	2,5	-0,67	0,5
3)Adopting conventional films but adverse to adopt SBO films	12	15	-0,33	0,33
4)Not adopting mulching technique but willing to adopt SBO films	12	15	0,33	0,25
5)Adopting conventional and willing to adopt SBO films	16	20	0,67	0,2
6)Adopting bio-films and willing to adopt SBO films	25	31,25	1	0,16

Source: my elaboration

The innovation threshold represents the resistance to innovate of the potential adopters. As we can see from Table 6.3, in correspondence of positive values of the persuasion score, the innovation threshold decrease with the increasing of this last. In fact a potential adopter with an higher value of persuasion has a lower resistance to innovate. Therefore a resistance even higher is in correspondence of negative levels of persuasion.

The *injection point status* (IP_i) was set true if the agent *i* is an IP, that is the agent *i* is the a node of the network where innovation is firstly inoculated. It has the role to spread information in the network to the potential adopters. *The education level* (E_i) was measured on the basis of the level of schooling the farmer had completed (Primary school, secondary school, technical course, university degree, PhD), and it is expressed in years. It ranges between 0 (the agent does not attend any school) and 21,5 (the farmer has a PhD degree). Indeed, 21.5 is the value of *maxE* representing the maximum number of years of education, including the achievement of a Ph.D. E_i and its proportion with respect *maxE* is an important parameter, since it regulates the part of information the agent *i* is able to process. In other words, the higher it is, the higher is its capacity to grasp its neighbor's knowledge. In fact, according to Rogers (2003), the level of education has a positive impact on individuals' innovativeness. Finally, *adoption* (Ad_i) represents the agent's decision on novelty adoption. If the single agent is set as injection point its Ad_i value at time 0 is set on true. It is set on true also when the agent decides to adopt the innovation, elsewhere it is set on false. At time t_0 only the agents that represent IPs have an Ad_i set on true.

6.4 – Simulation setting

In order to test the hypothesis set in chapter three, three kind of treatments were simulated. These represent three different innovation diffusion campaign based on different selection criteria for the IPs, specifically:

1) Random (R), that simulates a diffusion campaign in which IPs are selected randomly;

2) Degree Centrality (DC) that represents a diffusion campaign considering as selection criteria of the IPs the DC of the potential adopters;

3) Collective Influence (CI) that depicts a diffusion campaign based on the recruitment of IPs the actors with the higher CI.

For the first kind of simulations, agents were selected through the Random Excel function, that returns an evenly distributed random real number greater than or equal to 0 and less than 1. A new random real number is returned every time the worksheet is calculated.

For the second and third kind of simulation, I calculate the DC and the CI of each agent. In table 6.4 are reported the nodes classification based on DC and CI. In the columns there are the agents that occupy the twenty highest positions.

Table 6.4 – Selection of the IPs

		Position Number																			
Number of Ips	**Criteria**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	**CI**	"F17"																			
	DC	"F17"																			
2	**CI**	"F17"	"F31"																		
	DC	"F17"	"F2"																		
3	**CI**	"F17"	"F31"	"F30"																	
	DC	"F17"	"F2"	"F1"																	
4	**CI**	"F17"	"F31"	"F30"	"F10"																
	DC	"F17"	"F2"	"F1"	"F31"																
5	**CI**	"F17"	"F31"	"F30"	"F10"	"F2"															
	DC	"F17"	"F2"	"F1"	"F31"	"F12"															
6	**CI**	"F17"	"F31"	"F30"	"F10"	"F2"	"F39"														
	DC	"F17"	"F2"	"F1"	"F31"	"F12"	"F30"														
7	**CI**	"F17"	"F31"	"F30"	"F10"	"F2"	"F39"	"F42"													
	DC	"F17"	"F2"	"F1"	"F31"	"F12"	"F30"	"F10"													
8	**CI**	"F17"	"F31"	"F30"	"F10"	"F2"	"F39"	"F42"	"F43"												
	DC	"F17"	"F2"	"F1"	"F31"	"F12"	"F30"	"F10"	"F19"												
9	**CI**	"F17"	"F31"	"F30"	"F10"	"F2"	"F39"	"F42"	"F43"	"F93"											
	DC	"F17"	"F2"	"F1"	"F31"	"F12"	"F30"	"F10"	"F19"	"F20"											
10	**CI**	"F17"	"F31"	"F30"	"F10"	"F2"	"F39"	"F42"	"F43"	"F93"	"F33"										
	DC	"F17"	"F2"	"F1"	"F31"	"F12"	"F30"	"F10"	"F19"	"F20"	"F21"										
11	**CI**	"F17"	"F31"	"F30"	"F10"	"F2"	"F39"	"F42"	"F43"	"F93"	"F33"	"F1"									
	DC	"F17"	"F2"	"F1"	"F31"	"F12"	"F30"	"F10"	"F19"	"F20"	"F21"	"F39"									
12	**CI**	"F17"	"F31"	"F30"	"F10"	"F2"	"F39"	"F42"	"F43"	"F93"	"F33"	"F1"	"F12"								
	DC	"F17"	"F2"	"F1"	"F31"	"F12"	"F30"	"F10"	"F19"	"F20"	"F21"	"F39"	"F42"								
13	**CI**	"F17"	"F31"	"F30"	"F10"	"F2"	"F39"	"F42"	"F43"	"F93"	"F33"	"F1"	"F12"	"F8"							
	DC	"F17"	"F2"	"F1"	"F31"	"F12"	"F30"	"F10"	"F19"	"F20"	"F21"	"F39"	"F42"	"F43"							

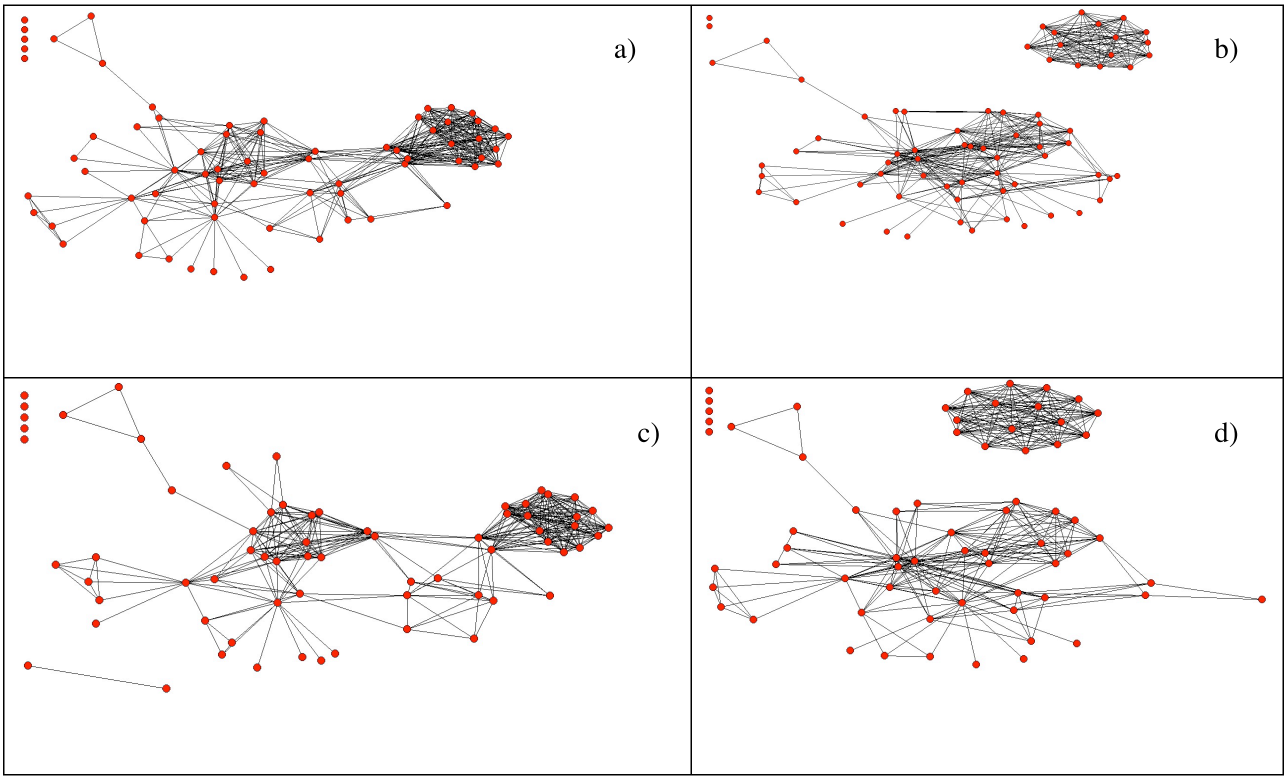
17	CI	"F17"	"F31"	"F30"	"F10"	"F2"	"F39"	"F42"	"F43"	"F93"	"F33"	"F1"	"F12"	"F8"	"F19"	"F20"	"F21"	"F6"			
	DC	"F17"	"F2"	"F1"	"F31"	"F12"	"F30"	"F10"	"F19"	"F20"	"F21"	"F39"	"F42"	"F43"	"F93"	"F6"	"F11"	"F32"			
18	CI	"F17"	"F31"	"F30"	"F10"	"F2"	"F39"	"F42"	"F43"	"F93"	"F33"	"F1"	"F12"	"F8"	"F19"	"F20"	"F21"	"F6"	"F35"		
	DC	"F17"	"F2"	"F1"	"F31"	"F12"	"F30"	"F10"	"F19"	"F20"	"F21"	"F39"	"F42"	"F43"	"F93"	"F6"	"F11"	"F32"	"F35"		
19	CI	"F17"	"F31"	"F30"	"F10"	"F2"	"F39"	"F42"	"F43"	"F93"	"F33"	"F1"	"F12"	"F8"	"F19"	"F20"	"F21"	"F6"	"F35"	"F36"	
	DC	"F17"	"F2"	"F1"	"F31"	"F12"	"F30"	"F10"	"F19"	"F20"	"F21"	"F39"	"F42"	"F43"	"F93"	"F6"	"F11"	"F32"	"F35"	"F36"	
20	CI	"F17"	"F31"	"F30"	"F10"	"F2"	"F39"	"F42"	"F43"	"F93"	"F33"	"F1"	"F12"	"F8"	"F19"	"F20"	"F21"	"F6"	"F35"	"F36"	"F33"
	DC	"F17"	"F2"	"F1"	"F31"	"F12"	"F30"	"F10"	"F19"	"F20"	"F21"	"F39"	"F42"	"F43"	"F93"	"F6"	"F11"	"F32"	"F35"	"F36"	"F33"

