Geographical Information Management and Applications

Coupling spatial and social networks in models of opinion dynamics.

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Summary

This thesis is focussing on coupling social and spatial networks in models of opinion dynamics. The research on spatial aspects and social networks in models of opinion dynamics is limited. In order to complement the existing research a literature study is performed. The outcomes of the literature study are used to develop and implement a model of opinion dynamics in which social and spatial networks are coupled. The outcomes of running the model are discussed and presented. An analysis of the sensitivity is performed to gain a better understanding of the outcomes. From the outcomes and the results of the sensitivity analysis the plausibility is discussed.

In the literature study many concepts related to opinions dynamics are discussed. From all the concepts combined can be concluded that geographical locations are not implemented yet in agent based models of opinions dynamics. Locations are only represented in cellular automata models. Social networks represented in models of opinion dynamics are often non-static and randomised during the run of the model.

In this agent based model all agents are placed with random coordinates on a fictive map containing a controversial area. All agents receive a random opinion about the controversial area at the beginning of the run. The social network is represented by assigning a random value to agents. This variable is called affinity. The difference in affinity between the agents determines whether they are socially connected or not. The spatial network is represented by the Euclidian distance between agents. If the distance is smaller than a certain threshold they are considered to be spatially connected. The model is based on turns. Each turn for all agents the connections are assessed based on a random weighted draw of the spatial and social connections. After a connection is chosen the opinion of the agent is averaged with the opinion of the connected agent.

Without the addition of a scenario a run of the model results after a certain number of time steps in a consensus with the average opinion of the whole population. A threshold was added to prevent agents to communicate with each other with large differences in opinions. The addition of a threshold resulted in different groups of opinions. A not in my backyard scenario was added in which all agents living within a certain distance from the controversial area receive a negative opinion each turn. The result of the not in my backyard scenario is a consensus with a negative opinion about the controversial area. In order to compensate for the negative influence of the controversial area a positive feedback was added for all agents living further than a certain distance from the controversial area. The positive feedback resulted in different and more realistic patterns. At last a scenario was added where the agents walk around freely across the map. The result of this scenario was a dispersed fluctuating distribution of opinions and it is no longer possible to distinguish different consensuses.

The method for analysing the sensitivity was one-at-a-time. Different sensitivity measures are developed in order to measure the sensitivity of the parameters. Compared to the zero scenario almost all parameters showed significant changes in the outcomes when there is a small change in the parameter. Only the moving agents scenario did not show much difference.

From the discussion of the plausibility can be concluded that not all scenarios could be considered as realistic. The most plausible results are caused by the combination of the NIMBY and positive feedback parameters. In general the model can be considered as plausible.

This thesis shows how a model of opinion dynamics that is coupling social and spatial networks can be developed, implemented and analysed. This thesis demonstrates a model which is a representation of a number of archetypical processes that are assumed to be important for spatial opinion dynamics. The model developed in this thesis proves not only the possibilities of coupling social and spatial networks in opinions dynamics, but also the importance of adding location to such a model.

Acknowledgements

If you are reading this part you are either curious if you are mentioned in the acknowledgements or you are generally interested in my research. In both cases I am thankful for you interests and I hope you will enjoy reading either my research or these acknowledgements.

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Kas Kroese
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Chapter 1: Introduction and research identification

Introduction

A model is a representation of the real world. By studying the results of models, researchers can obtain a better understanding of the real world. Spatial decision support systems is one of the academic disciplines for which researchers are trying to create models. Because decision making in spatial planning can be a long and complex process it could be useful to develop a model which helps to understand social processes. This thesis will focus on modelling social processes within spatial planning.

Problem and its context

Spatial decision making processes often consist of multiple actors, making it a system of human behaviour. Systems of human behaviour can be considered as complex (Couclelis, 1988). If a complex system is able to adapt itself to the problems posed by the surroundings it can be called a ‘complex adaptive system’ (Holland, 1992). The more realistic a model becomes the more complex it might become. According to Holland (1992) an adaptive complex system does have ‘deeper similarities’ that are easier to understand than basic observations suggest. By creating a model these deeper similarities or, underlying processes, can be examined. The goal of this thesis is not to model the complexity of the real world but to develop a model that represents some of the basic processes underlying a complex system, such as the process by which opinions are communicated among actors. A basic model will help understanding a complex system. Spatial planning is one of the processes which is considered to be complex (Ligtenberg & Bregt, 2014; Ligtenberg, Bregt, & Van Lammeren, 2001). In the paper of Ligtenberg et al. (2001) the aspects causing the complexity are narrowed down to four main aspects. In the following sections the four main aspects are explained.

Actors are the first aspect. Actors are part of a social network and influenced by other actors. The influences of other actors is called ‘social impact’ (Latané, 1981). The exact definition of social impact is described by Latané (1981) as *‘any of the great variety of changes in physiological states and subjective feelings, motives and emotions, cognitions and beliefs, values and behavior, that occur in an individual, human or animal, as a result of the real, implied, or imagined presence or actions of other individuals’.* In a social network actors interact and influence each other. These interactions are constantly changing and are also adapting to these changes.

The second aspect mentioned by Ligtenberg et al. (2001) is the *spatial environment.* In reality individuals interact and share knowledge with other individuals and most of the interactions are based on the location of both of the individuals. The location of the actors and the environment specific to their location can influence the actors themselves. Until now only little attention is paid in the scientific literature about the spatial environment of actors in a social network.

Actor based processes are the third aspect causing the complexity of spatial planning. Actor based processes are processes performed by actors based on their motives and opinions. If the motives of actors change their behaviour based on these motives will also change. Because opinions can change and can be influenced by other actors the actor based processes are adaptive to the changes in opinion.

The fourth aspect are *autonomous processes*. These processes are not caused by one of the actors but are the result of the changing environment. Autonomous processes are environmental aspects influencing the spatial planning process.

In order to obtain a better understanding of the decision making process of spatial planning it could be useful to understand the formation and exchange of opinions. These opinions about the region can slow down the spatial planning process. The concept of not-in-my-backyard (NIMBY) is a good example of how opinions can slow down planning projects (Dear, 1992; Wolsink, 2000). Dear (1992) describes NIMBY as '*the protectionist attitudes of and oppositional tactics adopted by community groups facing an unwelcome development in their neighborhood'*. If planners know how opinions develop and how they influence the actor based processes it could be possible to avoid the negative consequence of the NIMBY concept. In order to obtain this understanding it could be useful to develop a model in which the development and changes of opinions are being modelled. The social impact of opinions can only be modelled if the social network is being taken into account.

A similar process by which innovation is communicated among actors of a social system is called innovation diffusion (Rogers, 2010). In the book of Rogers (2010) diffusion is applied on innovation. The process by which opinions or information are communicated in a social system can also be looked at as a diffusion process. Because this thesis will focus on information exchange in social networks the diffusion of opinions will play an important role. According to Wejnert (2002) diffusion consist of spatial effects, such as proximity, and the pressure of social networks. Diffusion can, therefore, be treated as a spatial process.

The location of agents did not receive much attention in the scientific literature in the past. Because distance does play a role in a social network in the real world it is useful to create models where the location of agents play a role. The spatial aspects are not only influencing the social impact but also the other three aspects of spatial planning causing the complexity.

There is literature available that does focus on spatial aspects of opinion dynamics. Ligtenberg, Beulens, Kettenis, Bregt, and Wachowicz (2009) created a model that simulates knowledge sharing in land use planning. The link between opinion and location was in their research based on the type of actor and their opinion about a location. The location of the actor itself was not taken into account in their research. In a more recent study of Ligtenberg and Bregt (2014) the location of actors in comparison to other actors were taken into account using a neighbourhood representation. In their research the opinions of agents are more influenced by agents within a smaller distance than agents located at a longer distance from the specific agent. This choice was made because it was assumed that actors on isolated spots are more likely to change opinions than actors living in clusters with other actors with the same opinion. The social networks were only partly taken into account. In order to simulate social networks the social distance between actors was used. The social distance compares the opinion of two actors and if the two opinion are similar enough (within a certain threshold) one of the actors can adopt the opinion of the other actor. The paper of van Voorn, Ligtenberg, and ten Broeke (2014) examines the use of cellular automata (CA) for modelling the social distance more thoroughly, but this representation of a social network is still comparatively simple. There are more extended simulations of a social network possible (Acemoglu & Ozdaglar, 2011). In their paper, Acemoglu and Ozdaglar (2011) have summarised previous researches on social network models. Although the models described in the paper of Acemoglu and Ozdaglar (2011) are more complex, none of the models takes the location of the actors into account.

There are some basic models of opinion dynamics available. The most basic idea of opinion dynamics is described by Hegselmann and Krause (2002) where opinions are being averaged between agents. A more complex model is described by Deffuant, Neau, Amblard, and Weisbuch (2000). In their model the opinions can only be transferred to another actor if the difference in opinions between those actors is small enough. The point until where the opinions are similar enough for an exchange is called a threshold. This threshold is described by other authors as confidence level (Hegselmann & Krause, 2002). The confidence level is based on the confidence of an actor about its opinion. In this kind of model the resulting opinions of the two actors is the average between the two actors. Deffuant et al. (2000) found out that in such a model over time only one average opinions remain if the threshold is high. A high threshold means that there can be a larger difference between opinions for an exchange. If the threshold is low it will result in multiple average opinions in the population between which the difference is larger than the threshold.

The use of CA models as it is used in the paper of Ligtenberg and Bregt (2014) and in the paper of van Voorn et al. (2014) is not sufficient for modelling the spatial diffusion of opinions in a social network. A CA model does not take the interactions of agents into account and is therefore too simplistic for modelling the spatial diffusion of opinions within a social network. Because interacting agents will be modelled an Agent Based Model (ABM) will be a more useful model type than CA. The computational agents within an ABM are interacting in space and time (Page, 2005). In this way their behaviour can be observed and patterns can be explored.

From previous researches can be concluded that there is not much research done yet that is linking social networks to location in opinion dynamics. The problem being treated in this thesis is filling the gaps in the scientific literature by linking social networks to location in models of opinion dynamics.

Research objective

In the previous paragraph was concluded that, to better understand spatial decision-making processes there is clearly a need to couple models of opinion dynamics with social and spatial networks. In this paragraph the research objectives will be explained. The main goal of this research is focussing on the spatial aspects of opinion dynamics. The main research objective can be formulated as follows:

> *Develop and demonstrate an agent based model which couples social and spatial networks within a model of opinion dynamics.*

In order to develop such a model existing social network models and opinion dynamics models must be examined. From these models will be concluded if and how the existing concepts and models can be used to develop an opinion dynamics model where the social network and the spatial aspects play a role and where research is still missing. The result of the model must be tested before relevant outcomes can be concluded.

Research questions

From the research objective the research questions can be formulated. The main research question will address the main research objective and is as follows:

> *How can social networks be coupled to spatial networks in a model of opinion dynamics?*

In order to cover all aspects the research objective will be divided over four sub-questions. Below the four sub-questions are shown.

- What concepts are still missing in the scientific literature to couple social- and spatial systems in models of opinion dynamics?

- Which types of models are useful for modelling the spatial opinion dynamics within a social network?
- How can spatial opinion dynamics within a social network be modelled?
- How plausible is the developed model?

Because the research on location and social networks in models of opinions dynamics is limited this thesis will focus on filling the gaps in the literature. This will be done by developing and demonstrating an agent based model which couples social and spatial networks in models of opinion dynamics.

Research methodology

The thesis is divided in six chapters. Together, these six chapters are answering all five research questions. The sub research questions will help structuring the thesis for answering the main research question. Chapter 2, 3, and 5 will all answer one or more sub questions. In this paragraph the methodology of answering the research questions will be discussed.

In Chapter 2 an extended literature study will be performed. From the literature study will be determined which parts in the scientific literature are still missing and are relevant for this thesis. Relevant aspects of modelling the spatial diffusion of opinions in a social network will be examined. Literature about social networks, diffusions, social impact, ABM models, spatial planning and opinion dynamics will be needed in order answer the first sub-question. The result will be a summary of the literature about those aspects in the form of a chapter.

Chapter 3 will continue on the literature study from the previous chapter by finding relevant methods for modelling the spatial diffusion of opinions within a social network. With the help of existing literature a framework for a model will be developed. The framework will partly exist of existing methods and partly of newly developed aspects. The result will be a conceptual model, which will be used to develop a computer model. Chapter 3 will continue with the discussion of the development of a computer model from the conceptual model. The model will be written with a programming language in a suitable developing environment for computer models. In the background study of this thesis was explained that the type of model will be agent based. For modelling an ABM model the programs Netlogo (Wilensky, 2014) and GAMA ("GAMA - Platform," 2014) could be useful, because these programs are able to support multi agent models and are relatively easy to learn. Because the model will be useful for understanding underlying processes it will be a small scale model focussing on a fictive region where a controversial planning decision is about to be implemented such as a windmill farm or a nuclear power plant. The local community will have opinions about the implementation of the facility. The effect of controversial planning decision on the opinions is researched with the help of the NIMBY concept.

In Chapter 4 the model is evaluated by performing a sensitivity analysis. According to Crosetto, Tarantola, and Saltelli (2000) a sensitivity analysis is a prerequisite for building a model. Crosetto et al. (2000) defines sensitivity analysis as: '*sensitivity analysis studies how the variation in the model output can be apportioned to different sources of variations, and how the given model depends upon the information fed into it*'. A sensitivity analysis consist of changing the parameters of a model and interpreting the outcome. This type of sensitivity analysis is called one-at-a-time (OAT) and consist of multiple runs with slightly different parameter settings in order to examine the influence of the change in parameters (Saltelli, Tarantola, & Campolongo, 2000). A more complex sensitivity analysis would be preferable but will not be performed because of time restraints. The outcomes consist of assessable sensitivity measures. Because the sensitivity measures are dependent on the type of model they will not be discussed in the methodology. The sensitivity measures are based on the outcome of the model and will be discussed in Chapter 4.

After the SA the plausibility of the model will be assessed in Chapter 5. Such models of complex adaptive systems are difficult to validate. There are no observable variables in the real world with which the outcome of the model can be compared. At the moment there are no methods available to validate a model such as proposed in this thesis. It is only possible to check whether the result of the model is plausible or not. This will be done by interpreting the result of the model and by reasoning whether the result can be motivated as plausible or not.

Concluding remarks

The research on location and social networks in models of opinions dynamics is limited. This thesis complements the existing research by performing a literature study, developing a conceptual model, developing a model on a regional scale using NetLogo, performing a sensitivity analysis and analysing the plausibility of the developed model. The next chapter will start with finding gaps in the current literature.

Chapter 2: Literature study

Introduction

Many theories are related to opinion dynamics. In this chapter different theories related to opinion dynamics will be discussed. From these theories will be concluded what is needed and what is missing in order to couple social and spatial networks in a model of opinion dynamics. At the end of the chapter will be summarised what is missing in order to develop a small scale network model that couples social and spatial structures.

Theory of planned behaviour

An important theory for understanding social interaction is the theory of planned behaviour by Ajzen (1991). According to this theory all behaviour is based on the intention of performing an action and the perceived behavioural control of performing an action. The actual control over a behaviour is the combination of the intentional behaviour and the perceived control over the behaviour. In the figure below is shown how the theory of planned behaviour works.

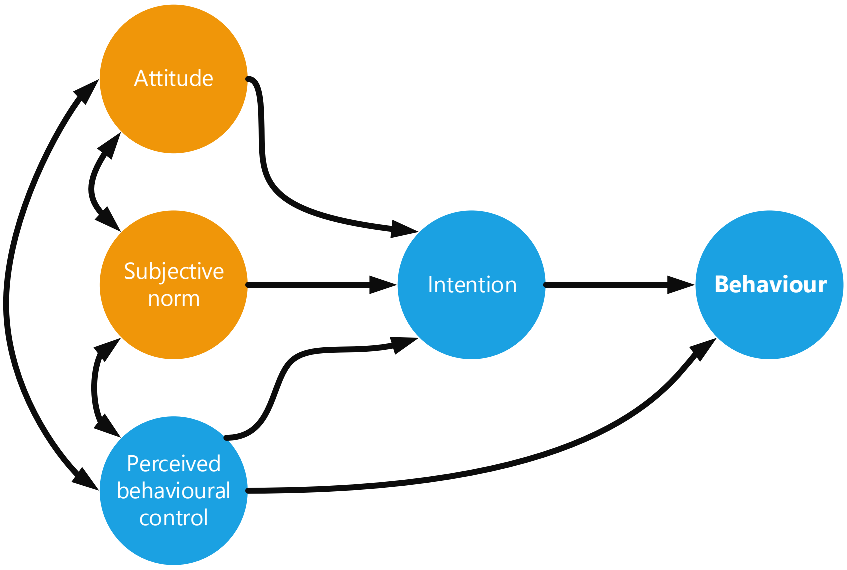

Figure 1: The theory of planned behaviour; the yellow entities are dependent on influences from other actors (Ajzen, 1991).

