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AGENT-BASED MODELLING OF STAKEHOLDER INTERACTION IN TRANSPORT DECISIONS

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ABSTRACT

Community Involvement, Public Engagement, Stakeholder Engagement, are all different ways to name the participation process of interested people to public decisions. In transport planning there are lots of decisions concerning several issues, with diverse stakeholders involved from organizations to citizens. Sometimes involvement is just a single, compulsory moment of the decision-making process and it lacks in its real purpose: engaging people to find the most shared solution in the shortest time, in order to make the process effective and (cost) efficient. The aim of this work is to improve the knowledge of the involvement process by building the network of relationships among stakeholders and analysing the opinion dynamics which leads to the final decision. The methodology proposed uses an agent-based simulation and a multi-state opinion dynamics and bounded confidence model as a basis to investigate the consensus formation phenomenon. It can be used as a tool both for a preventive analysis addressed to plan an effective participation process and to predict and foster the emergence of a coalition of stakeholders towards a shared decision.

Keywords: transport planning, stakeholder engagement, public engagement, agent-based model, opinion dynamics, sustainable mobility

INTRODUCTION

Community Involvement has become a relevant part of a decision-making process. The five Public Engagement (PE) levels described by Cascetta and Pagliara (2011) (stakeholder identification, listening, information giving, consultation, participation) are all linked with the different phases of the "bounded rationality transportation planning process" and they refer to levels of growing involvement. Social interaction is a key of success in transport planning, because it fosters the emergence of coalitions facilitating the convergence of different stakeholders to a shared solution. Therefore, planning becomes the management of a bi-directional communication process and it requires specific programs and skills, able to coordinate many players, conflicting interests and variables and anticipate problems. In this respect the use of Decision Support Systems, based on quantitative methods (Cascetta, 2009), can help to assess the outcome of different alternatives to increase the transparency and the reproducibility of the decision process.

Community Involvement is an important part of the decision-making process according to sustainability principles, as confirmed by the EU transport policy tendency. The Sustainable Urban Mobility Plan (Buhrmann et al., 2011) and the Sustainable Urban Transport Plan (Wolfram and Buhrmann, 2007) have become a reference point for a new way of transport planning. Sustainable Urban Mobility Plans mean "Planning for the People" (Buhrmann et al., 2011). They are the result of an integrated planning approach, with the aim to create a sustainable urban transport system, also through a participatory approach. In Italy, public participation in transport planning is required by law only for the Strategic Environmental Assessment (Directive 2001/42/EC), and it must be carried out all along the planning process from the beginning to the end.

Stakeholder theory and engagement

The concept of "stakeholder" was introduced by Freeman (1984) and it derives from Economy, where there is a well-established literature affirming that the power of a company lies on its relationships with them. Mitchell et al. (1997) report a chronology of the concept of stakeholder and the key constructs in their theory of stakeholder identification and salience.

In transport planning there are lots of different stakeholders to be involved, e.g. citizens, policy makers, public institutions, local communities, governmental organizations, NGOs, public transport operators, experts, retailers, the private sectors and the third sector. For example the authors, as partners of the PORTA project (www.porta-project.eu), supported by the European Regional Development Fund within the MED Programme, are experimenting the relevance of public participation of the diverse stakeholders involved in port planning and in particular the relationships between Port Authority and city/citizens. The complexity of the task requires specific tools; the methodology proposed in this work can help the knowledge of the information exchange among the diverse stakeholders involved in transport planning. In order to better understand the problem, it is possible to categorize stakeholders according to different classes:

1. Experts (key informants)
2. Stakeholders (e.g. institutions, groups, environmental associations, transport companies)
3. Citizens (singles or in groups)

While experts have high competence but low stake, stakeholders have competence and high stake, and citizens have low competence but act in the public interest, as represented in Figure 1 . They are all bounded together in the engagement process and directly linked with the decision-makers.

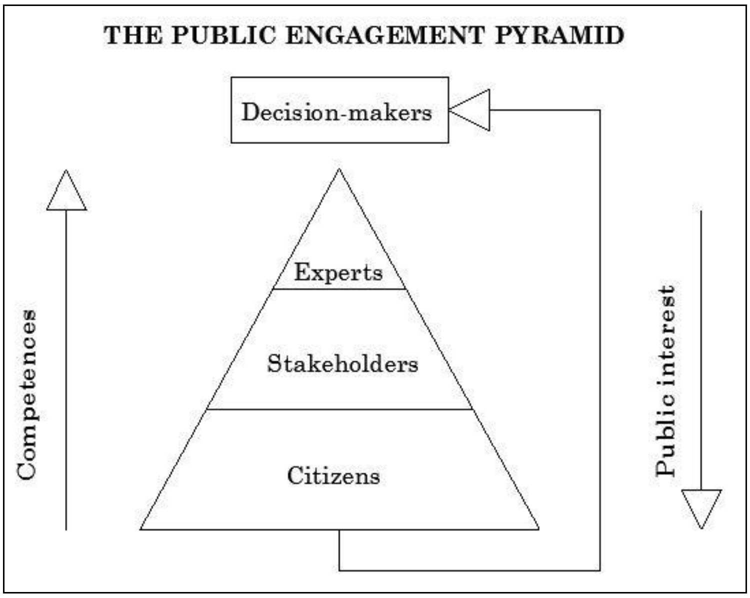

Figure 1 – The Public Engagement pyramid.

There are several tools that can be used to engage: Roden (1984) suggests to develop a “Community Involvement Plan”, the GUIDEMAPS Handbook (Kelly et al., 2004) reports the different tools coupled with the phases of the involvement process, Whitmarsh et al. (2007) propose a methodology divided into two phases (expert focus groups and questionnaires, citizen workshops and questionnaires), Mameli and Marletto (2009) propose a participate procedure by involving experts, citizens and stakeholders to implicate in different ways with “top-down” phases (results derived from the work of experts) and “bottom-up” phases (results derived from the participation of citizens and stakeholders). It is clear that all the methods are time-consuming and require money, so it is not easy to make a good involvement. Indeed there are lots of negative examples where decisions failed because of lack of Community Involvement (e.g. the High Speed Rail Turin-Lyon). In addition to the traditional tools, having a clear insight of the actors who take part in the decision-making and predicting the possible results of an interaction can be of great benefit for the planning process. In this respect linking together stakeholders in a social network and simulating the communication among them can help to improve the knowledge of the social interaction mechanisms. Therefore, in this work the focus is on a potential step of the participation process: the study of how the network topology and the initial conditions can influence the final decision, by simulating the opinion dynamics which takes place in the stakeholders’ network.