Source: my elaborations

In each row for all positions there are reported the actors with the highest CI and with the highest DC. Therefore, on the rows there are the packs of IPs to use in the simulations on the basis of the two selection criteria and of the number of the IPs. For example, in the case of two IPs it will be selected according the CI the actors “F17”, “F31”, while on the basis of D the nodes “F17” and “F2”.

As showed in Table 6.4 the main differences between CI and DC are in the first twelve positions, therefore I focused my attention on them and, for each kind of treatment, DC and CI, I executed 12 different simulations, one for each number of IPs activated. The 12 injection points selected with CI criteria, in comparison with those selected according to the DC criteria, following Morone and Makse (2015), should be the nodes that if removed from the network will generate the best fragmentation of this one. Therefore, to test this, before starting with the simulations, I tried to remove from the network, first the nine nodes with highest DC and those with the highest CI. Then I compared the fragmentation obtained in this way with those obtained after the removal of the first twelve nodes with the highest value of each of the two criteria (DC and CI) (see Figure 6.3). As can be seen from figure 6.3, it is obtained with the removal of nodes with the higher CI rather than those with the higher DC.

Figure 6.3 – Optimal network fragmentation



Source: my elaboration

In a), after the disconnection of nine nodes chosen through the DC the bigger component is formed by 75 nodes while in figure b) this one consists of 63 nodes, therefore CI (b) criterion leads, even with nine nodes, to a great networks' disaggregation compared to those obtained by eliminating the actors with the highest DC (a). In d) is represented the best fragmentation obtained with the disconnection of 12 collective influencers, in fact in this case, the bigger network consists of 59 nodes, compared to 68 nodes of the bigger network obtained with the disconnection of 12 actors selected on the basis of DC (c).

All the simulation has been made with the support of the NetLogo 5.2 platform (Wilensky, 1999), that is a widely used agent-based simulation tool. Since simulations are usually not deterministic, they contain several random elements, I carried out repeated simulation experiments (batch of 100 runs) in order to identify different trajectories of model behavior. Within the batch I took the average number of persuaded agents. Simulations results are showed in the following chapter.

CHAPTER 7

SIMULATION RESULTS

7.1 Introduction

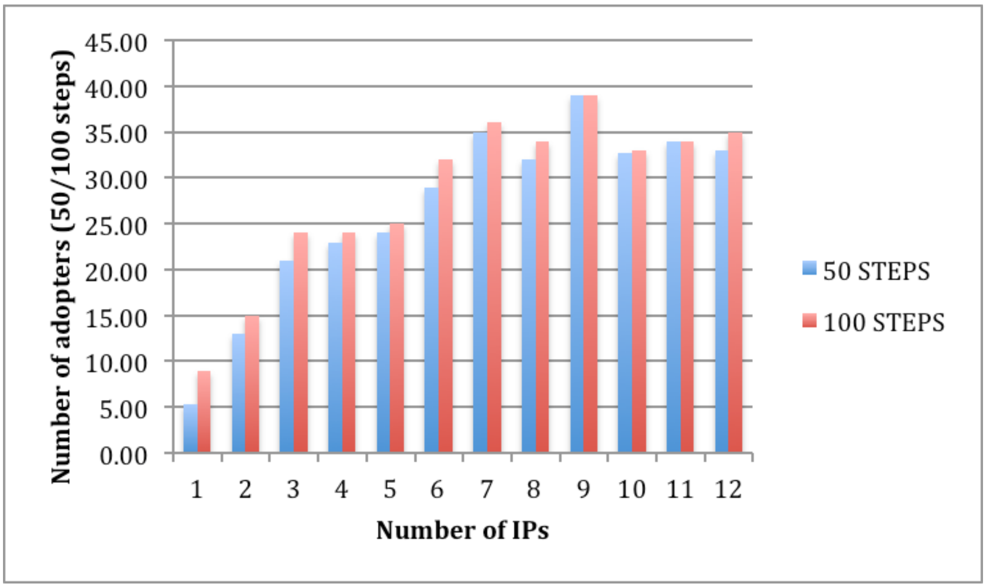
This chapter is devoted to test the basic ideas developed in this thesis, that are: 1) even in a very dense network, the diffusion rate reached during a diffusion campaign is not indifferent to the characteristics of the IPs chosen. In other words, we expect that the use of centrality measures to choose the best IPs leads to final diffusion rates greater than those reached by using random spreaders. The CI is the best criteria to choose effective IPs, in the sense that it guarantees 2) higher diffusion rates, and 3) higher speed in reaching the maximum level of diffusion, when compared with other centrality measures (i.e. DC)[4]. The data needed to perform this analysis was generated simulating the diffusion process using three treatments in the choose of the initial spreaders according to the description provided in the previous chapter, namely the random methods (R) that represents the baseline, the CI algorithm, and the DC methods. To test H1 I compared the baseline with the CI and DC results. Then, I tested H2 and H3 comparing the performances of CI and DC in terms of number of adopters and speed of adoption. The variables used to make these comparisons are 1) "level of adoption", expressed in absolute (number of adopters) and relative (fraction of adopters) terms, at half (50 step) and final time (100 step), it is indicated as $A_{p,t,i}$, where p denotes the period (half or final time), t the treatment (R, DC or CI), and i the number of IPs simulated; 2) "time max" that measures the period taken to reach the maximum number of adopters (speed of the novelty diffusion), denoted as $Tmax_{t,i}$, where t and i have the same meaning above[5]. Before the comparative analysis, the following three paragraphs reports some descriptive statistics of each treatment.

7.2 The baseline simulation

Figure 7.1 and in figure 7.2 show the adoption level obtained with the random treatment. As it emerges, the diffusion grows with the increase of the number of the IPs. This is true until the use of nine IPs in correspondence of which at the final time there are 39 innovation adopters. In other words, innovation is implemented by the 49% of the potential adopters. After nine IPs the level of diffusion, expressed both in absolute and relative terms, decreases to 35 adopters (44% of the sample). The differences between diffusion level at half and final time step, as can be seen from figure 7.1 and 7.2, are always positive, except in correspondence of nine IPs where the diffusion level at 50 steps is equal to those at 100 steps.