The attitude and subjective norm are influenced by the social network an individual is part of. The theory of planned behaviour shows the connection between opinion formation and actual behaviour. An opinion is a combination of attitude and a subjective norm. The importance of understanding the formation of attitudes is explained by this theory, because it results in certain behaviour.

Social impact

Social impact is described in the paper of Latané (1981). The exact definition of social impact is described by Latané (1981) as *'any of the great variety of changes in physiological states and subjective feelings, motives and emotions, cognitions and beliefs, values and behavior, that occur in an individual, human or animal, as a result of the real, implied, or imagined presence or actions of other individuals'.* Nowak, Szamrej, and Latané (1990) show in their paper that the theory of social impact can be useful for simulating opinion dynamics. In this chapter the definition of social impact by Latané (1981) will be discussed.

In his paper Latané (1981) describes three principles of social impact. The first principle of social impact is the notion that social impact (Q) is a multiplicative function of social sources. The formula of the first principal is as follows:

$$Q = f(S \cdot I \cdot N) \qquad (1)$$

Social impact is a result of strength (S), the immediacy (I) and the number of sources (N). The strength can be determined as the strength of the influence in terms of status, relationship with the target or power over the target. Immediacy is the distance between the source and the target in space or in time. The spatial aspect in this formula will be the immediacy of the sources. The number is the number of sources influencing the target.

The second principal is the notion that after the first source any other source influencing the target will have less influence on the target. The higher the number of sources the less the target is influenced by the individual sources. The formula of the second principal is as follows:

$$Q = sN^t, t < 1 \qquad (2)$$

In this formula N is the number of sources and s and t are constants. The constant t can only be smaller than one because the influence per source can only decrease. The total value of Q will always increase when the number of sources is increasing. The value of the two constants are dependent on the situation. They can be retrieved by plotting a hyperbolic trend line from observational data. An example of observational data is counting the number of yawns in a group after one member of the group yawns. In the case of a computer simulation it is important to understand that the influence per actor is decreasing with the number of influencing actors, but the constants cannot be determined in such a case.

The third principle of social impact is the notion that if a social network is influenced from an outside source the influence on the targets will be divided. If the sum of S, I and N becomes higher the impact on each target becomes smaller. The formula of the third principal is as follows:

$$Q = f\left(\frac{1}{S \cdot I \cdot N}\right) \qquad (3)$$

The variables S and I have the same meaning as in the formula of the first principle of social impact. In this formula N is the number of targets in the social network and not the number of sources. The impact becomes smaller as one of the values of the variables becomes higher.

Nowak et al. (1990) used the social impact theory to develop a computer simulation of the change of attitudes in a population. Their research is a good example of how social impact can be used to model opinion dynamics. In their paper the strength was represented as persuasiveness of individuals. If an individual is persuasive he or she is good in persuading other individuals and thus his or her strength of the influence on a target is high. The persuasiveness in the research of Nowak et al. (1990) is not based on the abilities of an individual of persuading, but based on his or her opinion and how convicted he or she is to this opinion. The persuasiveness changes when the opinion and the intensity of that opinion is changing. The actors in the simulation do not have abilities such as social status or natural persuasiveness.

For the reversed social impact, the third principal, supportiveness instead of persuasiveness was used to represent the strength. If a group of immediate people have the same opinion they can socially support each other. The influence from actors with different opinions becomes smaller because of the social support of immediate actors.

For the immediacy the Euclidian distance between actors was used (Nowak et al., 1990). The actors were represented as cells. The Euclidian distance between the cells of the source and the target were considered to represent the immediacy.

The social network was not really a part of the social impact model of Nowak et al. (1990). The spatial aspects were represented as Euclidian distances. A Euclidian distance is a direct representation of the real distance between two object and can be useful when taking the distance between agents into account. The agents were represented as cells in a grid. Every cell in this grid represents one agent, which makes the social network completely uniform.

Social Learning and opinion formation

Another process that can be considered as a diffusion process is social learning (Acemoglu & Ozdaglar, 2011). Social learning can be important for opinion dynamics because social learning is mainly about beliefs and opinions. According to Acemoglu and Ozdaglar (2011) social learning is a process "*whereby individuals obtain information and update their beliefs and opinions as a result of their own experiences, their observations of others' actions and experiences, the communication with others about their beliefs and behavior, news from media sources, and propaganda and indoctrination from political leaders and the state"*. The theory of social learning is not new and was already described by Bandura (1977). Social learning can be used to explain many different social aspects. In the case of Acemoglu and Ozdaglar (2011) social learning is linked to opinion dynamics in a social network. According to Acemoglu and Ozdaglar (2011) social learning is social because the information is received via a social network, the information needs to be socially interpreted and it can lead to dynamics of opinions.

Acemoglu and Ozdaglar (2011) distinguish three key components of opinion formation. The first component is that actors have priors. Priors are the opinions with which actors start. In a model, priors are not the result of simulations. In reality such opinions are already a result of social interactions. Prior opinions can also be called initial opinions when describing models (Deffuant et al., 2000). 'Initial' implies that these opinions are the starting points, while 'prior' implies that they existed before the model. In this thesis 'prior' will be used to describe prior opinions in the real world or opinions that are a result of a simulation and 'initial' will be used to describe a starting point of a model.

The second key component of opinions formation according to Acemoglu and Ozdaglar (2011) is the source of information. In the case of opinions dynamics the sources of information are the other actors in the social network. These actors are influencing the target. Whether these influences are updating the opinion of the target or not is dependent on certain variables such as the initial opinion of the target.

The method of information processing is considered to be the third key component of opinion formation (Acemoglu & Ozdaglar, 2011). The newly received opinions from the sources of information should be processed by the target, if the target will be significantly influenced, in such a way that the prior or initial opinions will be updated. The result can be a combination of the prior opinion and the new information or the prior opinion can be overwritten by the new information.

Social networks

Social networks are about the relationships between individuals (Degenne & Forsé, 1999). They focus on relationships among social entities (Wasserman, 1994). A social network representation can have a certain structure based on the choices of the researchers. In reality an individual can have many different connections to other individuals such as friends, family members, co-workers, neighbours or sport club members. When a social network is being modelled choices need to be made about the kind of connections that will be included. The number of connection types indirectly determines together with some other aspects the complexity of the model.

Graphs are essential for describing social networks (Degenne & Forsé, 1999). The graph theory is a mathematical theory that became important for the social sciences to represent social relations. A graph consist of nodes and arcs (Degenne & Forsé, 1999). The image below shows a graph in which the arc is directed. This means that there is a social relationship from A to B, but not vice versa.

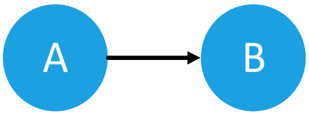

Figure 2: A directed graph with two nodes

If all the arcs have values, such as an opinion, it can be called a weighted directed graph. Some typical structures in a directed graph can be categorised. According to Degenne and Forsé (1999) a directed graph can contain chains, cycles, paths and circuits. A chain is a series of nodes connected in a row. A cycle is a chain where the first and the last node are the same node. A path is a chain where all nodes are connected in the same direction. A circuit is a cyclic path. The figure below shows examples of these four structures.

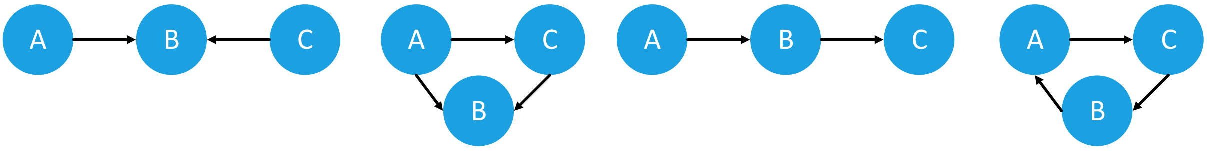

Figure 3: Examples of network structures; from left to right: chain, cycle, path and circuit

A path is always a chain and a circuit is always a cycle, but not always vice versa. Not all nodes are connected directly to all nodes. There is a difference between direct connected nodes and indirect connected nodes. All direct connected nodes represent the direct social relationships of an individual. The indirect connected nodes can be considered as part of the social network of the specific individual even though the individual does not know these indirect relationships. An example of such a connection of the first order is 'a friend of a friend' or 'the co-worker's wife'. Indirect connections can influence direct connections which in their turn influence the specific individual.

The most important concepts when analysing social networks are closeness, network density, betweenness and centralisation (Abraham & Hassanien, 2012). Closeness defines how close an agent is, spatially or socially, to all other agents, directly or indirectly. An agent in the centre of a social network is often more closely connected to all other agents than an agent at the edge of a network because the average distance to all other agents is generally the shortest from the centre. The network density is the proportion of the number of connections in a network compared to the total number of connections possible (Abraham & Hassanien, 2012). The network density always has a value between 0 and 1. The betweenness is based on the number of shortest paths going through a node. If the directly connected nodes are well connected to the rest of the network it means that this node is indirectly influential. A person with many influential connections is more likely to be influential as well. Centralisation measures how natural the network is divided. If the most central nodes are well connected, the centralisation has a high value.

The concepts of closeness, network density, betweenness and centralisation are important for examining the connectivity of agents. The connectivity of an agent can be translated to the real world as the social capital of an individual (Degenne & Forsé, 1999). Social capital can be defined as "*the ability of actors to secure benefits by virtue of membership in social networks or other social structures"* (Portes, 2000). Social capital is based on the idea that influence does not only consist of money and assets but also on the connections with other individuals. More important than having connections is the degree of influence on other individuals. Influential actors are more likely to project their ideas to other actors.

Aggregating actors can be a useful tool for examining social networks. Degenne and Forsé (1999) mention two types of aggregation in social networks. The first and most logical one is the concept of cohesion. If a group of actors are strongly connected they can be called a 'clique'. Within a clique the cohesion is high. If a clique has more or less the same opinions it is less likely that they will adopt another opinion because they influence each other more than they are influenced from outside. According to (Newman & Park, 2003) social networks differ from non-social networks because they show levels of clustering. A clique is such a clustering. The second type of aggregation is based on the connection type (Degenne & Forsé, 1999). In real life a connection between two individuals is based on their location in society. By dividing actors into groups based on their location in society such as their status, their job or their age it is possible to examine the relationships between levels in society. This type of aggregation is called equivalence (Degenne & Forsé, 1999).

Multi-agent systems

In the introduction was mentioned that the model will consist of multiple interacting agents. The proposed model will be an ABM. ABMs can also be called multi-agent systems (Bousquet & Le Page, 2004). In such models the macro-level dynamics are aggregated from the behaviour and the interaction of agents (Kiesling, Günther, Stummer, & Wakolbinger, 2012). The agents have a crucial role in a multi-agent system by behaving as independent individuals.

The definition of an agent is discussed in the paper of Wooldridge and Jennings (1995). According to Wooldridge and Jennings (1995) agents have weak properties such as autonomy, social ability, reactivity and pro-activeness. Next to the weak properties they give a strong notion of an agent as '*a computer system that in addition to having the properties identified above, is either conceptualised or implemented using concepts that are more usually applied to humans"* (Wooldridge & Jennings, 1995). An agent having and sharing an opinion is an example of a concept that is usually applied to humans.

There are many authors that have developed a multi-agent system for modelling social diffusion (Kiesling et al., 2012). According to Kiesling et al. (2012) many of these models are based on a model by Bass (1969), which is based on the diffusion of innovation theory by Rogers (2010). In the model by Bass (1969) a distinction is made between internal and external influences. The external influences of innovation diffusion are influences that are not communicated from agent to agent but from an external source such as mass-media. Word-of-mouth communication is considered to be internal (Kiesling et al., 2012). The model of Bass (1969) is about whether agents will adopt new products or not. The model can be used for any diffusion system. The probability (p) that a random agent (x) at time t adopts a new product is linearly dependent on previous adopters as internal influences (q) , and external influences (e) (Bass, 1969). The formula of this theory will be as follows:

$$\frac{p(t)}{1 - P(t)} = e + q \cdot P(t) \tag{4}$$

Where P is the cumulative distribution function of adoptions. Each timestep the cumulative set of internal influences is calculated to predict together with the external influences the probability that a single agent is adopting a new product. In the case of opinion dynamics the interactions within a social network is representing the internal influences. Because the original model of Bass (1969) is assuming that the population is homogeneous the internal influences are calculated as a simple aggregation. The interactions within a social network are more than an aggregation of values. Kiesling et al. (2012) propose a formula in which P is replaced by an average of all adopters:

$$p_A{}^t = \left(e + \frac{\sum_{A=1}^{n} p_A{}^{t-1}}{n} \cdot q\right) \cdot (1 - p_A{}^{t-1}) \tag{5}$$

Where $p_A{}^t$ is the probability that agent A adopts an opinion on time step t and n is a set of agents. The opinion of an agent is dependent on a probability caused by the average opinion of the complete set of agents. By using this formula it is assumed that the set of agents is homogeneous. The social network is not taken into account.

Bayesian and non-Bayesian networks

According to Acemoglu and Ozdaglar (2011) two types of social network models can be distinguished. A difference can be made between Bayesian and non-Bayesian networks. A Bayesian network is based on probabilistic rules. The status of an entity in a Bayesian network can change according to the state of other entities. In figure 4 three entities in a Bayesian network are shown as an example. The Bayesian rules in this example are that C can only be converted to green if A and B are green. Since B is red, C cannot be converted to green. Figure 5 shows what happens when the entities A and B are green.

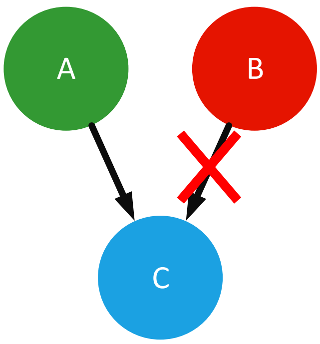

Figure 4: The entities A, B and C in a Bayesian network where A and B do not fulfil the requirements for changing the status of C

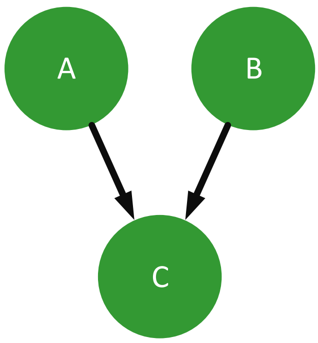

Figure 5: The entities A, B and C in a Bayesian network where A and B fulfil the requirements for changing the status of C

Any Bayesian network does have rules comparative to the given example. The initial status of C only changes if the statusses of A and B are true. This can be formulated as follows:

$$P(C|A \wedge B) \neq P(C|B) \neq P(A|C) \tag{6}$$

The probability (P) that C turns green when A and B are green is not equal to the probability that C turns green when A or B turn green. C can only turn green when A and B are green. This example shows the causal relationship of a common effect where two entities are influencing one entity together (Korb & Nicholson, 2003). There are other causal relationships possible in Bayesian networks. The figure below shows other examples of causal relationships within a Bayesian network.

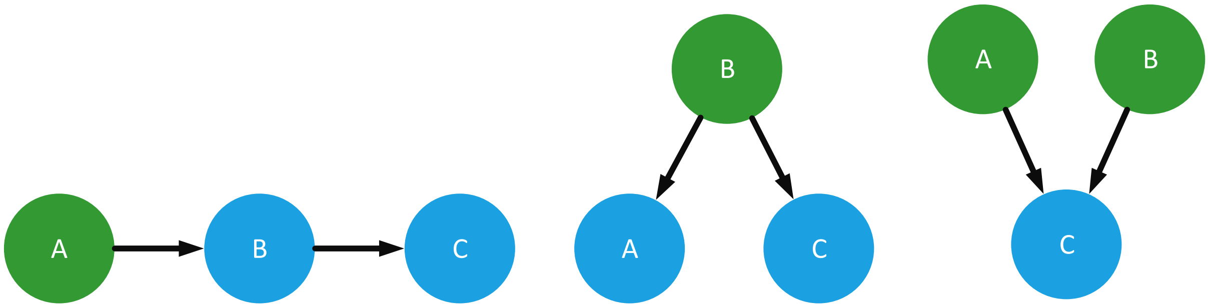

Figure 6: Bayesian network causal relationships. From left to right: causal chain; common cause; common effect. The blue entities are dependent (Korb & Nicholson, 2003).

In the example the dependent entities are blue and the independent entities are green. A Bayesian network does only accept binary numbers. The adoption of a part of an opinions is not possible by using a Bayesian network.