METHODOLOGY

The need to include Public Engagement in transport decision-making process leads to the effort to understand how to design and speed the process of taking a public decision and to find out if the communication among stakeholders can influence the process of governance.

Social network analysis (SNA) and opinion dynamics models can allow to know how the actors involved in the planning process are linked together, how the network structure can enable or limit a joint action and how the social and spatial architecture of the community network can influence the outcome of the planning process. It is worth to make a distinction between the two techniques:

- SNA can be used to make static measures of the network, improving the knowledge of the actors involved and helping to understand how a modified topology can foster the emergence of coalitions towards a shared solution;
- opinion dynamics models allow to make dynamic measures which can help to make prediction about the final decision that might derive from interaction.

The methodology proposed is based on an agent-based simulation of the opinion dynamics on a stakeholders' network, through the implementation of a multi-state opinion dynamics and bounded confidence model. It is not intended as an operative participative decision-making tool, but as a strategic and preventive mean to plan an effective participation process and to predict and foster the emergence of a coalition of stakeholders towards a shared decision.

Social network analysis and opinion dynamics models

The analysis of the network consists of finding proprieties which cannot be obtained by visualization. Social Network Analysis is a powerful instrument in doing so, because it allows to measure the centrality of the different stakeholders and the potential problems due to topology. The use of SNA in the field of Stakeholder Engagement can simply consists of stakeholder mapping or it can include centrality measures. Following Carter's stakeholder mapping (2009), Kazmierczak (2012) used SNA to investigate the relationships of communication (exchanging information) and collaboration (working together) among organisations involved in climate change adaptation through a questionnaire. The organisations were regarded as "nodes" while the communication or collaborative relationships were represented as "ties". Pitt (2008) investigated the participation of community organisations, university faculty and researchers in a community-university partnership with the help of SNA, used to examine the data produced through interviews and questionnaires. According to Schonk (2010), with social network visualization, project managers within construction projects are helped in identifying which stakeholders to engage, while stakeholders have clear insights of their positions in relation to the others. In addition to the manual method to map stakeholders and measure centrality, there are several automatic tools which can create a network and extract information from it. StakeSource is a web-based tool that uses social networks and collaborative filtering, a "crowdsourcing" approach, to identify and prioritise stakeholders and their requirements (Lim et al., 2011).

Stakeholder engagement is a dynamic process and it is characterized by several reassessment of the network. Together with the network analysis it can be helpful to simulate how the opinions flow through the set of connections in order to improve the knowledge of the involvement process at the earliest stage and to understand how to manage stakeholders. The opinion dynamics which should lead to consensus can be reproduced through different models. One of the most widely known is the Hegselmann and Krause (HK) compromise model (2002), where the nodes form their actual opinion by taking an average opinion based on their neighbours' ones (i.e. the nodes connected with an edge). This leads to a dynamical process which should flow into a consensus among all agents. Another typical model is that of Sznajd (2000) where only couples of neighbours with the same opinion can influence the other neighbours. This model was used to predict the Brazilian election results (Bernandes et al., 2001) and it resulted in good agreement with reality. The so called "Opinion Changing Rate" (OCR) model (Pluchino et al., 2004) considers the individual inclination to change (OCR) and it is a modified version of the Kuramoto model for synchronization in biological systems, here adapted to a social context. Therefore it is possible to simulate different types of people such as conservative individuals, more flexible people, people that run faster than the others in suggesting new ideas and insights, all by means of a *natural opinion changing rate*. All these models can be used to study the opinion dynamics on a network of stakeholders involved in a decision-making process. Once the relationships, the relative influence of the nodes and all the network characteristics are known, it will be possible to simulate how the information flows through the edges and how (or if) consensus will be reached.

Agent-based modelling using NetLogo to simulate the opinion dynamics on a stakeholder network

In general the opinion dynamics models consist of algorithms that can be analytically or numerically solved; the dynamics is usually simulated by means of Monte Carlo algorithms. Agent-based modelling is a powerful instrument in simulating the opinion dynamics for many reasons, such as the relative easiness to represent a network of nodes (agents) linked together with ties, the possibility to ask the agents (endowed with own properties) to have an opinion and act according to simple behavioural laws, the power of visualization, that can help the analysis, the opportunity to change the global variables, which makes generalization possible and especially for the emergence of collective behavioural patterns which are not predictable from the simple initial rules and that come out from simulations. For all these reasons, agent-based modelling has been chosen to represent the stakeholder network and to simulate the opinion dynamics. We used NetLogo (Wilensky, 1999), a multi-agent programmable modelling environment which can reproduce lots of characteristics of complex systems, following the time evolution and the significant parameters real-time. The spatial environment is represented by a two dimensional grid (World) of discrete cells, called "patches", whose topology can be chosen, and "turtles", i.e. the agents which can move in the grid and that are characterized by variable coordinates in floating point. It is totally programmable and it is possible to distinguish between three variables: global, local and own variables. The last ones are typical of NetLogo because they serve the purpose to define own attributes of the different agent categories. NetLogo was previously used in transport modelling, e.g. for the simulation of pedestrian behaviour (Camillen et al., 2009) and the impact of real time information on transport network routing (Buscema et al., 2009). In our case it can be used to ask the agents to do something (command "Ask"), for instance to have an opinion (from a discrete or a continuous interval) and to change it at the next step according to their neighbours' ones. In this way it is possible to simulate the opinion dynamics, with the implementation of a model, once the network is created.