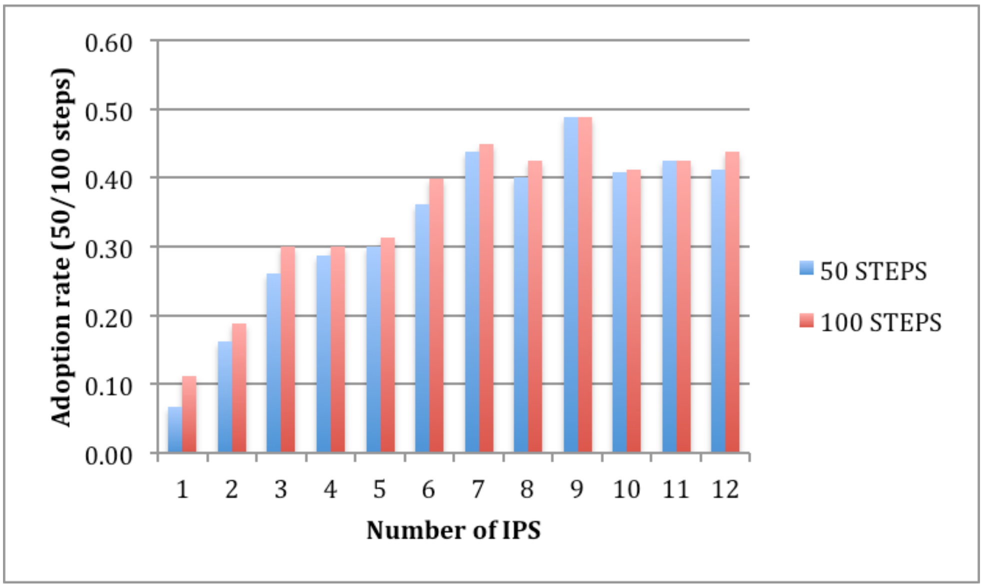
[4] For the full description of the hypothesis, see chapter three.
[5] For instance, the number of adopters at final time with seven *Ip* within the treatment CI is denoted as $A_{100,CI,7}$; while the time max for treatment R with 10 *Ip* is $Tmax_{R,10}$.

Figure 7.1 – Number of adopters (baseline simulation)



Source: my elaboration

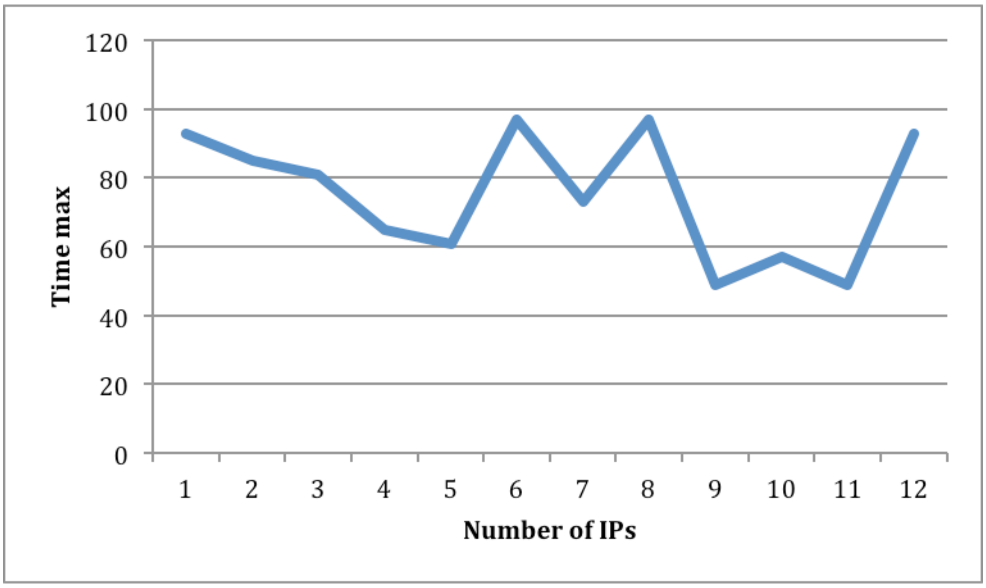
Table 7.2 – Fraction of adopters (baseline simulation)



Source: my elaboration

Regarding to the diffusion speed, it does not have a clear trend, (see figure 7.3). In fact, as I expected, it initially becomes faster (from 1 IPs to 5), after 5 IPs it starts to be very variable.

Figure 7.3 – Diffusion speed in the baseline simulation



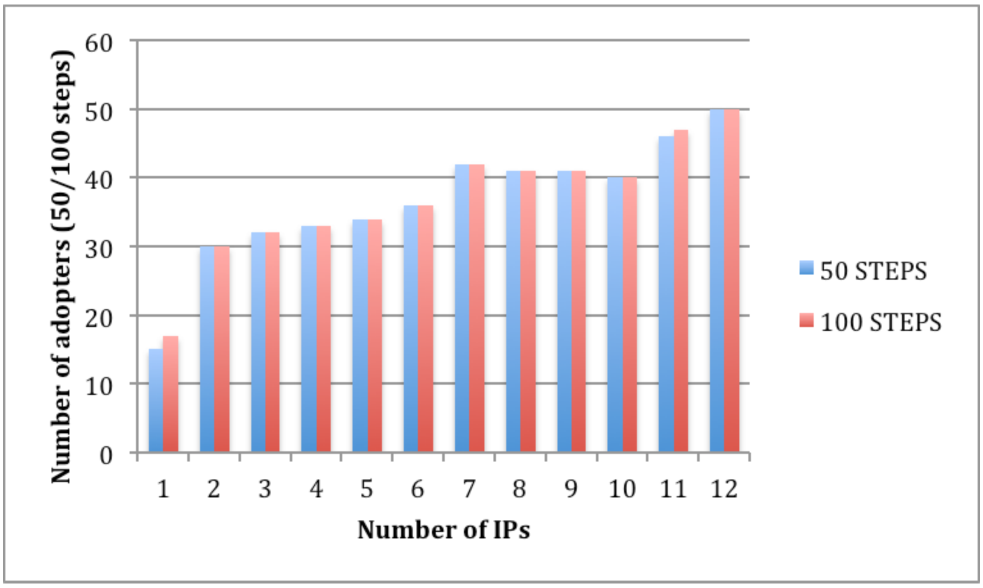
Source: my elaboration

7.3 The Degree Centrality simulation

The impact of a diffusion campaign conducted recruiting spreaders based on higher degree centrality, follows a positive trend (both at 50 steps and 100 steps), from 17 (21%) adopters reached with 1 spreader, it passes to 42 adopters (53%) with 7 IPs. For greater level of spreaders, as shown in Figure 7.4 and 7.5, the adoption rate decreases and then it grows up to 50 adopters (63%) in correspondence of 12 IPs.

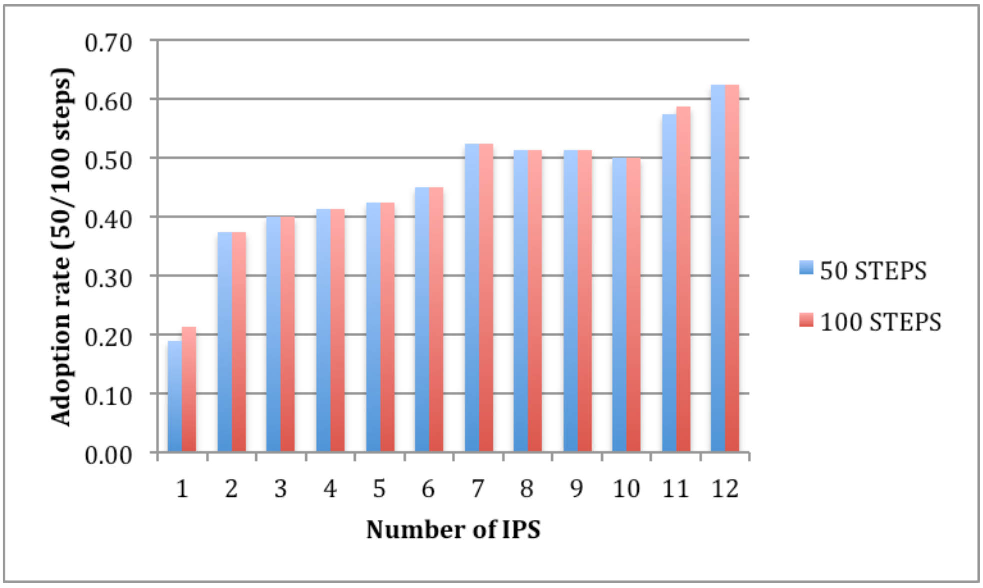
Moreover, it is interesting to note that there are not significant differences between diffusion level at 50 steps and 100 steps. The only differences are in the simulation with 1, 11 and 12 spreaders.