There are several non-Bayesian social network models available in the literature (Acemoglu & Ozdaglar, 2011). The model created by Deffuant et al. (2000) is one of those non-Bayesian models. This model can be classified as a social network model because it represents the interaction between social entities. This model does not only use an average between two opinions, but also uses a threshold, or confidence level (Hegselmann & Krause, 2002). The formula of the model of Deffuant et al. (2000) is as follows:

$$P_A = P_A + \mu \cdot (P_B - P_A) \tag{7}$$

Where P_A is the opinion of an agent (A) and P_B the opinion of another agent (B) where agent A is interacting with. μ is a convergence parameter between 0 and 0.5. It determines how much two opinions are allowed to converge. The threshold (h) must be larger than the difference between p_A and p_B:

$$|P_A - P_B| < h \tag{8}$$

The formula for adopting the opinion of agent B is the opposite of the formula of agent A:

$$P_B = P_B + \mu \cdot (P_A - P_B) \tag{9}$$

Deffuant et al. (2000) tried to simulate a social network by placing all agents in a two dimensional raster as in the model of Nowak et al. (1990), but in this model only connected agents were allowed to interact. A von Neumann neighbourhood was used to define which actors were connected. In this way the location of agents difined there social network.

Another important model is the model developed by DeGroot (1974). In the model by DeGroot (1974) a social network is simulated by using a stochastic matrix. The stochastic matrix of a DeGroot model is called a trust matrix (T). The values in the trust matrix represent the trust between agents. If the probability in the matrix is high for a certain vector it means that there is a high chance that the target agent will adopt the opinion of the source. Each timestep (t) the opinions of all actors will be updated. The formula for updating the opinions each timestep is written by Golub and Jackson (2010) as:

$$p^t = Tp^{(t-1)} = T^t p \quad (10)$$

Where p is the probability or vector of beliefs. In this formula is chosen to take the symbol for probability (p) to represent an opinion because the value of an opinion in this formula is a probability. Each timestep the vectors are updated with the values of the previous timestep. The update of a single agent is a result of the opinions of all other agents and the weight their opinion put on the target. The vector of beliefs between two agents A and B cannot be negative, thus $p_{AB} \geq 0$ (DeGroot, 1974). The formula for updating the opinion of agent A (p_A) from the opinions of all other agents is as follows:

$$p_A{}^t = \sum_{B=1}^{n} T_{AB} p_B{}^{t-1} \quad (11)$$

The DeGroot model takes all relationships between actors into account. The trust matrix represent aspects such as social status, age and family relationships.

Figure 7 below shows an example of a small social network of three agents A, B and C. The values of the vectors are showing the pressure that they put on the opinion of each other. If there is no pressure on one agent to another, the vector is not shown in the figure. The pressure of Agent A on agent B in this example is high. Agent B will adopt the opinion of agent A for 80 percent. Agent B is thus trusting agent A with 80 percent. If agent A would have an opinion of 0.5 of a random opinion the resulting opinion of agent B will be $0.8 \cdot 0.5 = 0.4$. Because the sum of each row of a stochastic matrix is equeal to 1 each agent can only put pressure on other agents for 100 percent in total. The percentage has to be divieded over the total number of agents. If the number of agents becomes higher the pressure on each agent from one particular agents become smaller.

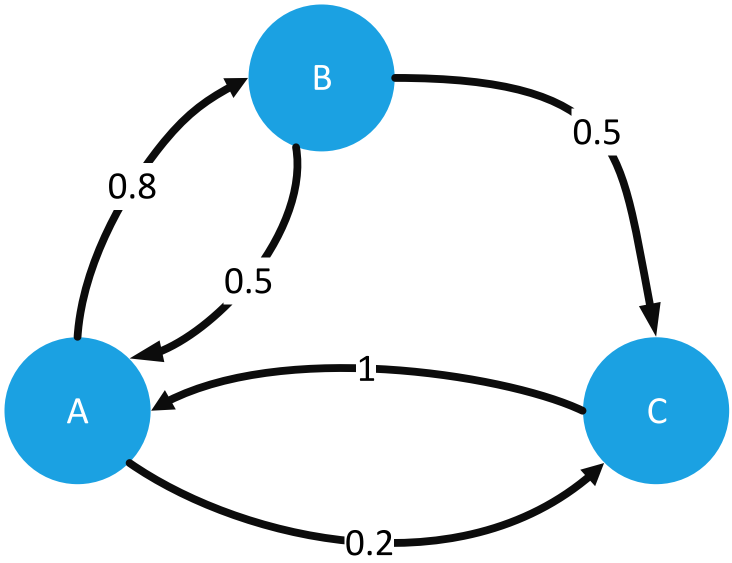

Figure 7: An example of a DeGroot model visualised as a weighted directed graph

The trust matrix of the example above would be:

$$T = \begin{bmatrix} 0 & 0.8 & 0.2 \\ 0.5 & 0 & 0.5 \\ 1 & 0 & 0 \end{bmatrix} \tag{12}$$

If the agents A, B and C have initial values of a random opinion (p^0) between 0 and 1 of respectively 0.5, 0.4, 0.8 then the initial situation can be written as:

$$p^0 = [0.5\ 0.4\ 0.8] \tag{13}$$

The weighted vectors pressing on each agent are calculated by averaging the weights of the vectors pressing on an agent together. The weighted vectors (v) pressing on each agent every time step is then:

$$v = [0.75\ 0.8\ 0.35] \tag{14}$$

In many cases using probabilities will result in binary opinions. Binary opinions are easier to compute, but are limited in modelling complex dynamics. A binary opinion can only have two options such as yes and no or agree and not agree. The simplicity of binary opinions result in short limited dynamics, because a consensus does also exist of one the two options. In some cases binary opinions can be really useful.

Conclusions

Although all theories related to opinion dynamics are important, not all aspects of all theories can be included in the model. The model should help understanding underlying processes and should therefore stay relatively simple. The model should be able to handle multiple agents in a social network. The opinions of the agents should be dependent on their spatial location and their location in the social network.

Some of the discussed models did use location as a variable. The mentioned literature used location in a CA model (Ligtenberg & Bregt, 2014; van Voorn et al., 2014) or as a more simple neighbourhood presentation (Deffuant et al., 2000). Spatial aspects in relation to actors in an ABM are generally missing in the literature. The location between actors is more often used, as it is already mentioned in the theory of social impact, as immediacy (Latané, 1981). Because immediacy can have multiple meanings it is more often used in a directed weighted graph as an assumption. The distance is then not used as a location on the earth's surface but as an aggregation of Euclidean distance and social distance. An ABM model where the distance between agents is based on the actual location on the earth's surface and where these locations play a role in the formation of opinions does not exist yet. A location is called measurable in this thesis when it can be calculated based on coordinates. The spatial and social network could be coupled by placing the actors on a map where they have a fixed location. In order to link spatial aspects with social aspects there must be a clear representation of spatial aspects.

From the literature can be concluded that the following spatial aspects are missing from the current literature about ABM:

- The distance between agents is not based on measurable locations
- Geographical locations are not used together with an ABM
- Opinions about an area are only represented as CA models

All opinion diffusion models use a simple representation of a social network. In most models the population is homogeneous. All actors are behaving exactly the same when fed the same inputs. In a computer model cannot be avoided that actors are behaving according to the same set of rules. The actors are thus behaving completely rational as a computerised individual. Giving each individual its own set of rules is not an option because it would make the model too complex. Diversity can only be modelled by giving each actor different initial variables. The location of the agent can be one of those variables. This method is often used in social network models. In some models location is used as a measure for social closeness. The model of Nowak et al. (1990) is an example of such a model.

In most models the initial variables are dependent. When the opinion of an agent is changing the ability of putting pressure on other individuals is also changing. This means that the position in society is not taken into account in such a model, but only is being focussed on how interactions between agents are working. None of the models used a mix of initial dependent and independent variables to determine the social network. Such a mix of variables is needed to represent the position of agents in society.

- Social networks are sometimes based on location only
- The position within a social network is only based on connections and not on initials
- Initials are often dependent

Although there is much literature available on the subject of opinion dynamics there are still many aspects that are not researched yet. The research on social networks and spatial networks is limited. In none of the researches is tried to couple social and spatial networks. In this chapter is listed what aspects of both social and spatial networks are still missing. The development and demonstration of a model could help filling these gaps.

Chapter 3: Model development

Introduction

In the previous chapter was discussed what is still missing in the literature to couple social- and spatial networks in models of opinion dynamics. In this chapter will be discussed how the gaps in the literature can be filled. A model will be developed where agents are interacting. The agents will have an opinion about a controversial area. The controversial area is called a 'power plant' in the model, but it represents any object the agents can have an opinion about. The chapter will start with a discussion of a conceptual model based on underlying theories. After the conceptual model the actual model and the results of running the model will be discussed.

Underlying theories of social interaction

According to Latané (1981) any type of social impact consist of the three variables strength, immediacy and number of sources. The variables can, except for the number of sources, have different meanings dependent on the type of social impact. In the case of this research the model should simulate opinion dynamics. The formation of opinions is described in the theory of social learning (Bandura, 1977). According to this theory there are three important aspects of opinion formation: priors, agents and the method of information processing. The concepts of social impact and social learning need to be placed in context of this research.

The strength of an opinion is difficult to determine. In many opinion dynamic models the update function is similar to the update function of Deffuant et al. (2000) where the resulting opinion is an average of the opinions of two interacting agents (Hegselmann & Krause, 2002; Ligtenberg & Bregt, 2014; Weisbuch, Deffuant, Amblard, & Nadal, 2003). There are also many models of opinion dynamics using binary opinions (Acemoglu & Ozdaglar, 2011; Föllmer, 1974; Martins, 2009; Martins, Pereira, & Vicente, 2009). Both types do not take social differences between actors into account. The model by van Voorn et al. (2014) is an improvement to the original Deffuant et al. (2000) model because they added social status as an independent variable. The strength of an opinion pressed on other agents is higher if the source has a high social status. Often the assumption is made that an opinion has more influence on a target if the opinion itself is stronger. 'Stronger' can mean that the actor has a more polarised opinion or that an actor is more convinced of its opinion. Because in this thesis will be attempted to model a representation of a social network the strength should at least depend on the differences in social status. The social status can represent any type of position in a social network. In order to keep the model dynamic the strength of the social impact should also be dependent on a dependent variable such as the strength of an opinion. The result could be a combined vector based on the social status and the opinion strength.

Immediacy can be defined as social distance or as measurable distance based on geographical locations. The neighbourhood in CA models is a popular method for modelling spatial information. CA models are limited for modelling the interaction of actors and are, therefore, not suitable for this research. If the geographical locations of actors are known the Euclidean distance is relatively easy to calculate. By using the Euclidean distance as immediacy it is possible to include spatial information as a variable which is influencing the communication of opinions. If the opinion is about a region the Euclidean distance between this region and an actor can also be used as a variable. In such a case the region can be seen as a source and the actor as a target. The influence of the region on a target is declining the further the target is located from the region. The social distance should be clearly distinguished from geographical distance, because this thesis is about coupling the two different aspects. The social distance can be used for representing a social network. Adding specific information about the relationships between agents is not an option because it will make the model too complex. It is, however, possible to add randomly chosen links between agents in varying strengths. The stronger the link between two agents the more immediate they are. Figure 8 explains the difference between the spatial and social distance. The length of the links are representing the spatial distance and the thickness is representing the social distance. In this example agent B is spatially closer to agent A than agent C, but agent C is socially closer to agent A than agent B.

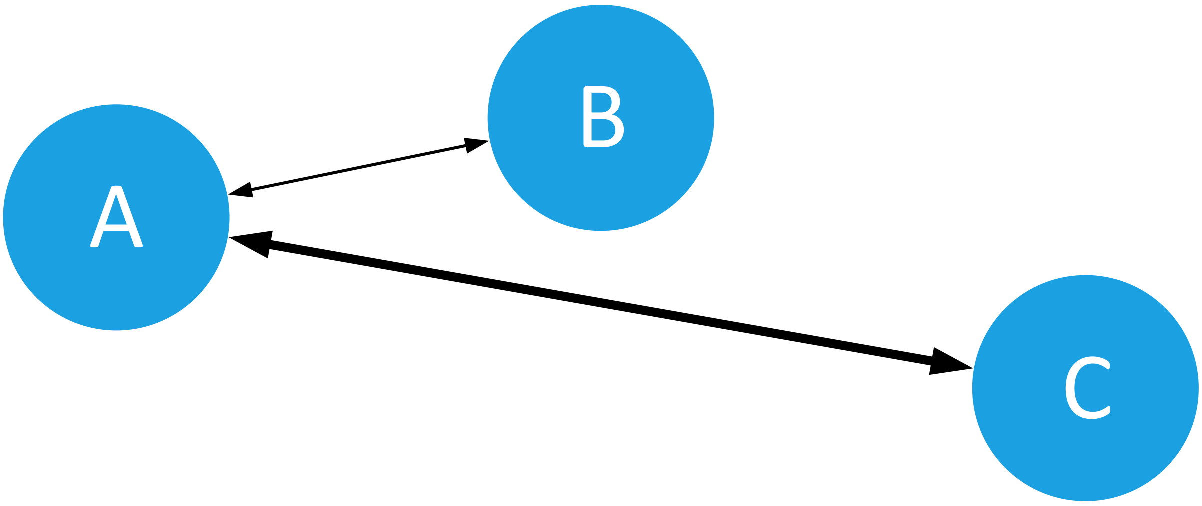

Figure 8: An example of the difference between spatial and social distance. The length of the links represents the spatial distance and the thickness represents the social distance

The agents will be randomly located on a fictive map. The number of agents should be adjustable because the size of the population could influence the outcome of the model. According to the theory of Latané (1981), each actor is being influenced by all sources. In reality opinions can only be transferred if there is some sort of interaction between agents. If two actors located far from each other have no relational interaction there cannot be an exchange of opinions. The number of sources in the formula of (Latané, 1981) should be interpreted as the number of all significant sources. The theory does not imply that all actors should be used for the calculation of the impact, but only those that are considered to be a source. In the research of Nowak et al. (1990) was decided to only include the actors with an opposing opinion.

The agents should represent individuals living in an area. In order to simulate a social network the agents should contain information about their social location in the network. This initial information is called priors (Bandura, 1977). Dependent on their location in a social network actors have a certain social status. It is assumed that actors with a high social status will have more influence over other actors. Social status can be represented as a prior randomly given to each actor. This prior will be independent and cannot change in time. The priors are divided randomly because it should be possible to have a social status while the number of social relationships is low. An example is a chief executive officer (CEO) of a large company without many family members or friends in the region. Social status as implemented in this model can be called persuasiveness. Persuasiveness is a combined variable of aspects that raises the ability of an actor to persuade others independent of the number of relationships. Next to a certain social status actors can have relationships with other actors. The degree in which actors are socially attracted to each other will be called affinity. If two actors have a high affinity towards each other they have a close relationship. A low affinity means that they have no or a weak relationship. The affinity can be distributed by giving all actors a random affinity value. The actors that have values close to each other have a high affinity towards each other. If the values differ significantly there is no social relationship between the two actors. Another important prior is the initial opinion. Each agent should already have an opinion about the region. This variable is a dependent variable. In the table below all variables per agents are listed with their dependency and an explanation of the initial values.

The spatial network is based on the Euclidian distance between agents. The social network is based on the difference in affinity between agents. In figure 9 and figure 10 respectively a visualisation of a spatial and a social network are shown. The links in figure 9 show neighbourhoods of connected agents. The links in figure 10 are clearly not dependent on the location of the agents.