Implementation of the multi-state opinion dynamics and bounded confidence model

The implemented model is inspired to the majority rule (MR) model (Galam, 2002), where all the agents at time *t* are endowed with binary opinions (+1, −1) and they can communicate with each other. At each interaction, a group of agents is selected at random (discussion group): as a consequence of the interaction, all agents take the majority opinion inside the group. This assumption can appear quite simple but, on the other hand, the MR model is the result of an extended interaction which is influenced by topological complexity and by the initial distributions of opinion. Therefore, it allows to simulate a community with distributed opinions that can change through frequent opportunities of interaction. Proposed to describe public debates (Galam, 2002), the MR model is suitable to reproduce transport planning decisional processes. For example, Sunitiyoso et al. (2011) demonstrated that extended social interaction can have remarkable effects on travel behaviour. Moreover the MR model has been extended to multi-state opinions and plurality rule (Chen and Redner, 2005) with a number of opinion states *s* and size of the interaction groups *G*. A comprehensive review of statistical physics of social dynamics is done by Castellano et al. (2009).
Our model can be considered a multi-state opinion model with $s = 3$, where agents are endowed with one opinion among approval, disapproval or neutral, denoted by +1, −1 and 0 respectively. The neutral opinion is considered less significant and "contagious" than the two others, so the latter were assigned with a double weight. Each node can change its opinion at time $t+1$ based on its neighbours' ones with a probability related to their influence. Indeed, each node (agent) is endowed with properties, such as the *influence*, which affects the dynamics. It is also a bounded confidence model, because of the definition of a *confidence bound* which limits the way a node can change its opinion: a node with +1 cannot directly change its opinion in −1 (and vice versa), but it must pass through the opinion 0 before. Considering the neutral state as a transit opinion is reasonable because it represents a phase of indecision. The nodes which assume the neutral state can change their opinion at the next step, so opinion changing is not conditioned by a specific time but it depends from the neighbours' opinions. Moreover the activation of the confidence bound depends on the node property *influenceability*, a random real number in the range [0,1], which represents the probability that a node directly changes its opinion without any confidence bound. If the parameter has a value close to 1, the probability to directly change its opinion without passing through the neutral stance is high and vice versa when the value is around 0. In conclusion, each node is characterised by a certain influence (which affects the neighbours' opinions) and by a certain "influenceability" (which expresses to what extent a node can be influenced by its neighbours).
The implemented algorithm consists of the creation, for each node, of a vector filled with the weighted opinions of all the neighbours. Let $x_i(t)$ be the opinion of the node *i* at time *t*; the opinion at time $t + 1$ will be:

$$x_i\,(t+1) = f(v_i(t), x_i\,(t))$$

where $v_i(t)$ is the vector of the neighbours' opinions, which are repeated, for each neighbour, a number of time related to the *opinion weight*, the *influence* and according to a *belonging factor*, considering that there are more possibilities to interact within the same group:

$$n_k\,(t) = \; belonging\ factor * influence\ factor * opinion\ weight$$

with $k = -1, +1, 0$.

At each time an element of the vector will be randomly chosen, therefore the most numerous opinion will be the most likely to be selected. At this point it is useful to distinguish "strong ties" from "weak ties", a standard description in community structure analysis for indicating, respectively, links between nodes belonging to the same group and links between nodes belonging to different groups. We call "degree" the total number of links (strong + weak) of a given node and "z-out" the number of weak links of the same node.

A numerical example can help the comprehension of the algorithm. The network represented in Figure 2 is a sub-graph of the network we used for the simulations (number of nodes = 450, divided into 8 groups). Being the node 1 linked with 8 members of its own group (strong ties) and with 2 members of another group (weak ties), the degree is 10 while z-out is 2. In order to fill the neighbours' opinion vector of node *i=1*, it is necessary to:

- repeat the opinion of a given neighbour as many times as its influence (*influence factor* = 10, 8, 6, 4);
- repeat the opinions of all the neighbours in the same group of node 1 for five times, according to the *belonging factor (belonging factor = 5)*;
- weight the different opinions: +1 and −1 are more significant than 0, so they will be considered twice (*opinion weight* = 2).

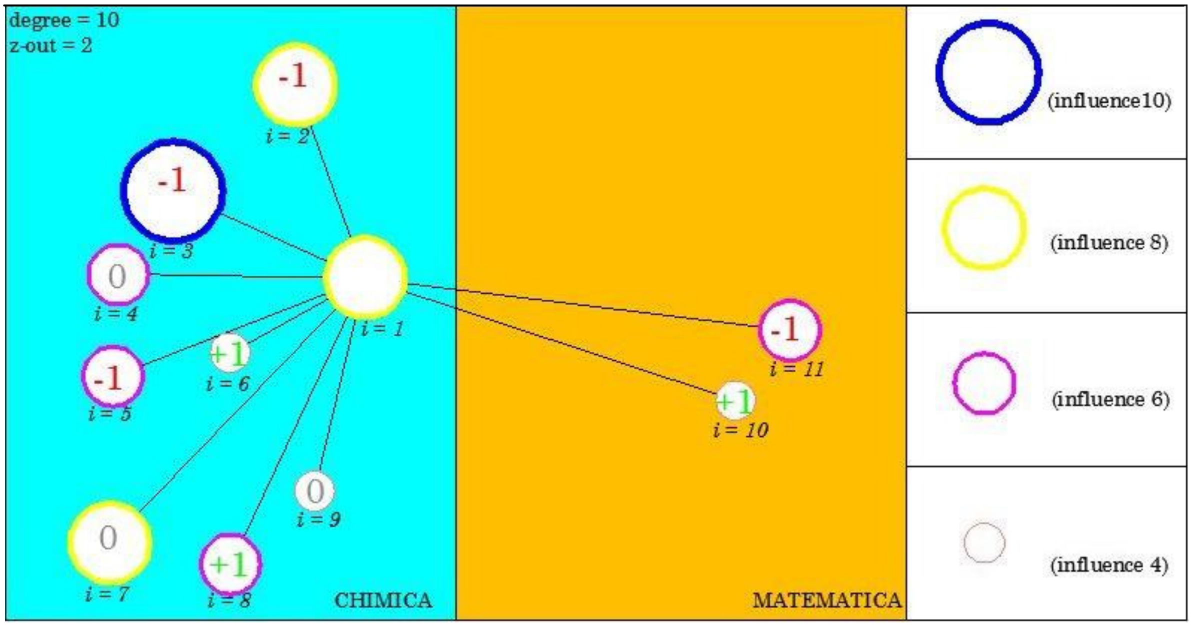

Figure 2 – Network example (degree 10, z-out 2).