Figure 7.4 – Number of adopters reached during the DC simulation



Source: my elaboration

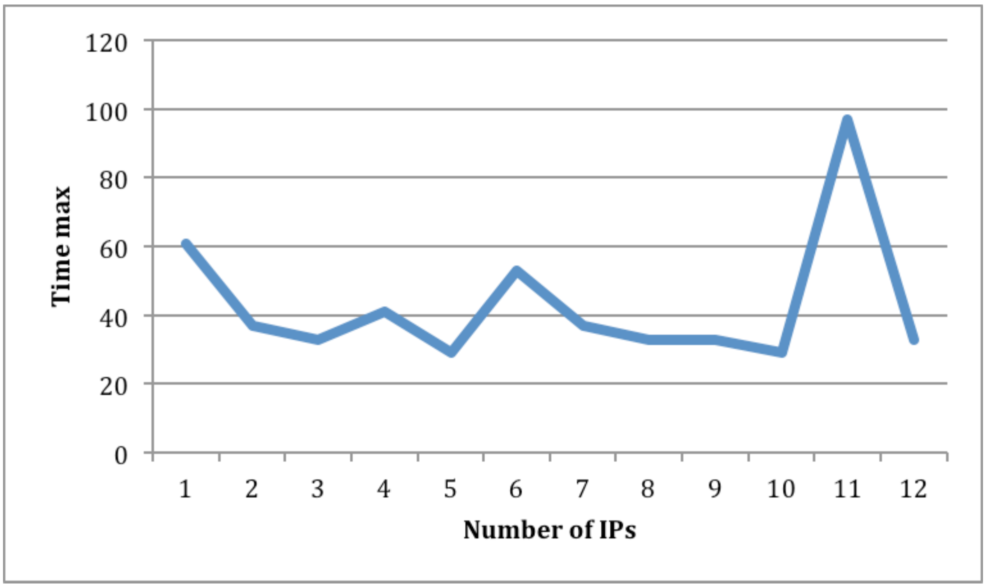
Figure 7.5 – Fraction of adopters reached during the DC simulation



Source: my elaboration

Finally, as shown in figure 7.6, the diffusion speed tends to follow a declining path with two peaks corresponding to 6 and 11 spreaders that need respectively 53 and 97 the time steps to reach the maximum level of diffusion.

Figure 7.6 – Diffusion speed in the DC simulation

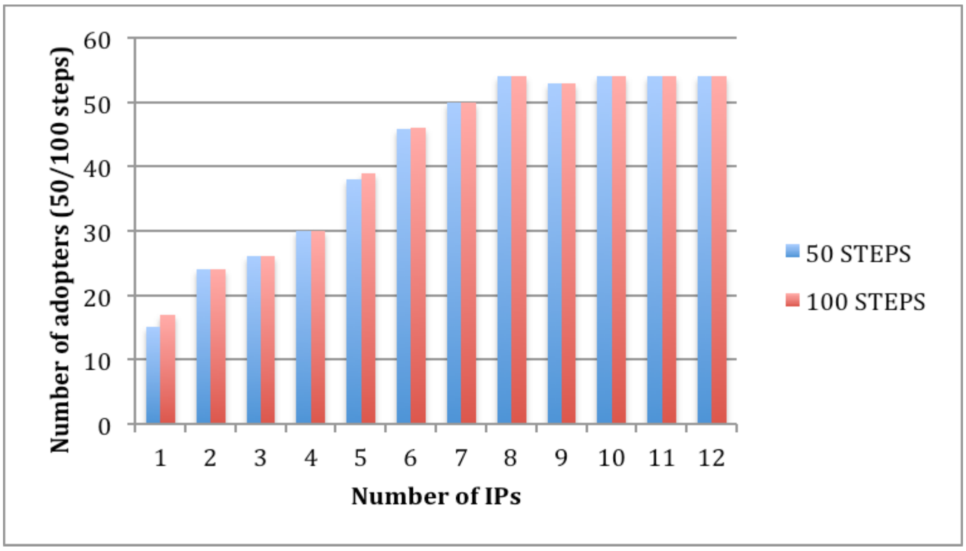


Source: my elaboration

7.4 The Collective Influence simulation

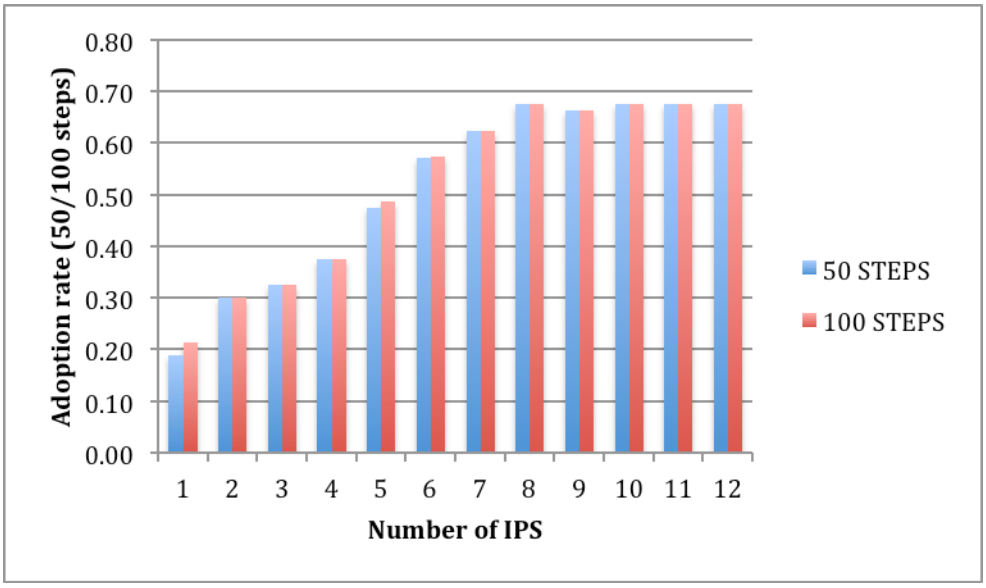
Differently from the previous treatments, the CI algorithm exhibits an almost uniform increasing trend (see figure 7.7 and 7.8). It reaches the maximum value of 54 adopters (68%) with only eight spreaders. With nine IPs, it decreases a little, and returns to the maximum rates for the rests of simulations (from 10 to 12 IPs). Moreover, there are not great differences between diffusion levels at half and final steps, indeed starting from the simulation seven no differences were observed.

Figure 7.7 – Number of adopters reached during the CI simulation



Source: my elaboration

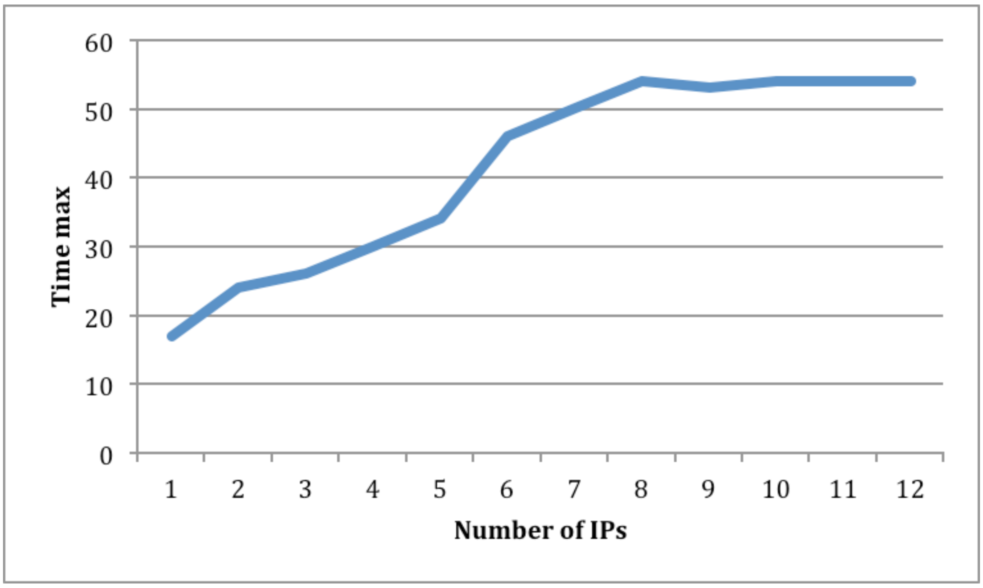
Figure 7.8 – Fraction of adopters reached during the CI simulation



Source: my elaboration

Interestingly, the speed of diffusion exibiths a costantly increasing trend. There is a little reduction of time max in corrispondence of nine spreaders, with a stabilization for the rest of the simulations (from 10 to 12).