Table 1: All variables per agent with their dependencies and an explanation of the initial values

Variable	Dependency	Initial value
Unique identifier	Independent	Each agent receives an unique number between 1 and the total number of agents
Coordinates (x/y)	Independent	Random coordinates within the boundaries of the map and not in the power plant
Opinion	Dependent on other opinions	Random value between 0 and 10
Affinity	Independent	Random value between 0 and 100
Initial persuasiveness	Independent	Random value between 0 and 10
Power plant distance	Dependent on the location	The calculated distance between the agent and the power plant

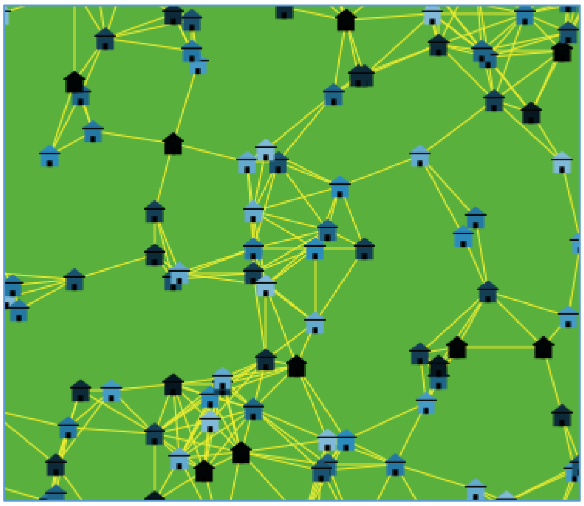

Figure 9: A visualisation of a spatial network. The yellow lines are connections between agents based on location

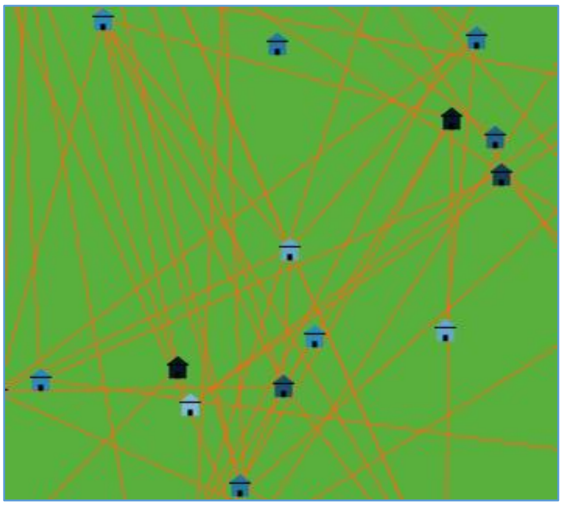

Figure 10: A visualisation of a social network. The orange lines are connections between agents based on the difference of affinity

The model consist of a number of agents on a fictive map. The power plant is represented as a red circle. Each time the model is run all agents are randomly distributed on the map. During the set-up phase all variables shown in table 1 are assigned to each agent. The number of agents, the size of the neighbourhood, the minimum distance in affinity needed for agents to be connected, and the influence distance of the power plant are parameters of the model. These parameters can be changed each time the model is run. After the set up phase the model will work in time steps. Each time step (t) the opinions of the actors will be reassessed according to the variables pressing on their opinions. The immediacy, the persuasiveness, the affinity, and the number of sources are influencing the opinion of a target with a certain probability. The probability is needed to make the model dynamic and to represent the uncertainty of the assumptions. As in the model of DeGroot (1974) the pressing variables will together be calculated as weighted vectors with a probability as weight. This probability is the chance that the aggregated vectorised opinion of the sources will be averaged with the current opinion of the target. The method of averaging of Deffuant et al. (2000) is used because it is assumed that an individual does not depend its opinion completely on the opinions of others. In the figure below is shown how each time step the opinion of a random agent will be updated.

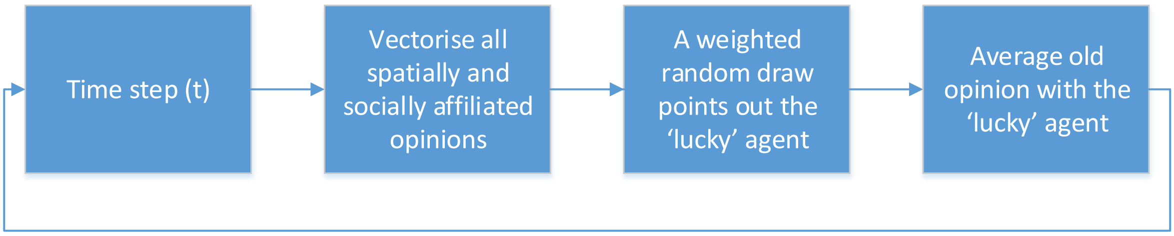

Figure 11: conceptual scheme of update rules of a random agent during a time step

Each time step (t) all opinions pressing on each agent are vectorised. From these vectorised opinions a weighted random draw will result in a 'lucky' agent. The opinion of the 'lucky' agent will be averaged with the currently active agent and transferred to the active agent. The source agent will not be influenced until it becomes active. Each turn all agents will become active. The described conceptual model will be used as framework to implement the actual model. It is mainly based on the theory of Latané (1981) and the models of Deffuant et al. (2000) and DeGroot (1974). The actual model and the preliminary results will be discussed in the following paragraphs.

Description of the model

The model is built in Netlogo (Wilensky, 2014). It was developed in several phases. First, the basic functions of the model were developed. When the basic model was working without any errors it was extended with several scenarios.

Each time the model is run a new empty map is created. All agents are randomly distributed over an area and are placed at least 1 fictional unit away from each other. Each agent will randomly receive all the initial values listed in table 1. The power plant has a radius of 10 fictional units. The shortest distance to the power plant will be added as a variable to all agents. Each turn all agents are being updated according to the opinion of another agent. The opinion can have a value between 0 and 10. The following rule is updating the opinion of agent A (P_A) with the opinion of agent B (P_B):

$$P_A{}^t = P_A{}^{t-1} \cdot (1 - w_B) + (P_B{}^{t-1} \cdot w_{\boldsymbol{B}}) \tag{15}$$

Where w_B is the persuasiveness of agent B. The basic updating rule is taken from the model by Deffuant et al. (2000) and slightly changed in order to add the persuasiveness. The persuasiveness is calculated from the initial persuasiveness (w_p) with a number between 0 and 10 with the following calculation:

$$w_b = \frac{\left(\frac{100}{I_{pt}+1}\right) \cdot \frac{(w_p + 2) \cdot 80}{12 \cdot 100}}{100} \tag{16}$$

Resulting in a percentage between $13\frac{1}{3}$ and 80. This choice is made to prevent an agent from completely adopting a new opinion without taking his or her prior opinion into account or rejecting an opinion completely. I_{pt} is the immediacy to the power plant calculated by subtracting the distance d to the power plant from the maximum influence distance d_{max}.

$$I_{pt} = \frac{((d_{max} - d) \cdot 80)}{d_{max} \cdot 100} \tag{17}$$

Where

$$d \leq d_{max} \tag{18}$$

The target and the source are being chosen by the model according to the deGroot model:

$$p_A{}^t = \sum_{B=1}^{n} T_{AB} \tag{19}$$

The trust matrix consist of agents living close by T_n or having a similar affinity T_a. The trust factors of the neighbourhood are calculated by taking the immediacy (i) as a probability.

$$p_B{}^i = 100 - \frac{d_{AB} \cdot 100}{d_n} \tag{20}$$

Where d_{AB} is the distance between agent A and agent B. d_n is the neighbourhood size. The trust factors of the affinity (a) is calculated as:

$$p_B{}^a = a_{max} - \frac{|a_A - a_B| \cdot 90}{a_{max}} \tag{21}$$

Where a_{max} is the maximum allowed difference in affinity in order to be connected, a_A is the affinity of agent A, and a_B is the affinity of agent B. The trust matrices are combined by taking the probabilities as proportions.

$$p_{adj} = \frac{100}{(\sum_{i=1}^{n} p_i) \cdot p} \tag{22}$$

Where p_{adj} is the adjusted probability and p the original probability from either the affinity or the immediacy.

Figure 12 shows an overview of four steps during the opinion updating process of a single agent of the basic model. During the first step all probabilities of the agents within the neighbourhood are collected. The second step is the collection of the probabilities of the social distance. During the third step the persuasiveness is corrected by the immediacy to the power plant if the agent is within the power plant influence distance. During the last step the opinion of agent A is updated. In this paragraph the basic model is explained. In the following paragraphs the results of the model will be explained and several scenarios will be added to the model.

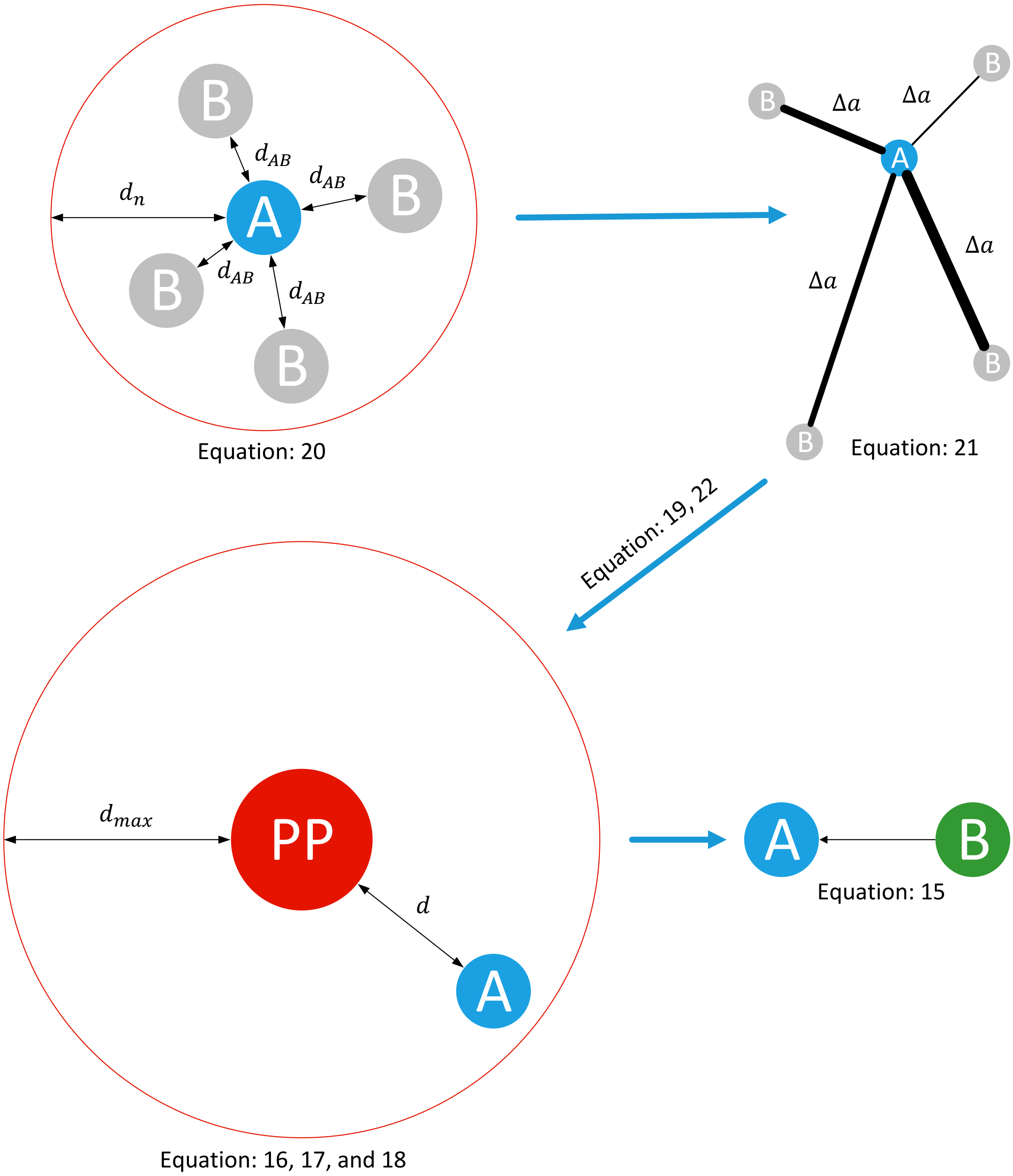

Figure 12: Explanation of the four steps of updating an opinion: collecting the probabilities of the spatial distance, collecting the probabilities of the social distance, calculating the power plant influence and updating the opinion; The circles with A and B represent different agents and the circle with PP represents the power plant; The red circles consisting of a red line are representing respectively the neighbourhood size and the power plant influence distance; blue agent: active agent; grey agent: a connected agent; green agent: 'lucky agent'; Δa = $|a_A - a_B|$.

Results

Because all connected agents are updated each turn there will always be one consensus as long as all agents are connected. Agents that are not connected do not interact and will not change their opinion. The result is similar to the results of Deffuant et al. (2000) without a threshold where the interactions are completely random. The time in which a consensus is reached is dependent on the number of connections. If the maximum difference in affinity is set to 100 it means that all agents are connected to all agents. It will take approximately 10 time steps to reach a consensus where $\Delta P < 1$. In the figure below is shown how the opinions are developing if all agents are connected.

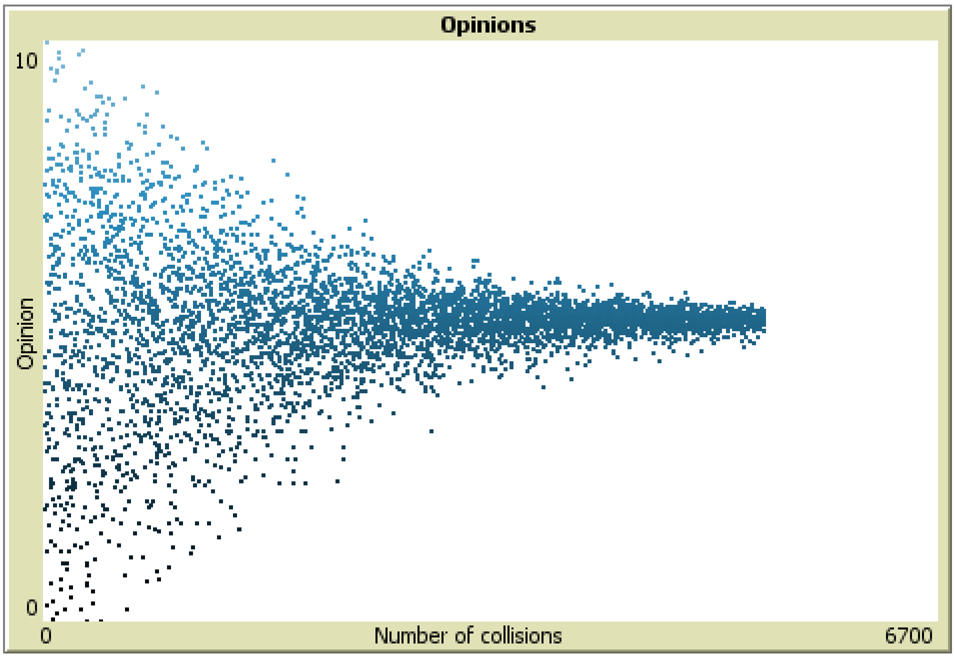

Figure 13: The reaching of a consensus when all agents are connected. The colour difference represents the opinion: dark blue: 0; light blue 10. Number of agents: 500; neighbourhood size: 100; maximum difference in affinity: 100; influence of power plant: 50 fictional units; no threshold.

The number of collisions represents the number of times that an opinion is being updated. Each time step the opinion of all agents are plotted in the figure. If the social network and the neighbourhood size are being limited it will take longer for the population to reach a consensus. The figure below shows the reaching of consensus when the neighbourhood size and the social network is limited. It will take about 40 time steps before a consensus is reached.

The choice with which agent an opinion will be averaged is based on a weighted draw. Because the choice whether an agent will average his or her opinion is not based on probabilities, the result of each run is similar. This choice is only dependent on whether an agent is connected or not. In large populations almost all agents are connected to another agent because the chance of being connected is higher. By taking the minimum difference in affinity (0) and the smallest neighbourhood size (1) with a population of 3000 the result will be a different consensus for each community. In figure 15 is shown how the resulting opinions are distributed.

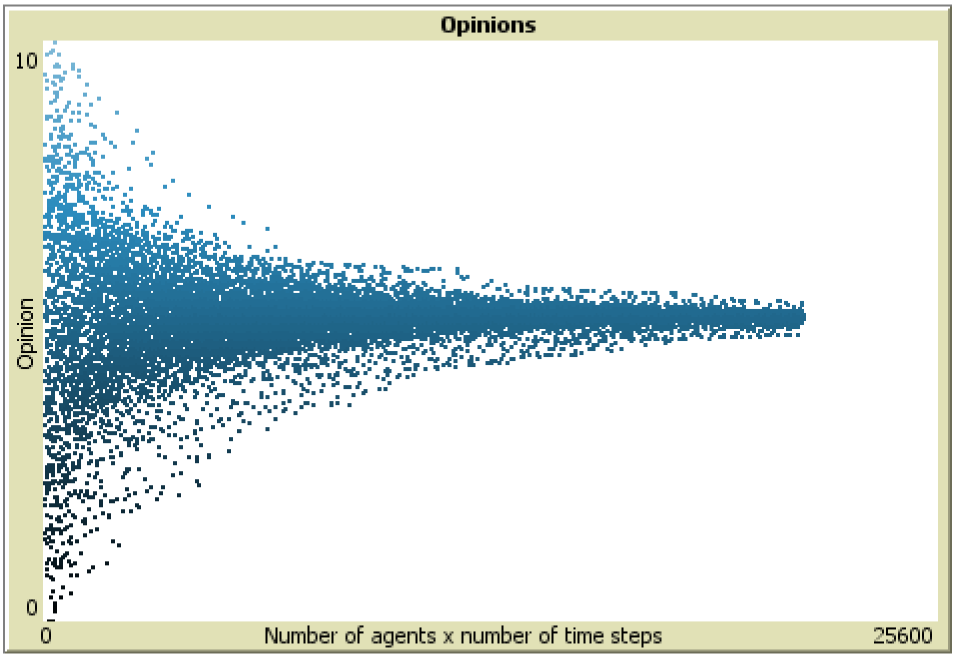

Figure 14: The reaching of a consensus with a limited number of connections. The colour difference represents the opinion: dark blue: 0; light blue 10. Number of agents: 500; neighbourhood size: 10; maximum difference in affinity: 0; influence of power plant: 50 fictional units; no threshold.