The number of times an opinion is repeated is then calculated:

$$n_{-1}(t) = 2 * (5 * 8 + 5 * 10 + 5 * 6 + 6) = 252$$
$$n_{+1}(t) = 2 * (5 * 4 + 5 * 6 + 4) = 108$$
$$n_0(t) = 5 * 6 + 5 * 8 + 5 * 4 = 90$$
$$\rightarrow n\,(t) = 450$$

Therefore, the resulting vector $v_i(t)$, with $n(t)$ = 450 elements, has the following aspect:

$$v_i(t) = (\overbrace{-1,-1,\dots,-1}^{252\text{ el.}},\overbrace{+1,+1,\dots,+1}^{108\text{ el.}},\overbrace{0,0,\dots,0}^{90\text{ el.}})$$

At this point we can finally calculate the opinion $x_i(t+1)$ at time $t+1$ by the following matrix, which sets the probabilities P of assuming one among the three possible opinions as function of $v_i(t)$ and $x_i(t)$:

x(t) \ **x(t+1)**	**+1**	**0**	**-1**
+1	$\frac{108}{450} = 0.24$	$\frac{90}{450} = 0.20$	0 / 0.56
0	$\frac{108}{450} = 0.24$	$\frac{90}{450} = 0.20$	$\frac{252}{450} = 0.56$
-1	0 / 0.24	$\frac{90}{450} = 0.20$	$\frac{252}{450} = 0.56$

Figure 3 – Opinion changing probability matrix.

As already said, the activation of the confidence bound depends on the node *influenceability*; this is why there is a double probability to directly change the opinion from +1 to −1 and vice versa: actually, we will choose the case P ≠ 0 with probability equal to the *influenceability* and P = 0 with probability (1-*influenceability*). For instance, if node 1 has $x_1(t) = 1$:

$$x_1\,(t) = 1 \begin{cases} x_1\,(t+1) = 1 \;\text{ with }\; P = 24\,\% \\ x_1\,(t+1) = 0 \;\text{ with }\; P = 20\,\% \\ x_1\,(t+1) = -1 \;\text{ with} \begin{cases} P = 56\,\% \text{ if } \textit{influenceability} \text{ is high} \\ P = 0\,\% \text{ if } \textit{influenceability} \text{ is low} \end{cases} \end{cases}$$

Moreover, in order to reproduce potential external influences to the opinions, we assumed that the dynamics can be modified by means of *Changing-Mind-Rate* (CMR), a factor we introduced to represent the probability that a given node would randomly change its opinion at a given time. It is possible to follow the dynamics in real-time by plotting three curves, each representing a different opinion against time (see Figure 4).
We considered a single event when, starting from a given distribution of opinions among the agents, it ends with all agents converging towards the same opinion. We also considered a multi-event version, with different (random) results related to the same initial distribution of opinions. For each event there is a struggle among the three opinions, which is clearly visible from the first plot in Figure 4; actually the main opinions (approval and disapproval) are die-hard, while the neutral stance is only a transition opinion.

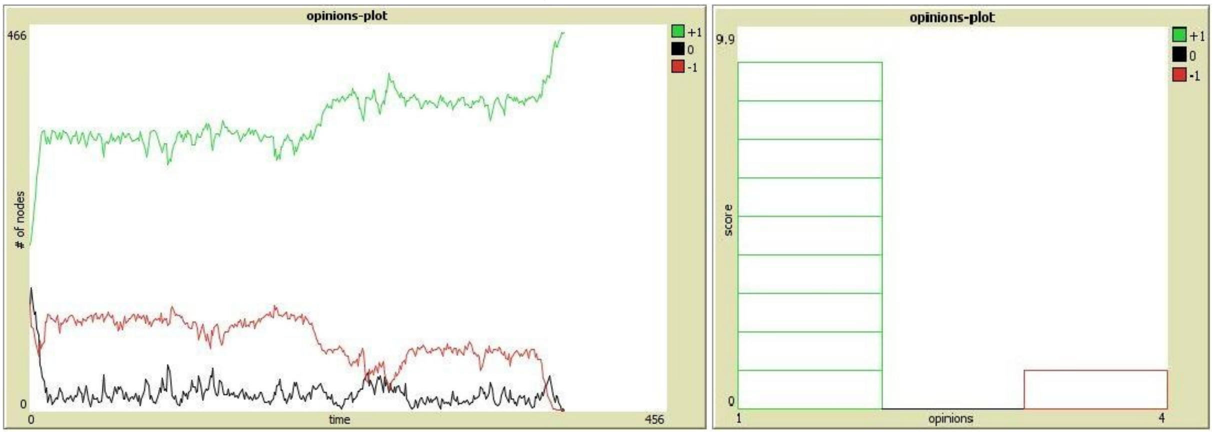

Figure 4 - Opinions' plot for a single event (single event version) and for ten events (multi-event version).