Figure 7.9 – Diffusion speed in CI simulation

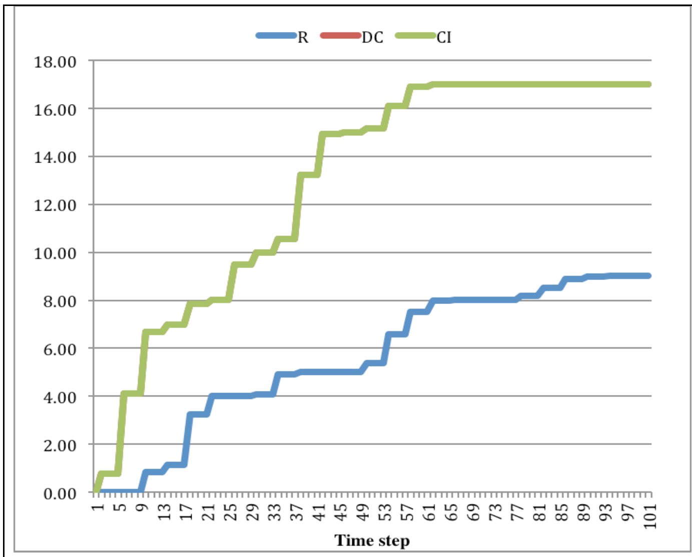


Source: my elaboration

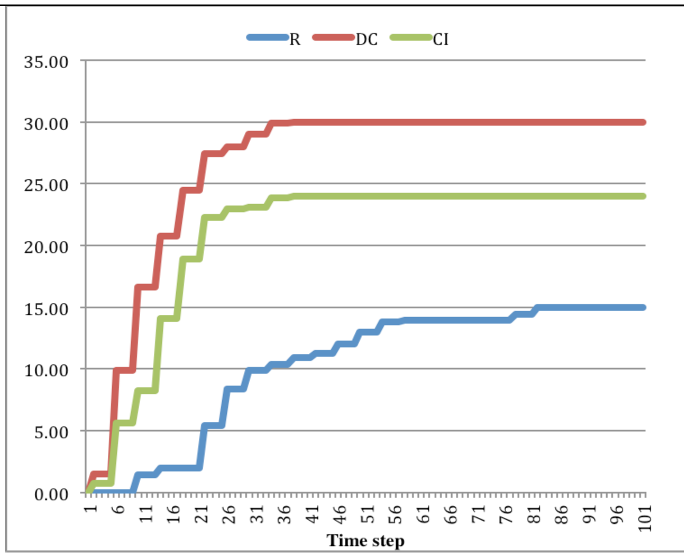
7.5 The comparison between simulations

This section is devoted to the analysis of the differences between the performances of the three simulated treatments. The comparison is based on $A_{p,t,i}$, and $Tmax_{t,i}$ relative to each simulation. Some descriptive statistics on these variables obtained with the three different methods (R, DC, CI) are shown in figures 7.10 and 7.11. Figure 7.10 reports the differences between the three treatments using a line diagram. Colors refers to the treatments: blue represents R, red represents DC, and the green line represents CI.