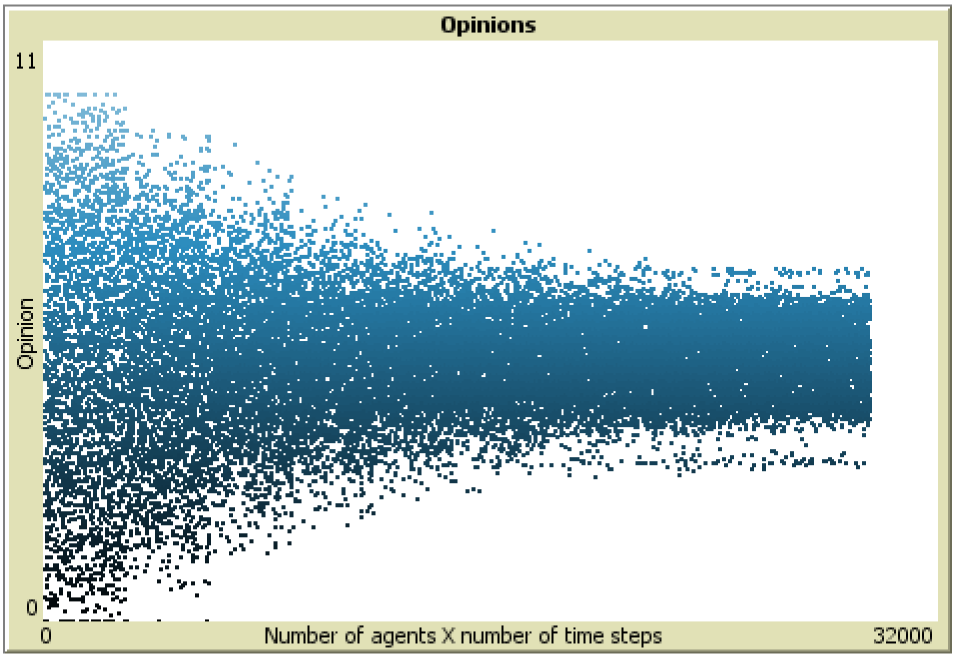

Figure 15: The result of having the minimum number of connections with a large population size. The colour difference represents the opinion: dark blue: 0; light blue 10. Number of agents: 3000; neighbourhood size: 1; maximum difference in affinity: 0; influence of power plant: 50 fictional units; no threshold.

Adding a threshold

Deffuant et al. (2000) and other models based on the model of Deffuant used a threshold in order to simulate the forming of different groups of opinions. In such a case there is no consensus, but different groups of opinions. If a threshold is added to this model similar results can be observed. The condition for agent A and agent B to average their opinions is exactly the same as the condition proposed by Deffuant et al. (2000):

$$|P_A - P_B| < h \tag{23}$$

Figure 16 shows an example of how a run with a threshold results in two clearly visible groups with the same averaged opinion.

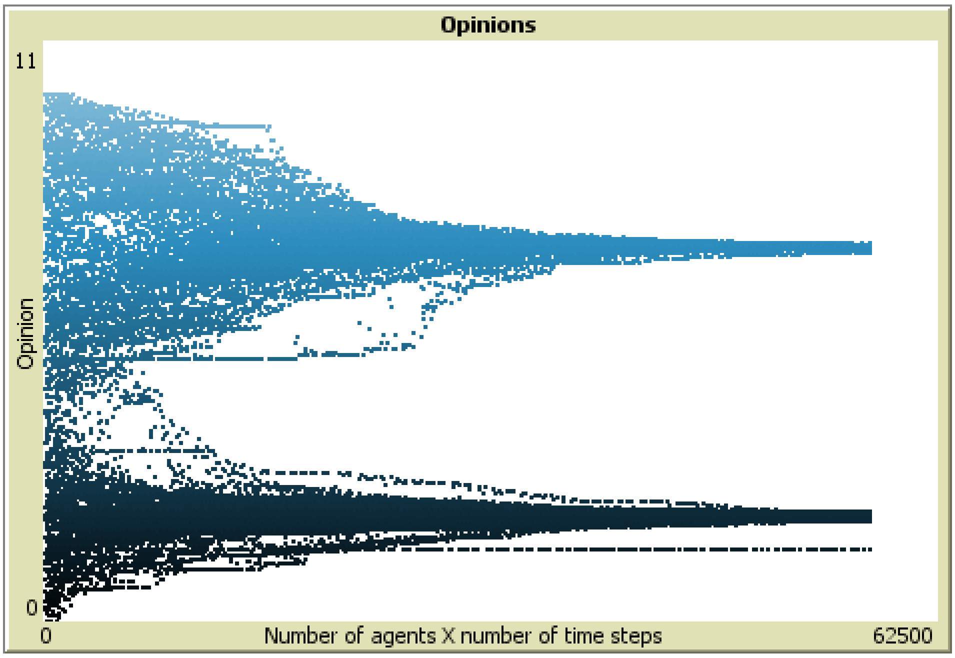

Figure 16 The result of adding a threshold to the model. The colour difference represents the opinion: dark blue: 0; light blue 10. Number of agents: 500; neighbourhood size: 10; maximum difference in affinity: 1; influence of power plant: 50 fictional units; threshold: 2.

The figure shows a third opinion of a single agent. It is possible that this agent is not connected to any other agents or that this agent is only connected to agents with an opinion in the upper half.

Not in my backyard

If it is assumed that the NIMBY effect exists and the power plant has a negative effect on the opinions of agents living close by, the model will have a different outcome. The NIMBY effect is added to the model as follows:

$$P_{new} = 10 \cdot \frac{P_p - (P_p \cdot I_{pt})}{10 - (P_p \cdot I_{pt})} \tag{24}$$

if

$$d \leq d_{max} \tag{25}$$

Where P_{new} is the adjusted opinion by the power plant and P_p is the prior opinion. The opinions within distance d_{max} of the power plant are adjusted each turn. The result of the NIMBY effect without thresholds is that the whole population is turning against the power plant. The result after 315 time steps is shown in figure 17.

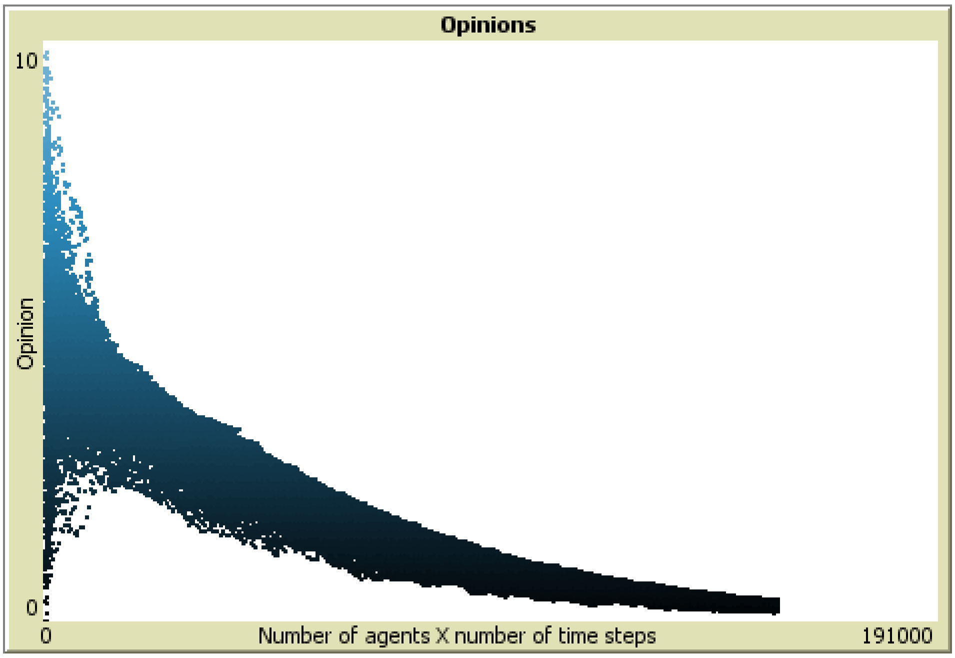

Figure 17: The result of adding the NIMBY-effect to the model. The colour difference represents the opinion: dark blue: 0; light blue 10. Number of agents: 500; neighbourhood size: 10; maximum difference in affinity: 0; influence of power plant: 50 fictional units; no threshold.

If next to the NIMBY effect a threshold of 2 is added to the model it will still result in a consensus with some exceptions.

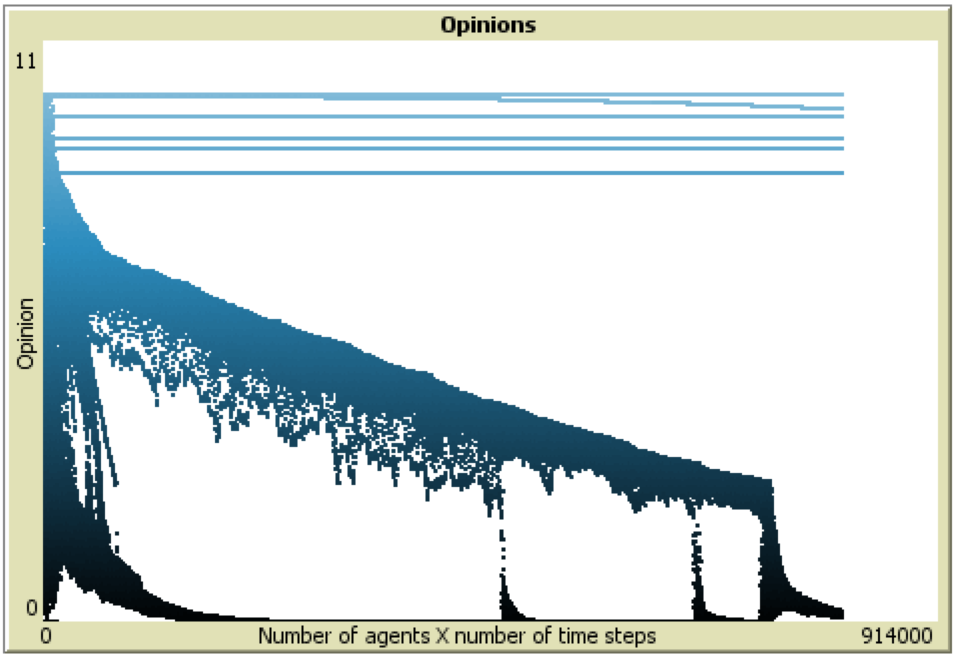

Figure 18: The result of adding the NIMBY-effect to the model with threshold. The colour difference represents the opinion: dark blue: 0; light blue 10. Number of agents: 500; neighbourhood size: 10; maximum difference in affinity: 0; influence of power plant: 50 fictional units; Threshold: 2.

Because some agents of the upper group are influenced by the power plant it is slowly decreasing the opinions of the agents belonging to the upper group. The thick decreasing line in the middle of the figure represents the upper group. The figure above is the result of 1640 time steps. There are some agents holding on to their opinions, because the difference in opinion with their connections is larger than the threshold. The scenario described above could be compared to a situation in which the public has a negative opinion about a local facility, even if it is not in their own neighbourhood. The people living close by are spreading their negative opinions to the public. An example of such a situation is a hydraulic fracking facility.

If the public would have a positive attitude towards a facility because it is generally accepted to be positive the model would have a different outcome. An example could be a windmill farm. This phenomena is added to the model by increasing the opinions of agents living farther away from the power plant than the power plant effect ($d_{\max}$) reaches. The adjusted opinions are calculated as follows:

$$P_{new} = 10 \cdot \frac{P_p + (P_p \cdot d_{adj})}{10 + (P_p \cdot d_{adj})} \tag{26}$$

Where

$$d_{adj} = \frac{(d - d_{max}) \cdot 80}{(d_{maxmax} - d_{max}) \cdot 100} \tag{27}$$

And

$$d > d_{max} \tag{28}$$

The variable d_{maxmax} is the distance between the power plant and the furthest agent on the map. Running the model without a threshold results in figure 19.

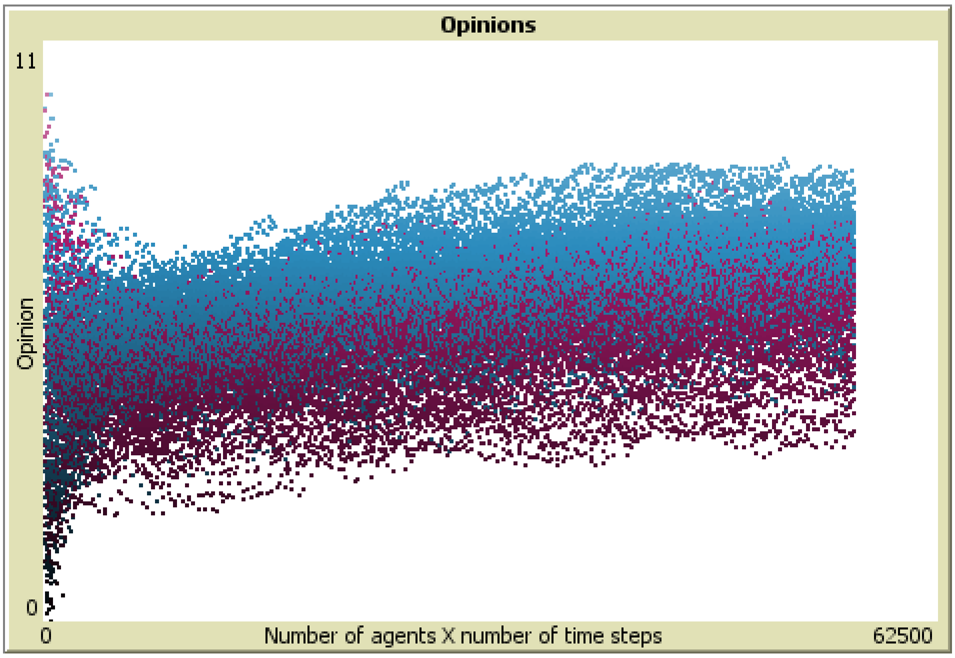

Figure 19: The result of adding the NIMBY-effect and a positive feedback from the public without a threshold. The colour difference represents the opinion: dark blue: 0; light blue: 10. The purple colours are the agents influenced by the power plant: dark purple 0; light purple: 10. Number of agents: 500; neighbourhood size: 10; maximum difference in affinity: 1; influence of power plant: 50 fictional units; no threshold.

The purple colour represents all agents influenced by the power plant. The average opinion is slightly increasing or slightly decreasing. This is because of the edge effect. The closer the power plant is situated to the edge of the map the more it loses it influence. There are less agents influenced by the power plant if it is situated close to an edge. The edge effect is the greatest when the power plant is situated in a corner. It can clearly be seen that the agents living close to the power plant are pulling the other agents towards zero and vice versa. In figure 20 a threshold was used.

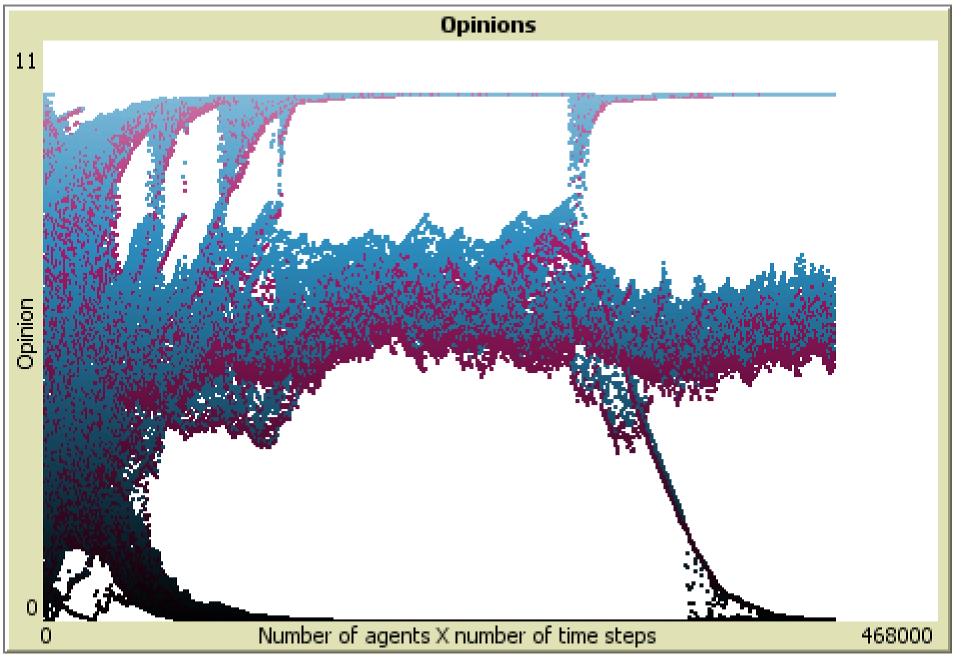

Figure 20: The result of adding the NIMBY-effect and a positive feedback from the public with a threshold. The colour difference represents the opinion: dark blue: 0; light blue: 10. The purple colours are the agents influenced by the power plant: dark purple 0; light purple: 10. Number of agents: 500; neighbourhood size: 10; maximum difference in affinity: 1; influence of power plant: 50 fictional units; threshold: 2.