The dynamics starts from a positive initial group, that is to say a group of nodes that initially have the +1 opinion. Therefore, for what concerns the simulations, there are three main elements that can be modified:

1. Topology (average degree, average z-out)

2. Initial conditions (positive initial group)

3. Opinion dynamics (CMR)

Considering N events for each simulation, we are interested into the following simulations' results: the number of events ended with a *complete consensus* (all the opinions equal to +1) or *complete dissent* (all the opinions equal to −1) and the average time for reaching consensus or dissent. In order to convert the final outcome of the events into a unique index we calculated the parameter W as the weighted average of the final network state, i.e. the net frequency of the events which end with +1:

$$W = \frac{N_{+1} * (+1) + N_{-1} * (-1)}{N}$$

where N_k is the number of events ended with consensus (k = +1) or dissent (k = −1) and N is the total number of events. W is included in the interval [−1,+1], where the extreme values −1 and +1 represent, respectively, 100% of events ended with dissent or consensus. It represents a statistics of the events and it does not indicate the rate of agents which have the opinion +1 at a certain step of the simulation or the degree of sharing of a project. On the other hand, it is an index which measures the tendency of the final state of the system towards the full consensus or the full dissent, so it represents the final configuration of the opinions.
A time threshold was defined in order to exclude the cases in which the process took too long time (t > 500) before reaching consensus (or dissent). Therefore, when time exceeds the threshold without reaching any convergence of opinions, we say that the simulation outcome is "no consensus/dissent". The graphic interface of the implemented model is reported in Figure 5.

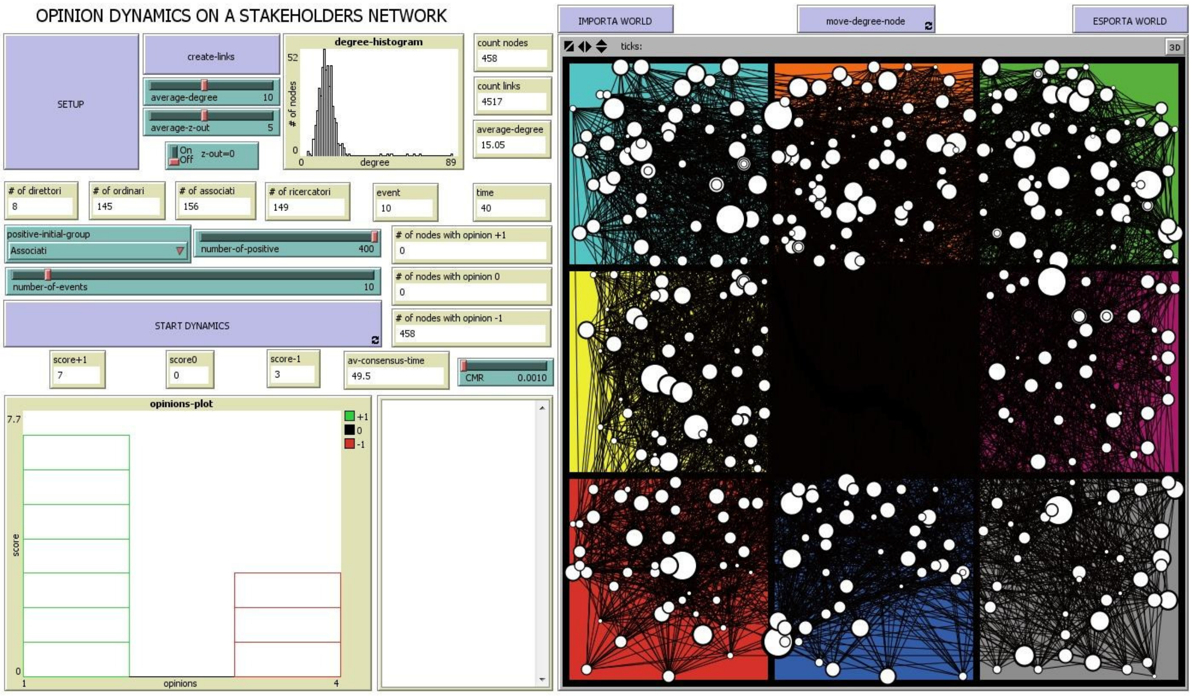

Figure 5 - The implemented model in NetLogo (multi-event version).

CASE STUDY

The decision-making process regarding transport planning is characterized by a high level of complexity and it is not simple to be described with a model. Therefore, in order to apply our methodology to a case study, we decided to represent a simple, real situation of a decision-making process regarding transport issues. In particular we depicted a well-known situation of a narrow and homogeneous community of people with the same interest, i.e. easy access to the workplace. Indeed, accessibility is one of the dimensions of social sustainability and it is a priority for a modern society. Among the modes of transport, nowadays private cars are the most used, so the problem of parking is a big deal. In particular, the case study of this work is about the idea of adopting parking pricing inside the Campus of the University of Catania (see Figure 6), as one of the main transport policy for sustainable mobility proposed by the mobility management office of the University. The topic involves all the University staff, including full professors, associate professors and assistant professors, while students are excluded because they cannot access those parking spaces. Some observations carried out during several meetings on these issues, though not systematic and statistically significant, were useful for the construction of the model. The network was created according to relationships derived by roles and by department organization (institutional relationships). Thanks to the knowledge of all the elements it was possible to build the network and simulate the opinion dynamics which should lead to a consensus/dissent (see Table I). The "institutional network" was reproduced by dividing all the departments' members into the three categories (assigning the role of head of department to one of the full professors), and then creating the links among them according to their roles.

Table I - Details of departments' structure.

DEPARTMENTS	FULL PROFESSORS	ASSOCIATE PROFESSORS	ASSISTANT PROFESSORS	TOT
1) Architecture - DARC	10	22	15	47
2) Physics and Astronomy	27	27	24	78
3) Civil and Environmental Engineering	14	17	10	41
4) Electric, Electronic and Informatics Engineering	21	20	13	54
5) Industrial Engineering	16	9	17	42
6) Maths and Informatics	23	27	30	80
7) Chemical Sciences	28	14	18	60
8) Pharmacy	14	20	22	56
TOT	153	156	149	458