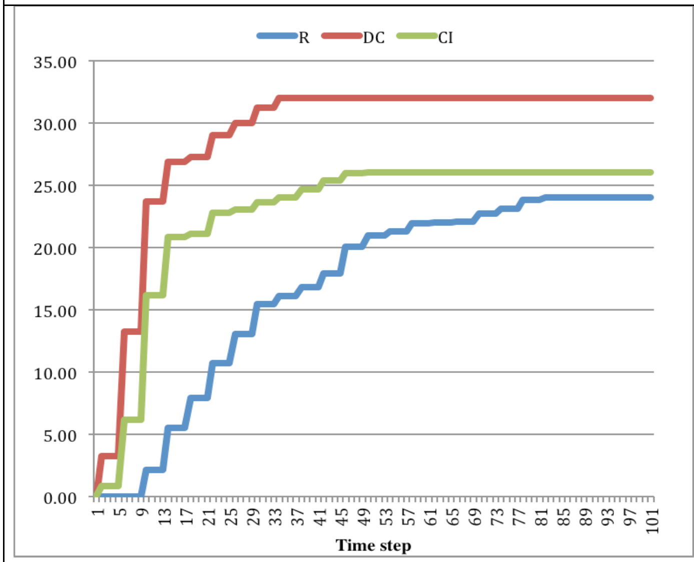
Figure 7.10 Level of diffusion



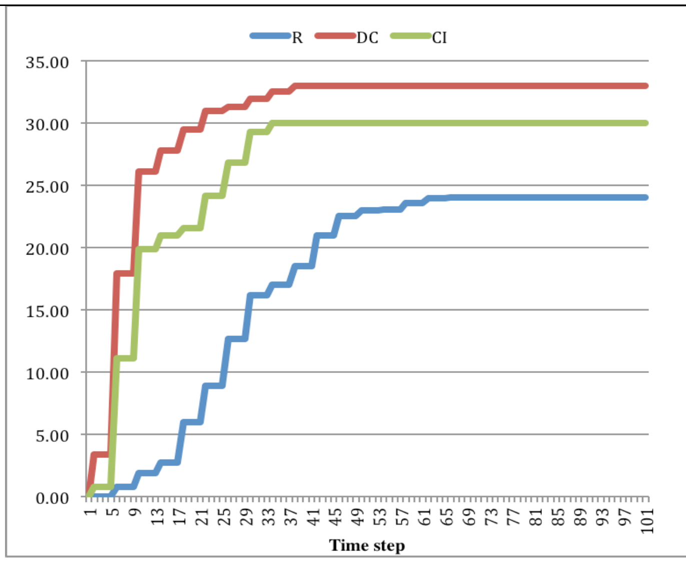
1 IPs



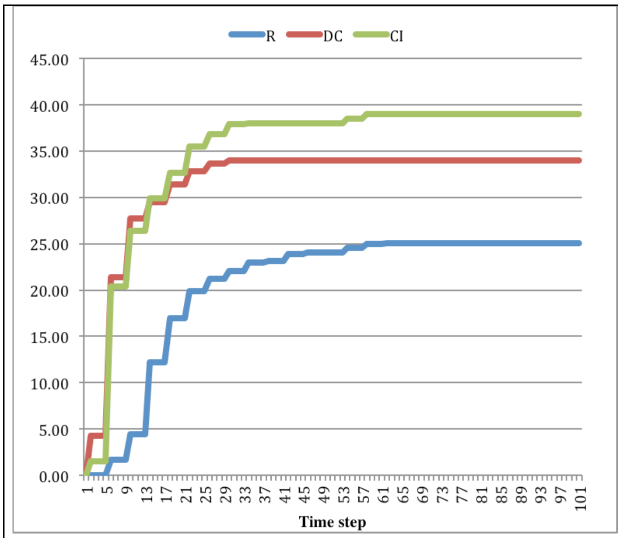
2 IPs



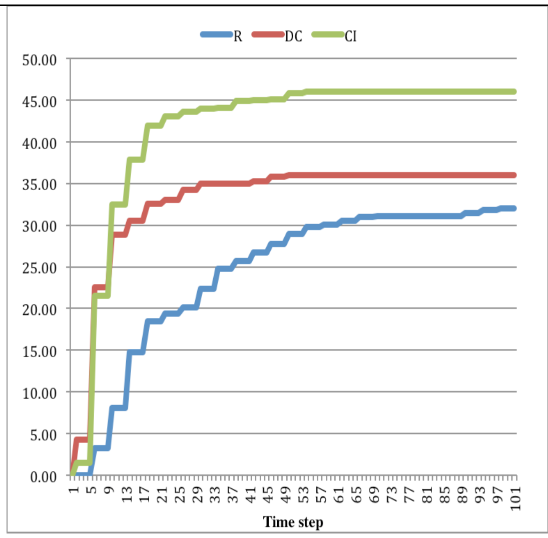
3 IPs



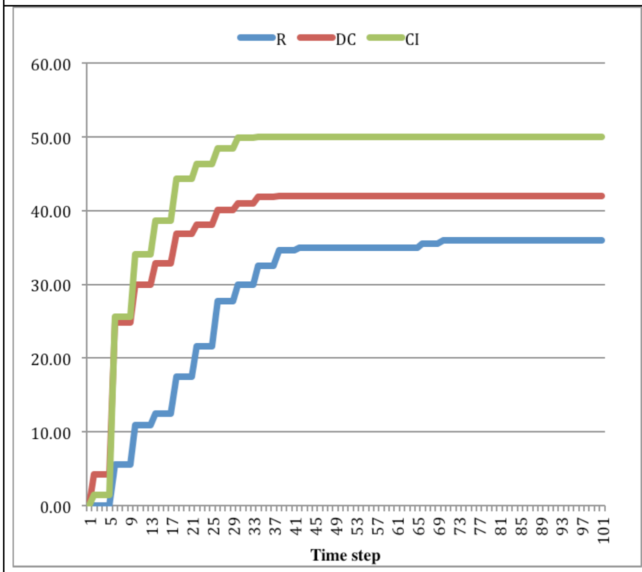
3 IPs



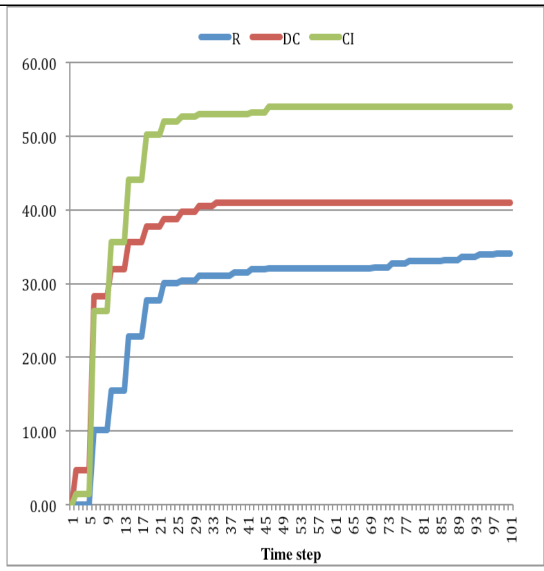
5IPs



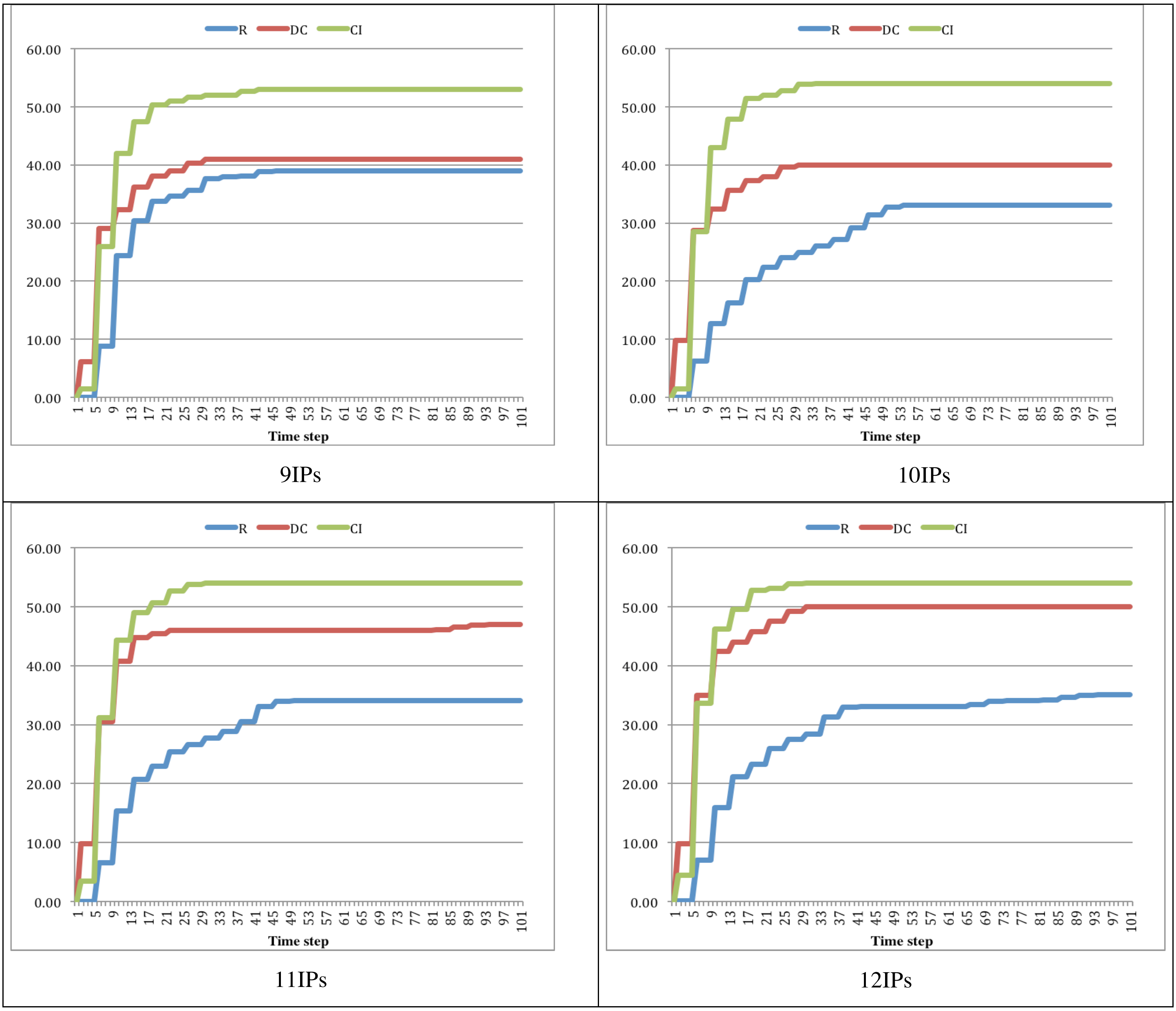
6IPs



7IPs



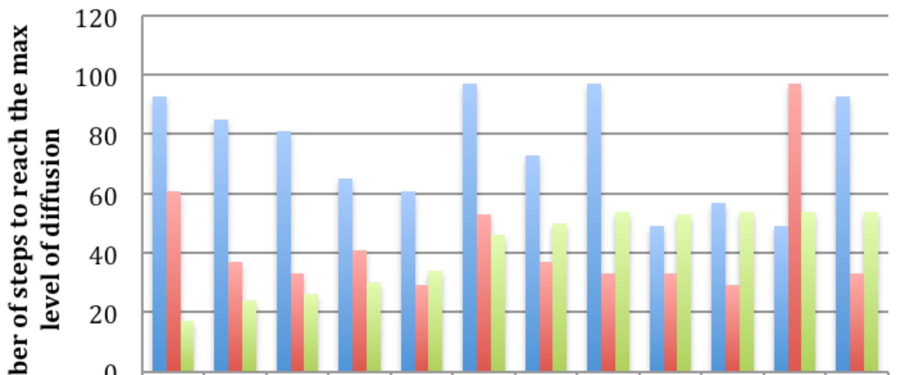
8IPs



Source: my elaboration

For each number of IPs used, the treatments with D and CI, reaches higher levels compared to the random one. Therefore, the simulations confirms that a targeted choice of the IPs over performs the casual peaks of IPs. In the condition with one IPs, the rates of diffusion with CI trace those of the DC (the green line perfectly overlaps the red one). This depends on the fact that the firs IPs is the same in the two treatment, proven that the agent with the highest DC has also the highest CI. Surprising, for the conditions with two to four the DC is more effective of CI. The maximum difference is in correspondence of 2 and 3 IPs. From the fifth simulation onwards, the results are overturned, since CI systematically reach higher diffusion rates. Regarding to the speed of the diffusion, measured by the time max, we can see from table 7.11 that 1) the rational criteria (DC and CI) are always faster than the treatment with random method; 2) for the first six IPs the CI exhibits an higher speed (denoted by very small bars) compared to the others two criteria, instead from the seventh simulation onwards the DC is the fastest treatment excluded the condition with 11 spreaders.