Some agents are completely in favour of the power plant, some are completely against and some are in the middle of the spectrum. In this case most of the agents are in favour (74.2 %). The smallest group did not decide on a side (9.2%) and are constantly pulled to against and in favour. If the same situation is ran for 4000 time steps all agents are fully in favour or fully against. Figure 20 shows that the social network as well as the spatial aspects can have an influence on the final opinion. In general people living closer to power plant tend to have a more negative opinion. In the figure can be seen that people living close to the power plant can still be convinced to have a positive opinion and the other way around. These opinions are most likely caused by the social network.

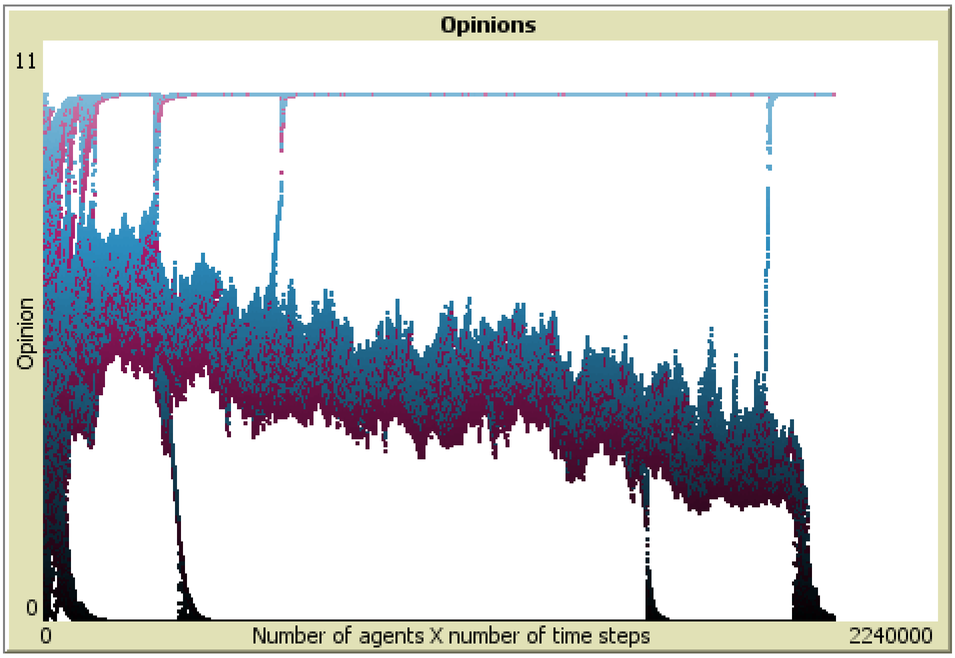

Figure 21: The result of adding the NIMBY-effect and a positive feedback from the public with a threshold after running 4000 time steps. The colour difference represents the opinion: dark blue: 0; light blue: 10. The purple colours are the agents influenced by the power plant: dark purple 0; light purple: 10. Number of agents: 500; neighbourhood size: 10; maximum difference in affinity: 1; influence of power plant: 50 fictional units; threshold: 2.

Moving agents

The map used in the model is static and all agents have a fixed position. The model can be easily adjusted by letting the agents walk around freely. The rationale behind the model changes slightly if agents are allowed to move around. The power plant then represents a facility of which the public is in favour and has a negative influence on people passing by. An example could be installed solar panels in an old city centre on which the public discussion has a positive influence. The people passing by generally do not like the view of the solar panels attached to an old building. The only barriers the agents have are the borders of the map and the power plant. All agents start with a random direction. Each turn at random they change their position in a direction between 50 degrees to the right and 50 degrees to the left. Reaching a border or the power plant will make the agent turn around for 180 degrees. All other variables are based on the previous updating rules. The result of letting the agents move around freely is that there will not be an equilibrium. The figure 22 shows the result of more than 1000 time steps.

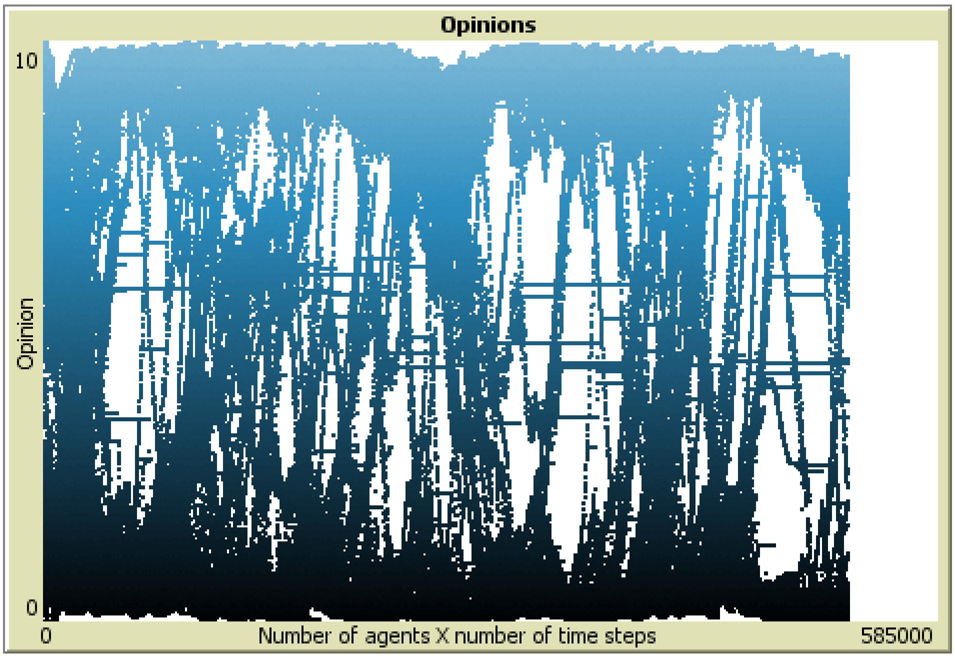

Figure 22: The result of letting the agents move freely over the map. The colour difference represents the opinion: dark blue: 0; light blue: 10. Number of agents: 250; neighbourhood size: 10; maximum difference in affinity: 0; influence of power plant: 50 fictional units; threshold: 2.

Leaving the model running for another 6000 time steps result in figure 23.

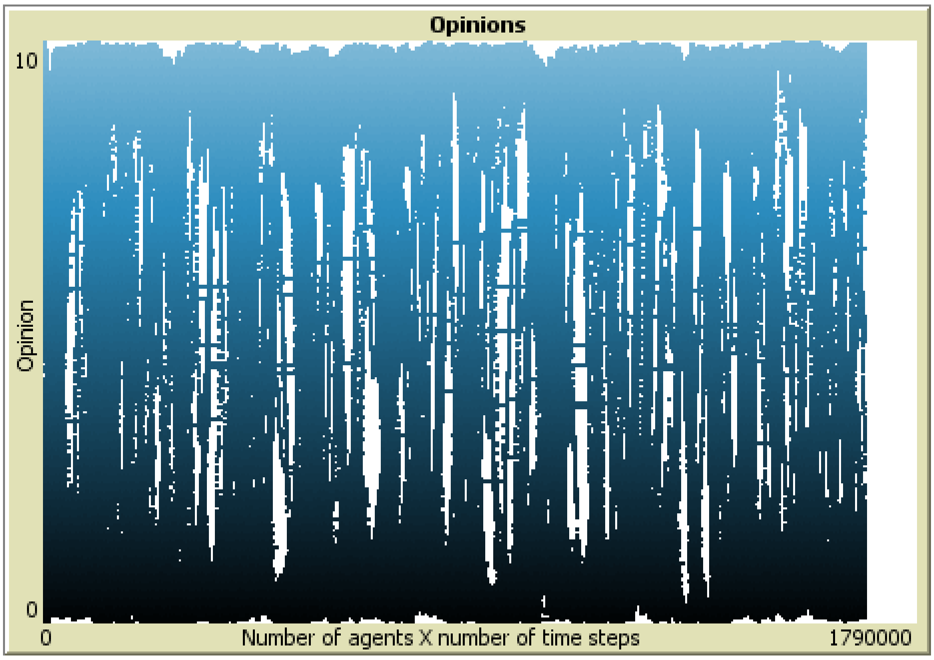

Figure 23: The result of letting the agents move freely over the map after more than 7000 time steps. The colour difference represents the opinion: dark blue: 0; light blue: 10. Number of agents: 250; neighbourhood size: 10; maximum difference in affinity: 0; influence of power plant: 50 fictional units; threshold: 2.

Without a threshold the result is similar to the result shown in figure 19 .

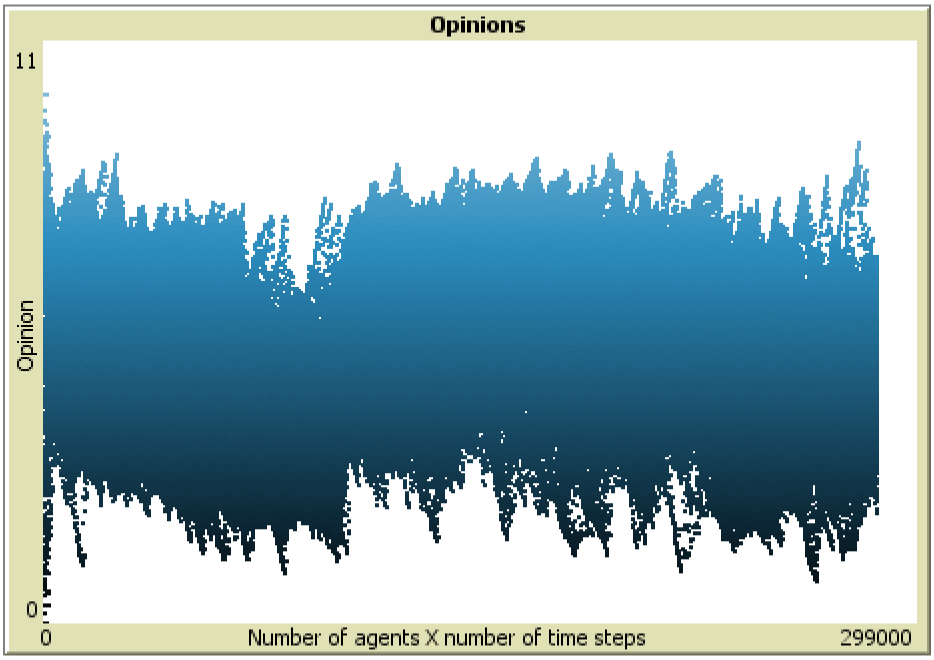

Figure 24: The result of letting the agents move freely over the map without threshold. The colour difference represents the opinion: dark blue: 0; light blue: 10. Number of agents: 250; neighbourhood size: 10; maximum difference in affinity: 0; influence of power plant: 50 fictional units; no threshold.

Conclusions

Running the developed model results in many different outputs. The visual outcomes of the different scenarios differ significantly. The outputs need to be tested in order to determine the plausibility of the model and to draw any conclusions. In the next chapter the sensitivity of the parameters will be assessed.

Chapter 4: sensitivity analysis

Introduction

A sensitivity analysis is needed in order to understand the influence of changing the parameters of the model better. A difference must be made between ratio parameters and Boolean parameters. The Boolean parameters represent scenarios that are added later to the model in order to explore how the model behaves on different scenarios. A Boolean parameter can only be turned on or off. In the table below all parameters and their types are listed. The outcome of the model is defined as a set of sensitivity measures. These sensitivity measures will be discussed in the following paragraph.

Table 2: All parameters and their types

Parameter	Type
Number of agents	Ratio
Neighbourhood size	Ratio
Difference in affinity	Ratio
Threshold size	Ratio
Power plant influence	Ratio
Nimby effect	Boolean
Positive feedback	Boolean
Moving agents	Boolean

Sensitivity measures

Determining the sensitivity measures is one of the challenges of assessing an ABM. Because all ABMs are different and can have different goals, the way of measuring those goals differ as well. The most important result of the proposed model of opinion dynamics is the pattern and dispersion of opinions among the population. The easiest computable measure is the average opinion. The average opinion shows in which side of the spectrum most of the agents are situated. The average opinion is easily calculated by the following calculation

$$P_{av} = \frac{1}{n}\sum_{i=1}^{n} P_i \tag{29}$$

Where P_{av} is the average opinion of the whole population and n is the total number of agents. Because from the average opinion cannot be concluded whether there is a consensus or all agents are scattered over the whole spectrum, there is a need for sensitivity measures that are focussing on the patterns of the opinion dispersion.

By defining a consensus the number of time steps needed to reach this consensus can be used as a measure. A consensus will be defined as a cluster of equal or more than 50% of the agents with a difference in opinions smaller than 1. A threshold of 50% is chosen because the consensus should always be the largest cluster. The opinions can be at most 0.5 higher or lower in order for an agent to be considered a part of the cluster. The percentage can be calculated as follows

$$n_{prop} = \frac{n_{similar}}{n} \tag{30}$$

Where n_{prop} is the percentage of agents in the cluster and $n_{similar}$ is the number of agents with

$$(P_A - 0.5\,) > \; P < (0.5 + \; P_A) \tag{31}$$

The percentage of similar agents is being calculated for all agents (P_A). The number of time steps needed to reach $n_{prop} \geq 0.5$ is defined as the first consensus. If no consensus is reached before the maximum number of time steps is reached, the first consensus is 0.

The average opinion and the first consensus cannot be used to examine the dispersion of agents or to examine different groups of opinions. Therefore the average percentage of similar agents is calculated for different band widths. Whether an agent is considered to be similar is dependent on the band width. The average percentage of agents with a similar opinion can be calculated as follows

$$N_{av} = \frac{1}{n}\sum_{i=1}^{n}\frac{n_{similar,i}}{n} \tag{32}$$

Where $n_{similar}$ is the number of agents with

$$(\, P_A - W \,) > P < (W + P_A) \tag{33}$$

Where W is the band width $\{0.5,1,2,3,4,5,6,7,8\}$. By making the band width variable it is possible to examine the dispersion of opinions across the spectrum. If all agents would be equally scattered, each band would contain a slightly higher percentage of agents. A consensus or groups of opinions would be visible because the percentage will in such a case not grow proportionally with the band width. In figure 26 an example of a bar graph of the consensus bands is shown. Figure 26 shows that there are two groups of opinions with a difference between 4 and 5.

One more sensitivity measure was used in order to visualise the clustering patterns. The consensus bands only give an overview of the dispersion of one moment in time. By mapping the clusters on a scatterplot the patterns emerging over time can be studied. The clusters are being calculated with the same calculation as the first consensus. For every agents with $n_{prop} \geq 0.1$ a point is drawn on the plot. The y axis shows the opinion of the agent and the x axis the number of time steps. The percentage of the total number of agents surrounding the agent is divided in 5 categories to show the difference in cluster density. Figure 25 shows an example of a cluster density scatter plot.

Baselines

The parameters are slightly changed in order to observe the difference in outcome. Before the sensitivity analysis can be performed the baseline of the parameters must be determined. The number of agents will have 250 as baseline. 250 is the median of the total number of agents and will take less computation time than the maximum of 500. 250 is also a sufficient number for studying the influence of networks. Making the number of agents too small will make this impossible. The baseline of the neighbourhood size will be 15. 15 is 10% of the diameter of the maximum circle that fits within the fictional study area. The neighbourhood size should be big enough to have an influence but should not cover too much of the total area. The baseline of the difference in affinity will be 2. High values for the difference in affinity will result in long computation time and large influences of the social network. An affinity of 2 will result in an average number of connections of 5 connections per agents when there are 250 agents. The baseline for the threshold will also be 2. The reason of adding a threshold is to prevent the population of reaching a consensus. Because of the relatively large number of connections in this model the threshold should be small in order to prevent a consensus from happening. The power plant influence will be 50 because it is the median of the maximum value and $\frac{1}{3}$ of the diameter of the maximum circle that fits within the study area. The scenario with the baseline settings will be called the zero scenario. The result of using all baseline settings is shown in figure 25 and figure 26. All agents are clustered in two groups with a difference in opinion between 4 and 5.

More agents are in favour than against, but the average is 5.0. The first time a consensus is reached is after 29 time steps.