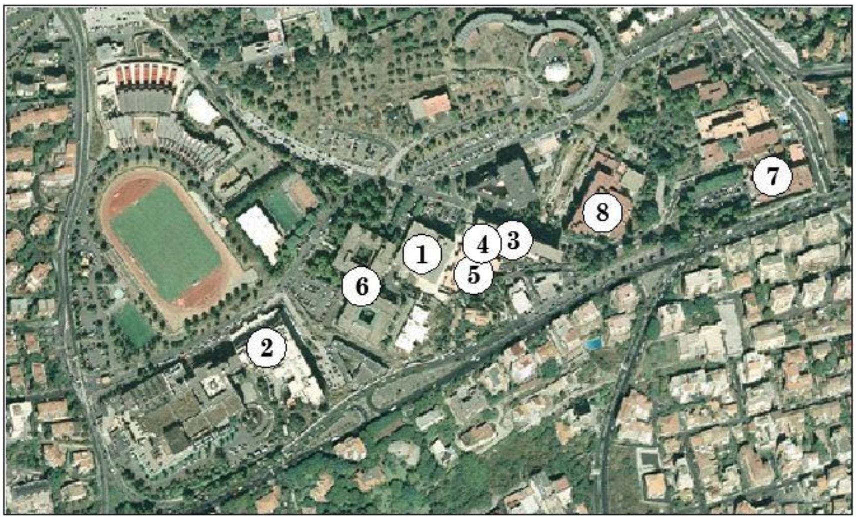

Figure 6 - Departments inside the campus of the University of Catania.

Simulations and results

Taking into consideration topology, in order to reproduce realistic situations, two cases were considered:

1. average degree 10, i.e. on average each node is connected with other 10 nodes;
2. average degree 20, i.e. on average each node is connected with other 20 nodes.

The simulations were performed by varying the number of weak ties, i.e. with a parameter z-out ranging, in average, from 1 to 5 for degree 10 and from 5 to 10 for degree 20 (both degree and z-out are extracted from normal distributions). We considered 10 different (random) realizations of the initial distribution of opinions (multi-event version with $N = 10$). For what concerns the initial conditions, we selected all the initial positive groups, that can consists of: nodes with the same role (heads of departments, full professors, associate professors, assistant professors), nodes belonging to the same department and number of departments (1 department, 2, 3 or 4 departments), number of random positive nodes (from 0 to 400), random +1, 0, −1 nodes. It is useful to notice that when the number of initially positive nodes is the initial variable condition (from 0 to 400), the remaining nodes will randomly take one of the two other opinions, so they have the same probability to initially assume the negative or the neutral opinion (e.g. the initial condition is that 200 nodes initially have the positive opinion; the other 258 nodes will assume the negative or the neutral opinion with the same probability). To understand the impact of external influences on the final decision, a series of simulations was made with average degree = 20, CMR = 0.5% and z-out varying from 5 to 10. The next tables show some results in terms of the parameter *W,* as above defined (see pag. 9).

Table II - Parameter W with random initially positive nodes (av. degree = 10, CMR 0.0%).

W	average degree = 10, CMR = 0.0				
	average z-out				
number of random	1	2	3	4	5
0	-1.0	-1.0	-1.0	-1.0	-1.0
50	no consensus/dissent	-1.0	-1.0	-1.0	-1.0
100	no consensus/dissent	no consensus/dissent	-1.0	-0.8	-0.8
150	no consensus/dissent	no consensus/dissent	0.4	-0.6	0.2
200	no consensus/dissent	no consensus/dissent	0.8	0.8	0.6
250	no consensus/dissent	1.0	1.0	1.0	1.0
300	no consensus/dissent	1.0	1.0	1.0	1.0
350	no consensus/dissent	1.0	1.0	1.0	1.0
400	1.0	1.0	1.0	1.0	1.0

Table III - Parameter W with initially positive groups (av. degree = 10, CMR = 0.0%).

W			average degree = 10, CMR = 0.0				
			average z-out				
positive initial group			1	2	3	4	5
average influence	number of nodes	role					
10	8	head of department	no consensus/dissent	-1.0	-1.0	-1.0	-1.0
8	149	full professors	no consensus/dissent	no consensus/dissent	0.2	1.0	0.4
6	156	associate professors	no consensus/dissent	no consensus/dissent	-0.6	0.0	-0.8
4	149	assistant professors	no consensus/dissent	-1.0	-1.0	-1.0	-1.0
random nodes			no consensus/dissent	no consensus/dissent	0.4	-0.2	0.4
1 department			no consensus/dissent	no consensus/dissent	0.2	0.4	0.6
2 departments			no consensus/dissent	no consensus/dissent	0.4	0.2	0.6
3 departments			no consensus/dissent	no consensus/dissent	1.0	1.0	1.0
4 departments			no consensus/dissent	1.0	1.0	1.0	1.0

Whatever the initial conditions are, it is clear that a too small number of weak ties critically slows down the information exchange; actually, when a node has on average 10 links, it is evident that we need more than 2 weak ties in order to reach convergence of opinions. Furthermore, the parameter *W* is minimum when the positive initial nodes are heads of departments (a minority, but very much influent) or assistant professors (more numerous, but less influent), that is to say that it is very difficult to reach consensus when only one of these groups is originally positive about the given topic (in our case the parking pricing). On the other hand, higher *W* values are achieved with entire positive departments. In Table II it is useful to make comparisons by column, in order to notice the change from total dissent (i.e. 100% of events ended with dissent) to total consensus (i.e. 100% of events ended with consensus) as the number of initially positive nodes increases. Analysing the results by row in Table II and Table III it appears that, in the transition phase (and in particular in proximity of the critical threshold), which is an area of "turbulence", there are fluctuations in the results (e.g. for 150 random positive nodes) also due to the limited number of simulations with the same starting conditions. This result is also visible if we study the behaviour of the parameter W versus an increasing number of randomly chosen initially positive nodes (ranging from 0 to 400), where a transition from dissent ($W = -1$) to consensus ($W = +1$) clearly appears in correspondence of around 150 positive nodes and can be appreciated plotting the parameter W within a scatter diagram (Figure 7). Indeed, all the events end with dissent up to 50, then there is a transition phase with some events ended with dissent and some others with consensus (from 50 to 250 nodes) and where the lines for different z-out can intersect, whilst all the events end with consensus when there are more than 250 (randomly chosen) initially positive nodes. It is interesting to make a comparison between this last result and an analogous one found in the context of the OCR model (Pluchino et al., 2004). In the latter, authors found a second-order phase transitions from an incoherent phase to a synchronized one, separated by a region of partial synchronization (Figure 8), which looks very similar to the transition we found in our simulations (as can be appreciated by comparing the two last figures). It is important to notice that in our model there are not states of "partial synchronization" as in the OCR model. The analogy with it is only in the transition phase, because the passage from total dissent to total consensus, where not all the events end with the same result, reminds the "partially synchronized phase" of the OCR model.