Table 7.11 – Diffusion speed



	1	2	3	4	5	6	7	8	9	10	11	12
R	93	85	81	65	61	97	73	97	49	57	49	93
DC	61	37	33	41	29	53	37	33	33	29	97	33
CI	17	24	26	30	34	46	50	54	53	54	54	54

Source: my elaboration

In order to allow the comparison among treatments, the variables $A_{p,t,i}$ and $Tmax_{t,i}$ were operationalized. More in depth:

- the number of adopters per injection point at time p for the treatment t with n IPs ($N_{p,t,i}$) is calculated as:

  $N_{p,t,i} = A_{p,t,i}/n$ [1];

- the standardized level of adoption obtained by treatment p with i IPs ($S_{p,t,i}$) is calculated as:

  $S_{p,t,i} = A_{p,t,i}/ A_{p,R,i}$ [2];

  in other words, with the [2] the levels of adoption reached with DC and CI were standardized with respect to the baseline values. This is made to remove the effect of the growing number of the IPs;

- the standardized time max of the treatment p with injection point i ($sTmax_{t,i}$) is calculated as:

  $sTmax_{t,i} = Tmax_{t,i} – Tmax_{R,i}$ [3];

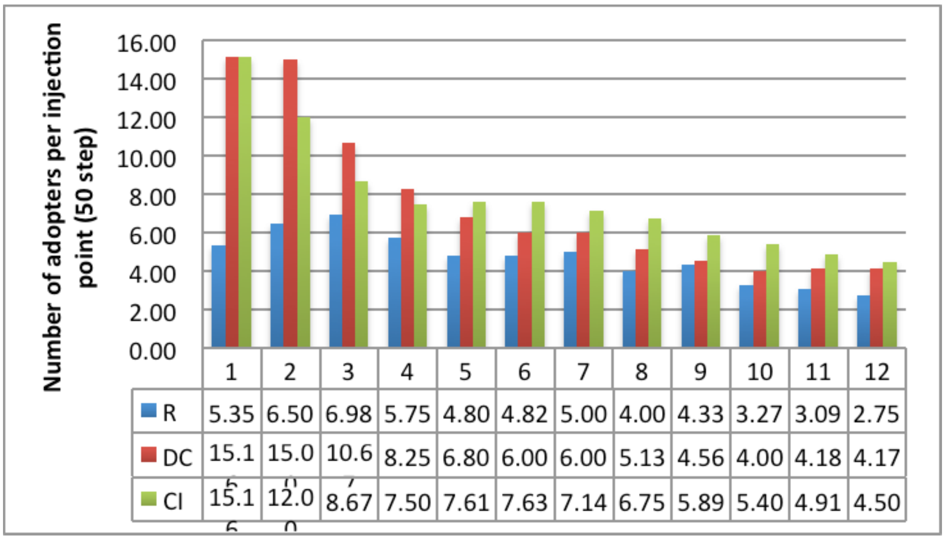
  That is the diffusion speed of the treatment with DC and CI is standardized considering the differences of their time max with the time max of the random treatment. To test the research hypothesis, I applied at these variables obtained with the three kind of treatments the Mann-

Whitney U test. This is a non-parametric test used to know if there are differences between two independent groups of a study design where it is measured the same continuous or ordinal dependent variable in two independent groups. Specifically, with this test I verify if $N_{p,t,i}$, $S_{p,t,i}$, $sTmax_{t,i}$ are significantly different between the treatments. The test is performed for each hypothesis as explained in what follows.

H1: is verified if $N_{p,DC,i}$ and $N_{p,CI,i}$ is significantly different from $N_{p,R,i}$, that is the number of adopters per *Ip*, obtained with DC and CI at a certain step, is significantly different from those observed in random treatment.

As shown in figures 7.12-13 the level of adopters per injection point ($N_{p,t,i}$) of DC and CI is always higher than the one of the random treatment both at half and final time. This difference is statistically significant.

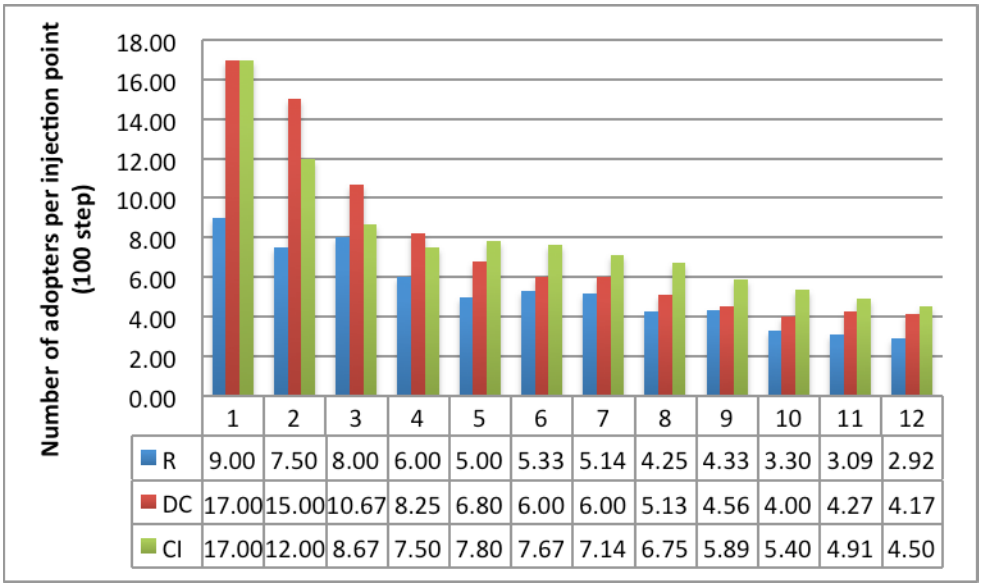
Figure 7.12 – Comparison results between the three criteria (50 step)



	1	2	3	4	5	6	7	8	9	10	11	12
R	5.35	6.50	6.98	5.75	4.80	4.82	5.00	4.00	4.33	3.27	3.09	2.75
DC	15.15	15.00	10.67	8.25	6.80	6.00	6.00	5.13	4.56	4.00	4.18	4.17
CI	15.16	12.00	8.67	7.50	7.61	7.63	7.14	6.75	5.89	5.40	4.91	4.50

Source: my elaboration

Figure 7.13 - Comparison results between the three criteria (100 step)



	1	2	3	4	5	6	7	8	9	10	11	12
R	9.00	7.50	8.00	6.00	5.00	5.33	5.14	4.25	4.33	3.30	3.09	2.92
DC	17.00	15.00	10.67	8.25	6.80	6.00	6.00	5.13	4.56	4.00	4.27	4.17
CI	17.00	12.00	8.67	7.50	7.80	7.67	7.14	6.75	5.89	5.40	4.91	4.50

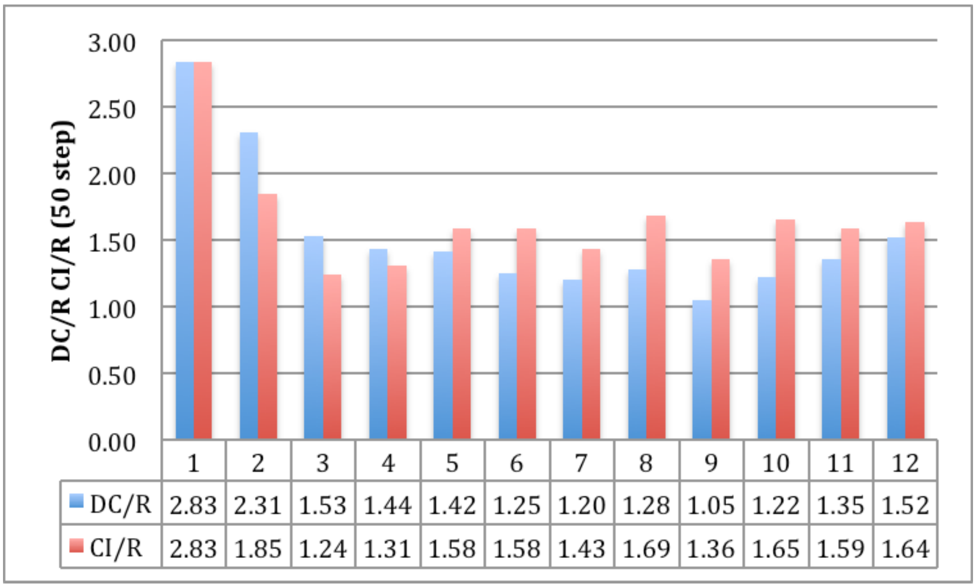
Source: my elaboration

Specifically, the comparison across treatments shows that the use of rational methods in the choice of IPs significantly increase the number of adopters per IPs. This is true both for the use of DC ($P < 0.05$) for the diffusion rates at half time, and for the use of CI at half ($P < 0.01$) and final time ($P < 0.05$) using the Mann-Whitney U test. Only the rate of diffusion reached with the DC treatment at final time is not significantly higher than the random treatment rate. Thus, the first hypothesis is largely verified, confirming that the different choice criteria of the IPs widely affect the novelty diffusion rate.

H2: is verified if $S_{p,CI,i}$ is significantly different from $S_{p,DC,i}$, in other words the standardized number of adopters per injection point, obtained with CI at a certain step, is significantly higher from those reached with DC.