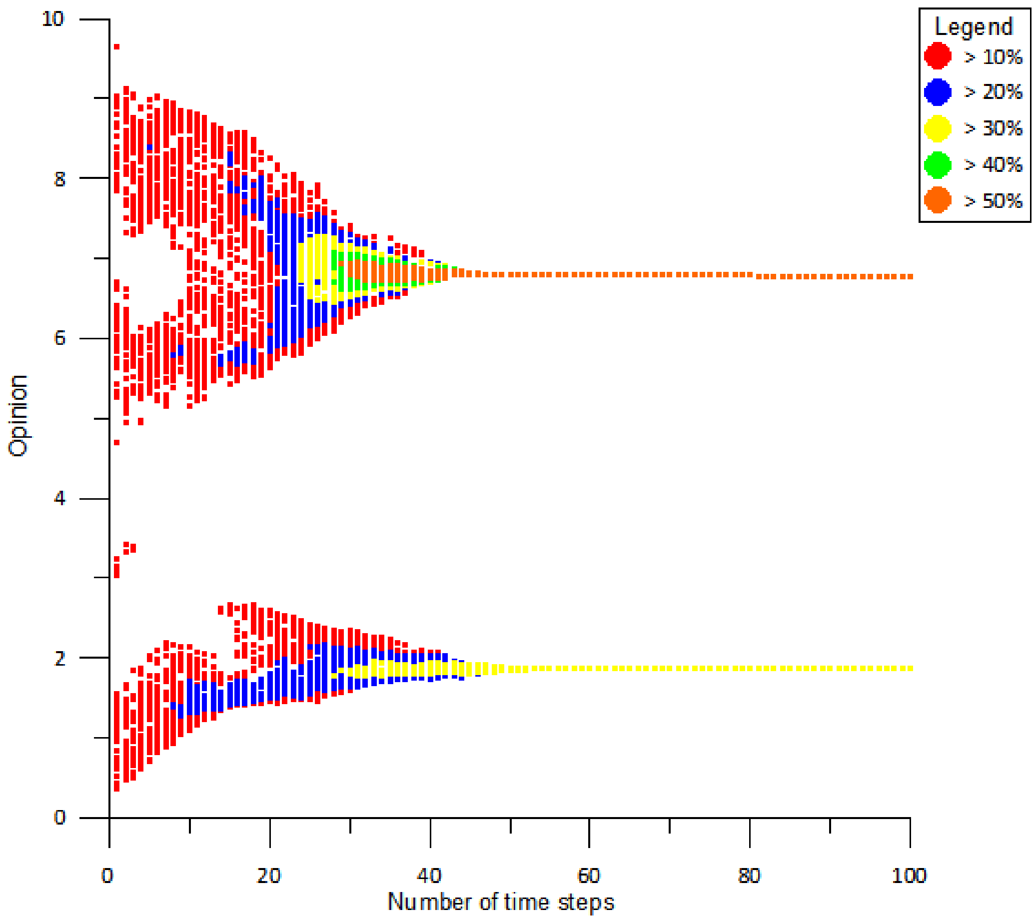

Figure 25: Cluster density plot with the baseline settings. The different colours represent the percentages of agents with a similar opinion. Number of agents: 250; neighbourhood size: 15; maximum difference in affinity: 2; influence of power plant: 50 fictional units; threshold: 2

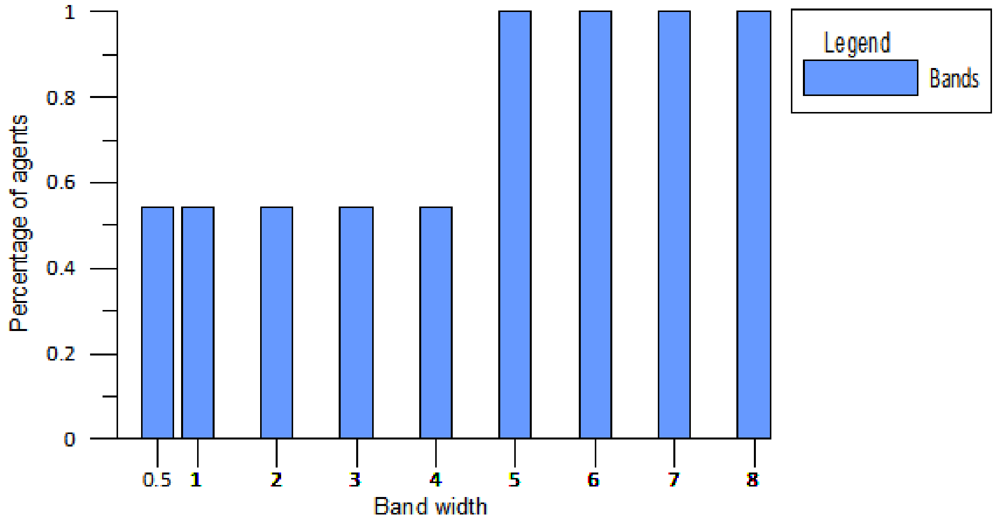

Figure 26: Dispersion bands bar graph with the baseline settings. Number of agents: 250; neighbourhood size: 15; maximum difference in affinity: 2; influence of power plant: 50 fictional units; threshold: 2

The number of agents

In order to assess the sensitivity of the number of agents the model will be run in steps of 10. Because the total range of the parameter is 500, not all values can be assessed. The lower values do not result in a consensus and result in small clustered groups. Figure 27 shows an example of a run with 50 agents.

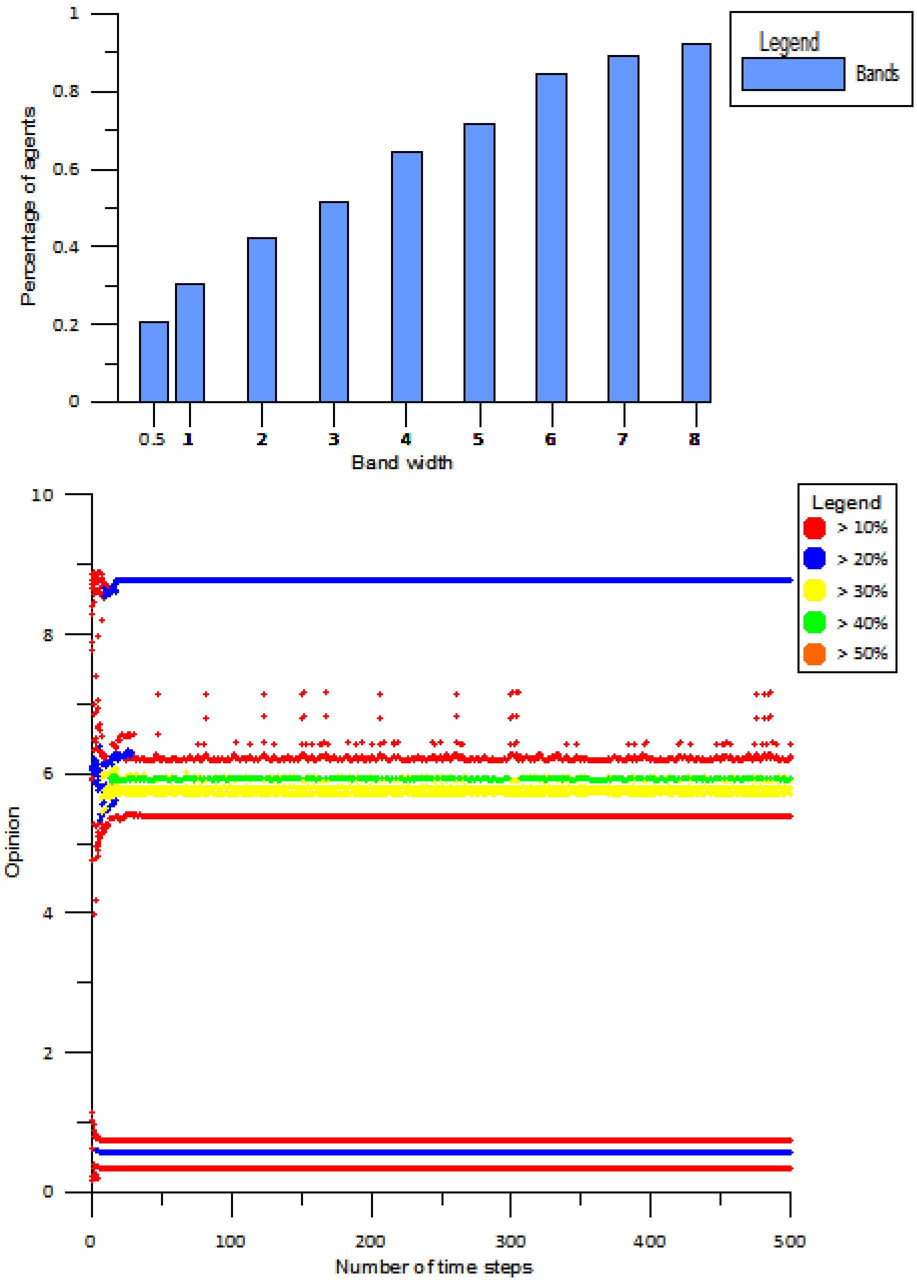

Figure 27: dispersion bands bar graph and a cluster density plot. The different colours represent the percentages of agents with a similar opinion. Number of agents: 50; neighbourhood size: 15; maximum difference in affinity: 2; influence of power plant: 50 fictional units; threshold: 2

The higher values always result in two groups of which one of the two contains more than 50% of the agents. The minimum value of the number of agents needed in order to reach a consensus is 110. The difference between the two groups is always between 4 and 5. Figure 28 shows the average opinion for the different settings of the number of agents parameter. There is no observable increase or decrease in the average opinion. The figure is fluctuating because the model is stochastic.

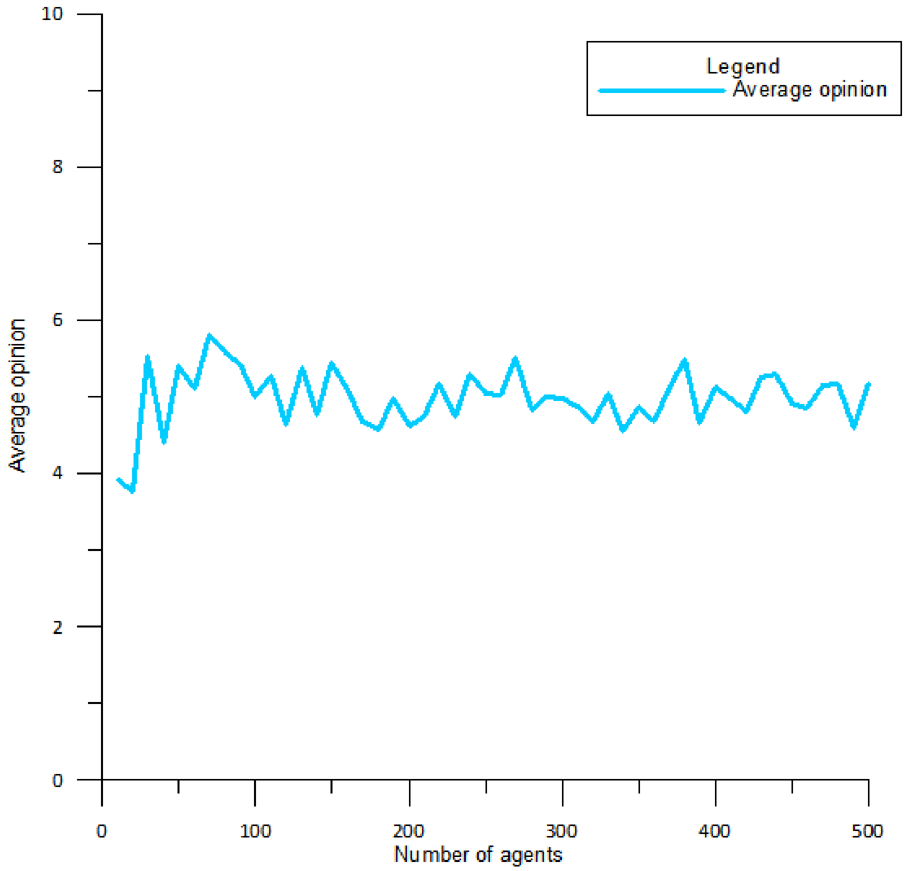

Figure 28: average opinion with different values for number of agents

Figure 29 shows the number of time steps needed in order to reach the first consensus. Up to 110 agents no consensus is reached. From this figure can be concluded that the higher the number of agents the fewer time steps are needed to reach a consensus. From 300 agents and more the first consensus is stabilising and not decreasing any further.

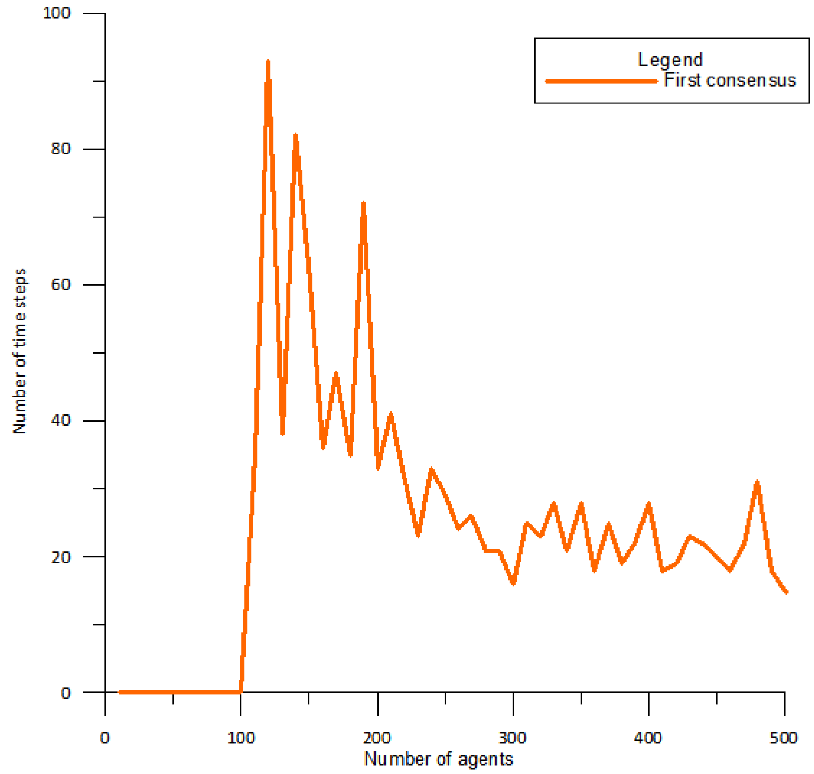

Figure 29: The number of time steps needed to form a consensus for different values for the number of agents

The neighbourhood size

Steps of 5 are chosen to assess the neighbourhood size. The maximum neighbourhood size is 50. A neighbourhood size of more than 50 would include too many agents to distinguish the spatial aspects from the social aspects. The average opinion is fluctuating when the size of the neighbourhood changes. The fluctuation is small and does not show a significant relation with the neighbourhood size. The fluctuation is most likely caused by the stochastic aspects of the model. If the neighbourhood size is small it takes a long time before the first consensus is reached. From a neighbourhood size of 20 and up it takes about 20 time steps to reach a consensus. Only when the size of the neighbourhood is small it has an effect on the number of time steps needed to reach a consensus. Figure 31 shows the number of time steps needed to reach a consensus for different values of the neighbourhood size.