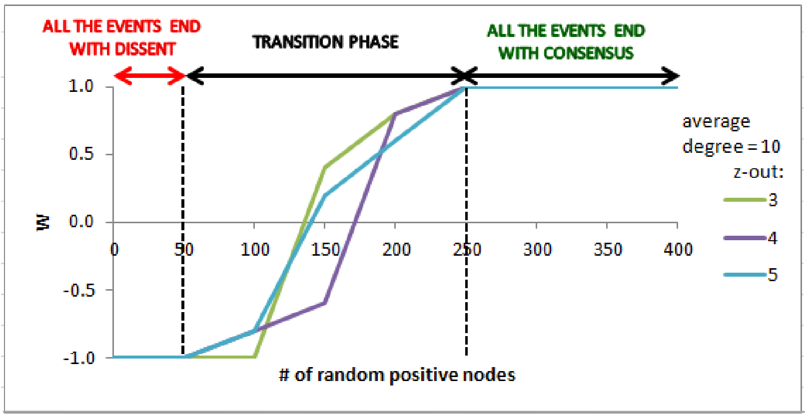

Figure 7 - The parameter W as a function of the number of random positive nodes on varying z-out (av. degree = 10, CMR = 0.0%).

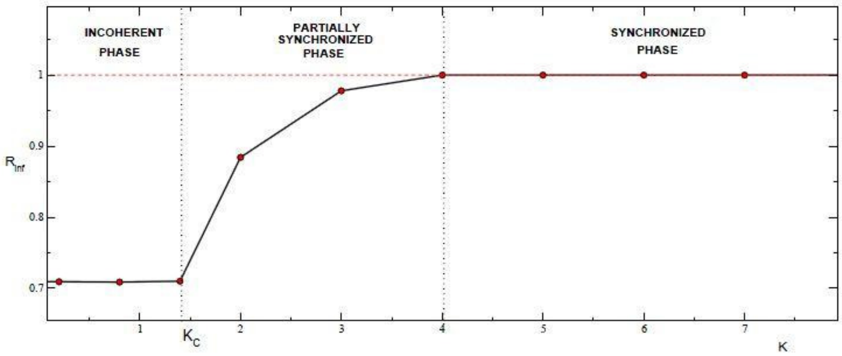

Figure 8 - Asymptotic order parameter as a function of the coupling K in the OCR model (Pluchino et al., 2004).

For what concerns the average time to reach the final decision, it is possible to plot it as a function of the number of random positive nodes and for several values of z-out (Figure 9).

It results that the convergence time presents a peak exactly in correspondence of the transition from total dissent to total consensus. Such a peak is much more pronounced for smaller values of the average z-out, i.e. when the small number of weak ties does not allow the positive opinions to spread over the entire networks. Even in this case it is possible to find interesting similarities with another opinion dynamics model. Indeed, using the continuum opinion dynamics of HK compromise model (Fortunato et al., 2005), the authors discovered that the convergence time to reach consensus, as a function of the confidence bound, follows the same trend represented in our Figure 9. Actually, the convergence time shows a divergence in correspondence of the consensus transition and, more in general, whenever the opinion clusters of a given configuration merge into a smaller number of clusters (Figure 10). In our case, the peak occurs when the number of random positive nodes is between 150 and 200 nodes (out of 458): this means that there is more struggle for reaching a compromise when almost half of all the nodes are initially positive, while consensus/dissent is achieved in a smaller time when the initial number of positive nodes is small (dissent) or big (consensus).

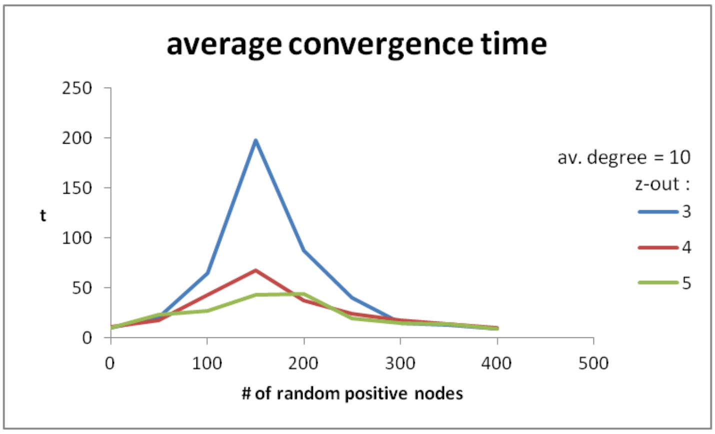

Figure 9 - Average convergence time as a function of the number of random positive nodes on varying z-out (av. degree = 10, CMR = 0.0 %).