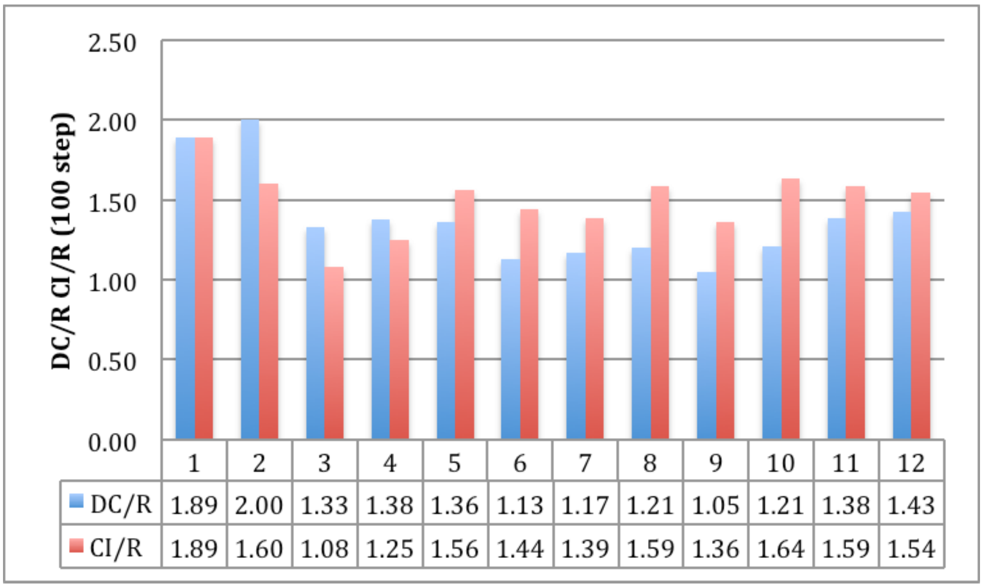
Figures 7.14 and 7.15 shows that saved the initially little overperfomance of DC, the CI leads always to higher diffusion rates both at half and final time.

Figure 7.14 - Comparison results between DC and CI (50 steps)



Source: my elaboration

Figure 7.15 - Comparison results between DC and CI (100 steps)



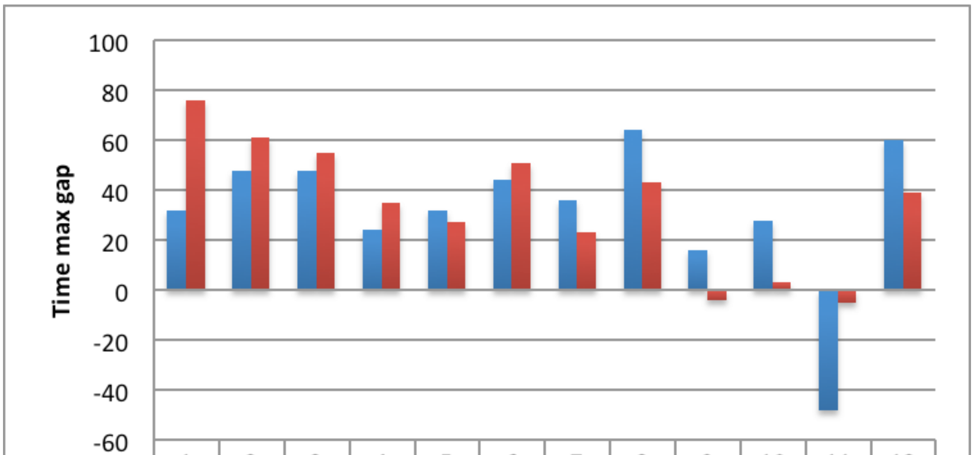
Source: my elaboration

In particular the use of the CI algorithm takes to an overall increment of the global diffusion rates statistically significant both at 50 and 100 steps (p-value < 0,05) with respect to a network treated with the DC. Therefore it can be concluded that CI chosen criteria of IPs has higher performances in terms of diffusion level with respect to the DC.

H3: is verified if $sTmax_{CI,i}$ is significantly different from $sTmax_{DC,i}$, in other words the treatment with CI is faster than those with DC.

In figure 7.16 it can be observed that differences between CI and DC in terms of diffusion speed do not have a regular trend. In fact, initially, from one to four IPs the CI is faster than the DC, after from seven to twelve IPs the DC over performances the CI.

Figure 7.16 – Comparison results between innovation diffusion speed



	1	2	3	4	5	6	7	8	9	10	11	12
R-DC	32	48	48	24	32	44	36	64	16	28	-48	60
R-CI	76	61	55	35	27	51	23	43	-4	3	-5	39

Source: my elaboration

Moreover the use of CI algorithm doesn't leads to a significantly increase of the novelty adoption speed. Hence I can't say that CI is faster than DC. Finally, on the basis of the results showed in this chapter, I can conclude that the first hypothesis of my thesis is largely verified, the second one, that is the most important, is completely verified, in the sense that it is verified at half and final time too. However, it needs to bear in mind that in correspondence of treatments with a small number of IPs it seems to be is a little advantage of DC on CI. Therefore particularly for short-term and small-scale objectives it needs to consider the implementation of DC. At contrary the third hypothesis is not confirmed by the results above mentioned. This probably happens because the diffusion process needs time to exploit the overall potential of the CI methods.

CHAPTER 8

CONCLUSIONS

8.1 Conclusions

In this work I developed an agent-based model aimed at investigating how innovation broker can influence the diffusion of a new Sustainable Agricultural Practice in a farmers network located in Province of Foggia . A large number of studies show that the decision to adopt a novelty depends not only on individual preference of the potential adopters but on the neighbors influence about the innovation too. Taking into account this evidence, the innovation broker can consider this neighbors influence as a strategic resource to induce diffusion choosing specific injection points (members of the network where the novelty is first inoculated) in order to boost adoption speed and adoption level. The primary issue for the innovation broker is what are the injection points to recruit to obtain more effective diffusion results and if there are rational criteria to choose them.

Considering this question my thesis objective was to prove that there are specific network properties belonging to the actors that can be used like rational criteria for the choice of the best injection points.

The ABM developed in this thesis allows to operationalize some fundamental concepts of Rogers innovation diffusion and word of mouth (W-o-M) theories. It is grounded on six basic assumptions deriving from the theory and., The model reproduces, a typical W-o-M innovation diffusion model used to test three different criteria with which innovation broker can select the injection points to diffuse information about the innovation: the Random method (R), the Degree Centrality (DC) method and the Collective Influence (CI) algorithm. The last two criteria takes into account the agents position in the network and the number, respectively, of direct links and undirected links. After the implementation of these influence measures, the model was used to investigate, through repeated simulation experiments, what is the best strategy to select the injection points, in terms of diffusion level reached at half and final time and in terms of speed,. In particular, through the simulations and a statistical non parametric test (Mann-Whitney test) on the results, three hypothesis on the possible diffusion performances of the different method were tested. Simulations results confirmed two out of three hypothesis. One interesting result is that, even in a dense network, the injection points characteristics are not indifferent to the final rate of adoption, therefore the diffusion rate reached during the diffusion campaigns is not invariant with respect to the role and the position of the injection points chosen. Moreover, the CI was proven outperforming with respect DC in terms of rate of adoption, particularly with a great number of injection points. In this case, the results showed that the rate of diffusion is higher if the injection points are chosen according to the CI algorithm rather than the DC measure.

At contrary, results showed that the third hypothesis on the dominance of the CI with respect to DC in terms of diffusion speed cannot be confirmed. In fact, the time taken to reach the maximum number of adopters in the dissemination campaigns realized using as injection points the agents with the higher collective influence, is not significantly different from those in the diffusion campaigns realized using as injection points the agents with the higher DC.

Results observed through this model simulation allowed to conclude that the innovation broker can reach higher level of diffusion choosing injection points with CI rather than with the DC or the R criteria, this is particularly true if he has long-term and large-scale objectives. In fact CI is greater than DC in correspondence of an high number of injection points and of the final time steps.

The innovation broker besides to have as objective an high level of diffusion could have as final goal to reach the maximum level of diffusion after which the novelty diffusion becomes self-sustaining, in a short period of time. Regarding this objective results showed that among the two rational chosen criteria considered in the simulation model, DC and CI, there is no clear dominance between them in terms of diffusion speed. A reason for this is that the DC is a measure of the direct influence of a nodes on its neighbors that is exercised immediately over all the adjacent nodes. Instead, the CI measures partly the influence exerted by the single node on the neighbors direct linked to it and partly the influence exercised on the nodes that are at a certain distance. Therefore this influence is not direct but it is mediated by performances of the closely adjacent nodes. From this derives that the innovation broker should bear in mind that the diffusion process needs a certain time to exploit all the potential of the influence captured by the CI measure, and to program long terms diffusion campaigns.

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