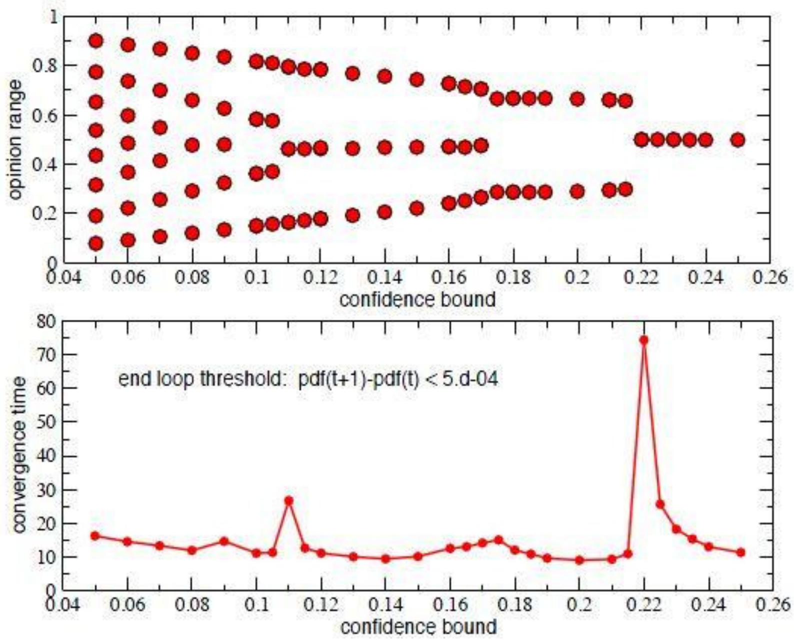

Figure 10 - (Top) Final configuration of the system as a function of the confidence bound ε. The circles indicate the positions of the surviving clusters in opinion space. (Bottom) Variation of the convergence times with ε. (Fortunato et al., 2005).

If we increase the number of links (average degree = 20) the results are similar. The greater number of links improves the communication among nodes, so consensus/dissent is always reached, even when the number of weak ties is small. If we consider the presence of external influences, represented by non zero values of the CMR indicator (CMR = 0.5%) in general it produces an increase in convergence time but does not significantly affect the transition from dissent to consensus, which occurs between 150 and 200 initially positive (randomly chosen) nodes (Figure 11). The external influences represent "rumours" which modify the dynamics and slow down the process. Indeed people will be changing their mind at some steps (related to the CMR) at random, without following the opinion dynamics model's rules. This is the reason why the convergence process slows down.

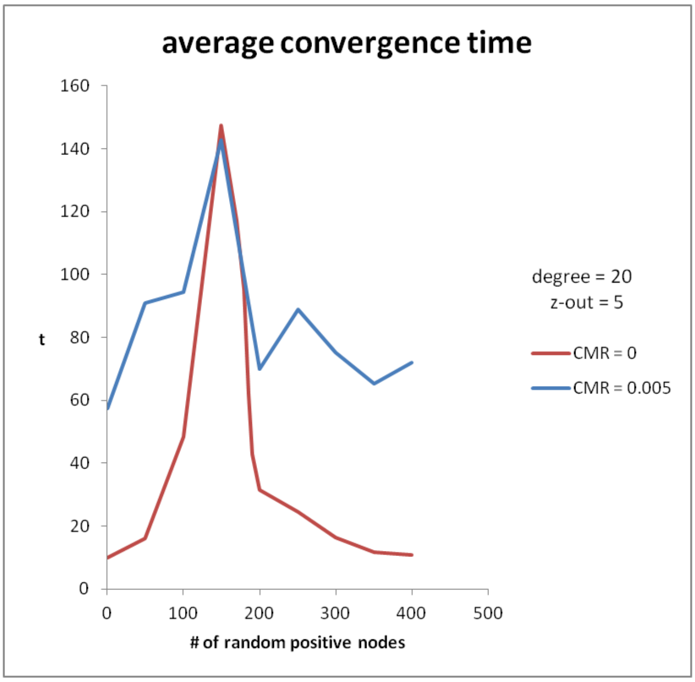

Figure 11 - Average convergence time on varying CMR (average degree = 20, z-out = 5).

CONCLUSIONS AND DISCUSSIONS

Transport planning is mainly a complex decision-making process, with many actors involved and different conflicting objectives and opinions. In this paper we propose an agent-based model that can simulate the opinion dynamics on a network of stakeholders involved in transport planning, in order to support the decision-making process. The presented model is a multi-state opinion model with 3 different opinions. It is also a bounded confidence model because of the presence of a confidence bound which limits the opinion changing from approval to disapproval (and vice versa) by means of the neutral opinion. We applied our model in a very simple case study, both to test the model and to capture the intrinsic essence of the complex phenomena of social interaction. The decision-making process regards the adoption of a new parking pricing system inside a University Campus, where a well-known situation of a narrow and homogeneous community of people (professors) with the same interest, made quite reasonable the opinion dynamics model we implemented. The simulations' results are in agreement with other opinion dynamics models (HK continuum model, OCR model). For what concerns topology, many links help the communication among nodes and it takes few time to reach the final decision, while few links slow down the process and sometimes it requires too much time to reach consensus or dissent. Giving the initial positive opinion to some groups, such as heads of departments (a minority, but very much influent) or assistant professors (with low influence) consensus will be never reached, while full professors are more “persuasive”. Choosing random initial positive nodes, there is a transition from dissent to consensus within which the time required for the convergence of opinions has a peak. Introducing external influences which affect the dynamics, the process slows down and it requires more time to reach a decision.

Further research will tend to modify the opinion dynamics, for instance increasing the number of possible opinions or changing the model from a discrete choice model to a continuum one, or including the possibility that the stakeholders could change their mind by policy persuasion or awareness raising. Indeed, our model considers that some people can have a greater weight than others through the parameter *influence*, but we are neutral about the result. For what concerns the stakeholder network, it would be useful to see how the geographical distance and the department affinity influence the topological distance of the nodes, affecting the information exchange. Moreover, in order to calibrate the model, it would be helpful to compare the results of the simulations with a real situation with systematic observations to see if the model results are in agreement with reality.

In conclusion, Stakeholder Engagement is an integral part of the transport planning process. It involves all the stakeholders from the very beginning of the planning process, with different levels of involvement during the planning phases. Its aim is to foster the emergence of coalitions among stakeholders towards a shared solution.

Our model can be useful to the design of the stakeholder involvement at an early stage of the planning process, because it can predict and, therefore, raise the awareness of the possible results of interaction; consequently it allows to set up the priority for information and it helps to understand how to improve the linkages among stakeholders in order to facilitate the involvement process; moreover it investigates the probability that external influences can modify the convergence towards a shared solution. Therefore, studying the stakeholder network and the opinion dynamics can help to understand how to make a good involvement process and can be helpful to make the planning process transparent, effective and (cost) efficient.

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