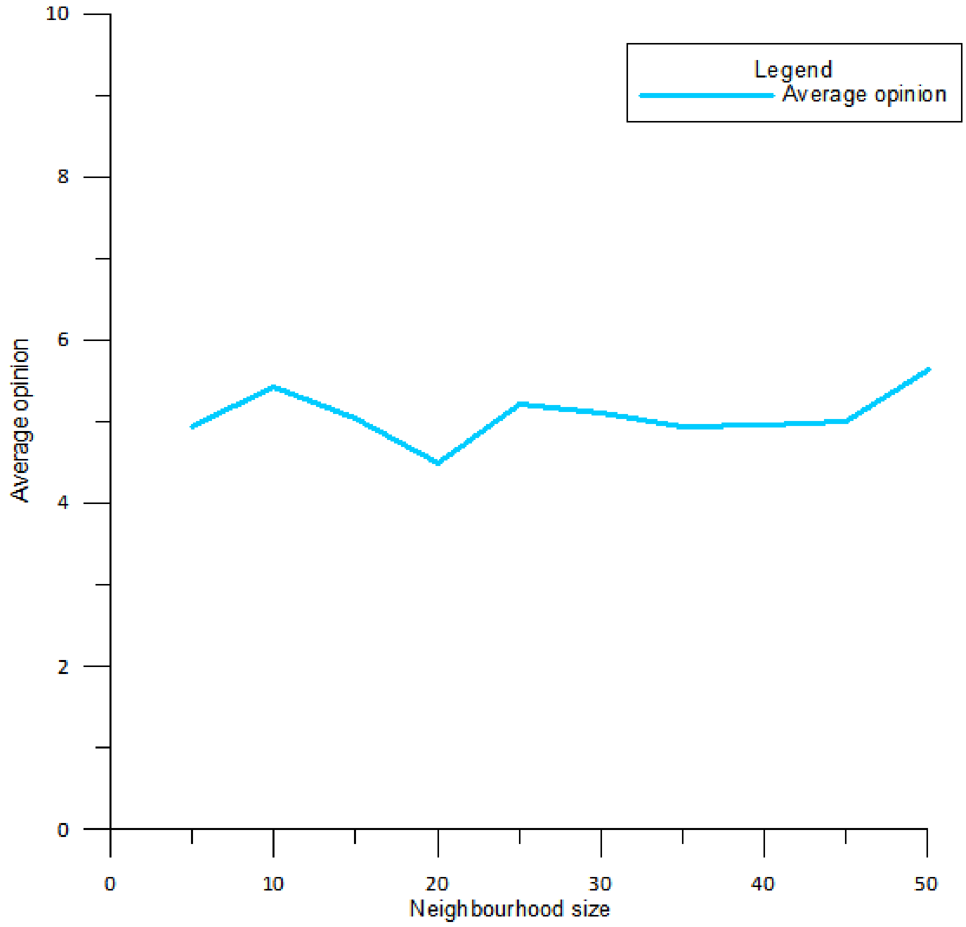

Figure 30: average opinion with different values for the neighbourhood size

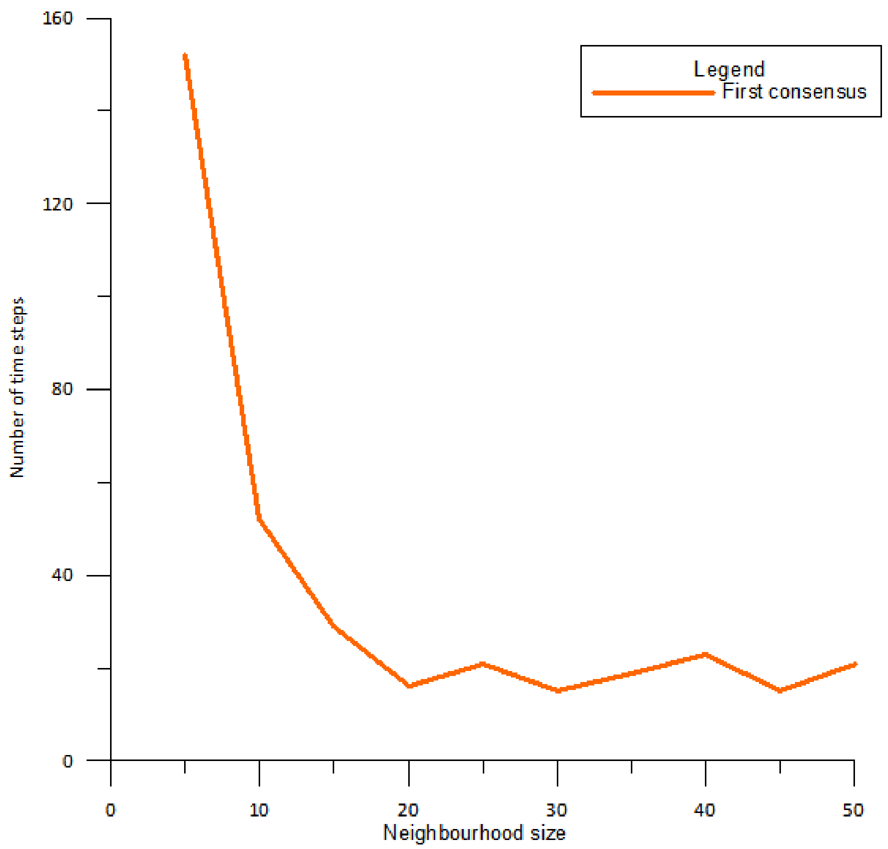

Figure 31: The number of time steps needed to form a consensus for different values for the neighbourhood size

The difference in affinity

Steps of 1 were chosen to assess the sensitivity of the difference in affinity. A small increase in the maximum difference in affinity can have large influence on the outcome because it affects all agents independent of their location directly. The maximum difference in affinity used is 30. A difference in affinity of 30 means that in average each agent is connected to 30 percent of the population. It is expected that a higher maximum difference in affinity no longer results in a different outcome because most agents are indirectly connected in one network. Increasing the maximum difference in affinity will result in a longer computation time. There is almost no influence on the average opinion if the maximum difference in affinity is being changed. It looks like the average opinion is less fluctuating for higher values of the maximum difference in affinity. This could be the result of the low number of time steps needed to form a consensus. This number is decreasing when the maximum difference in affinity is increasing. The number of time steps needed to form a consensus is stabilising between a maximum difference in affinity of 10 and 20 with one exception where no consensus was reached at all.

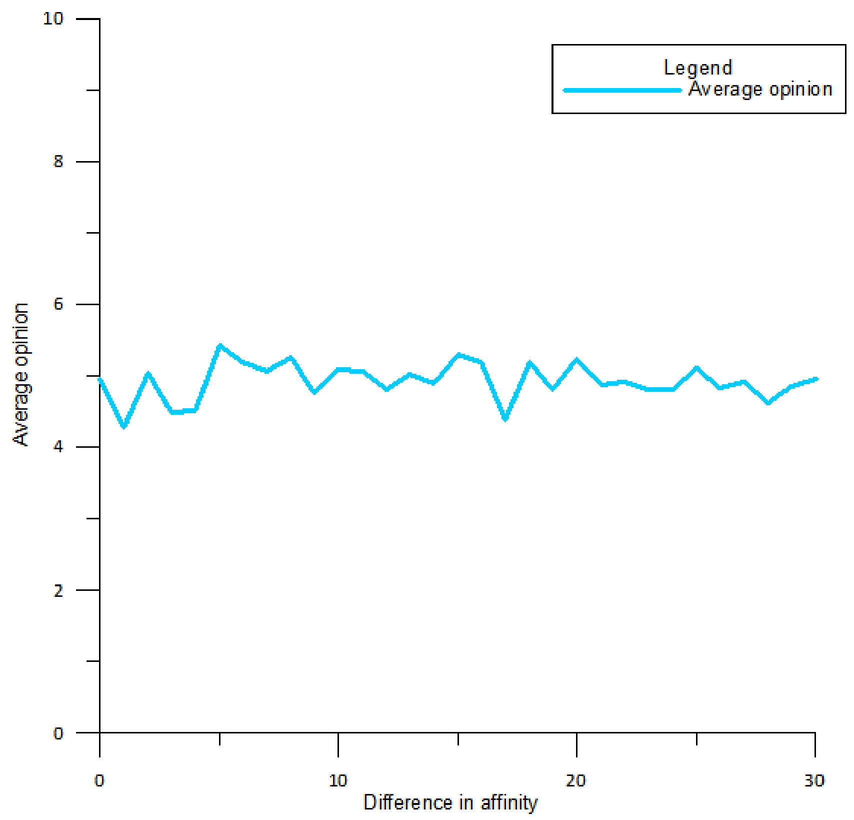

Figure 32: average opinion with different values for the maximum difference in affinity

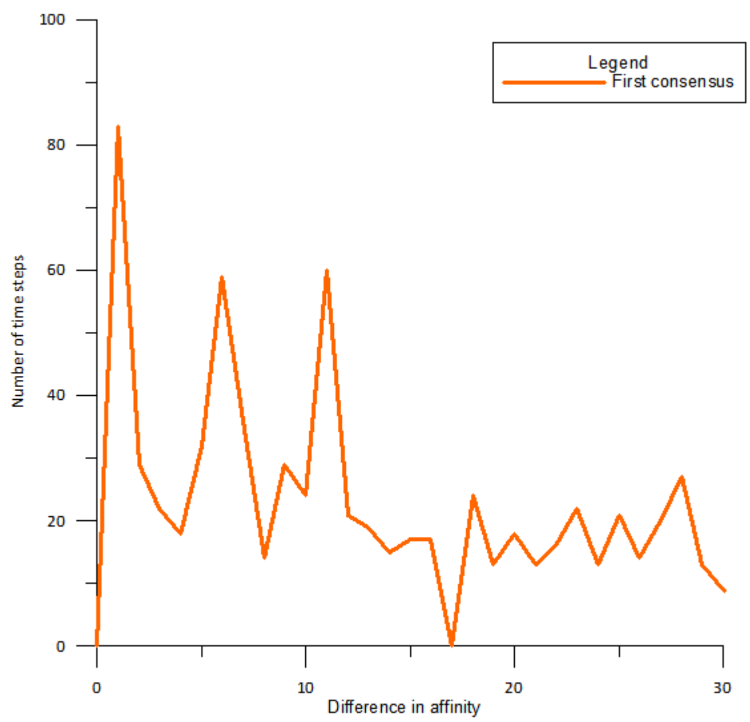

Figure 33: The number of time steps needed to form a consensus for different values for the difference in affinity

The threshold size

The sensitivity of the threshold size was assessed by decreasing the threshold size with steps of 1. The sensitivity analysis of the threshold size is inversed because a high value for the threshold size implies that the threshold size does not alter the number of exchanges of opinions while a low threshold size significantly alters the number of exchanges. The maximum threshold size is 10 and the minimum is 1. The threshold size cannot be lower than 1 for agents to still be able to interact. A threshold size larger than 10 does not have any effect because it exceeds the maximum value for an opinion. Like the other parameters there is little influence on the average opinion. It looks like the number of time steps needed to form a consensus is increasing exponentially until it becomes infinite. The threshold size has an important influence in the number of time steps needed to form a consensus. If the threshold is really low it prevents the population from even reaching a consensus.

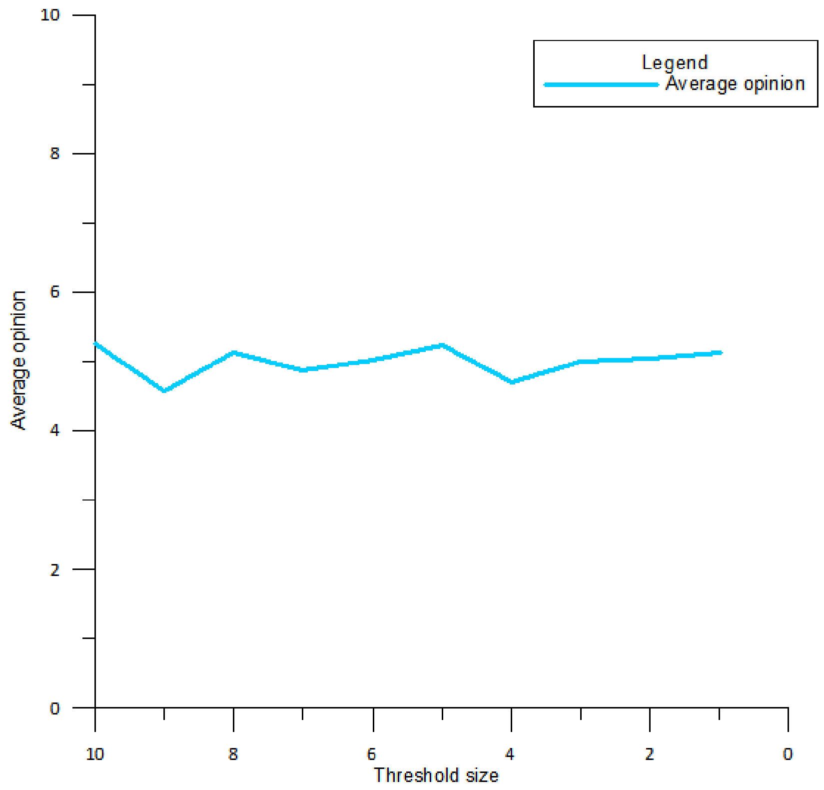

Figure 34: average opinion with different values for the threshold size

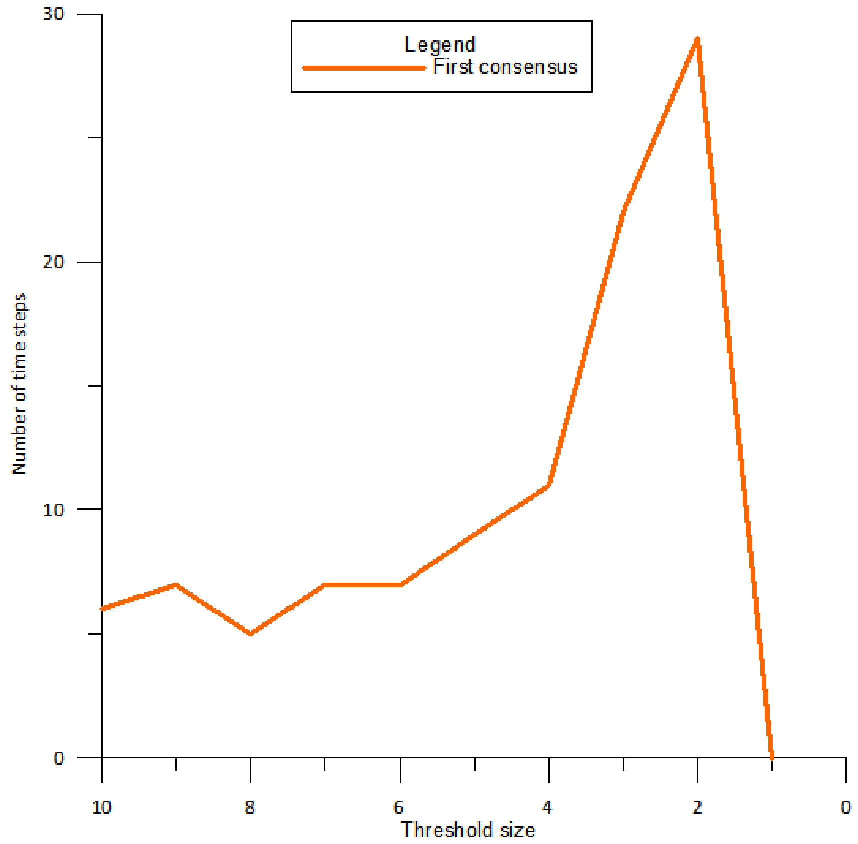

Figure 35: The number of time steps needed to form a consensus for different values of the threshold size

The power plant influence

The maximum length for the power plant influence distance is 100. The fictional world has a maximum width and length of 150. With a maximum size of 100 most of the area is covered. Increasing the power plant influence distance more will result in a scenario where all agents are influenced by the power plant. The area influenced by the power plant is dependent on the location of the power plant and the 'edge effect'. The closer the power plant is situated near the edge of the world, the smaller the influence area. Because of the edge effect and the random allocation of the power plant there is a high stochastic factor in this parameter. The average opinion is relatively stable. As expected the number of time steps needed in order to reach a consensus is fluctuating. In average it becomes higher. It is unclear if this is the result of the fluctuation or an effect of the parameter. By increasing the power plant influence distance more agents are becoming harder to convince. A logical outcome would be a slight increase in the number of time steps needed. The figure is exactly showing a slight increase.

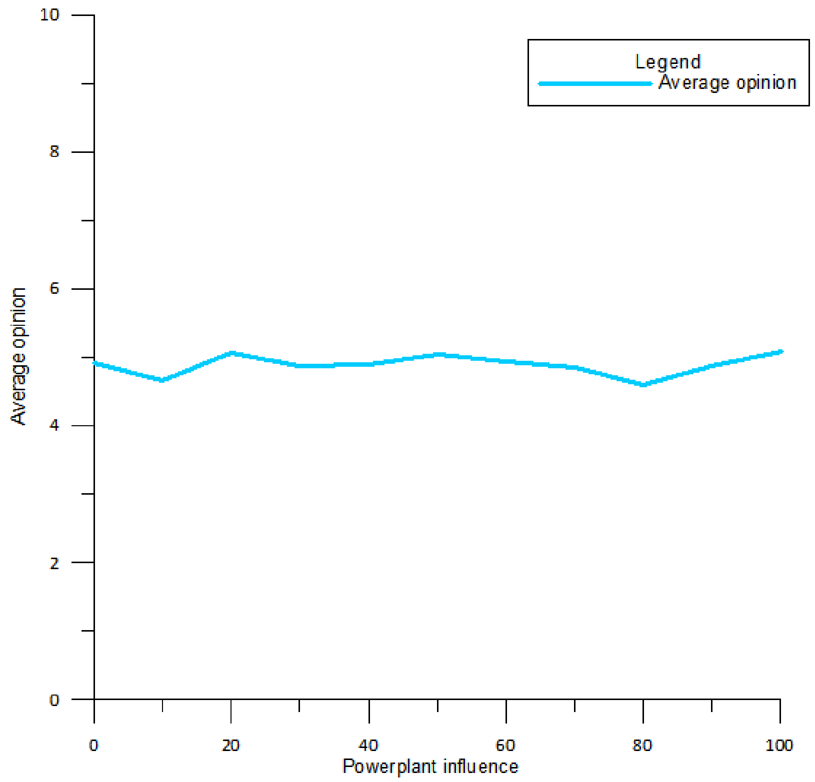

Figure 36: average opinion with different values for power plan influence distance.

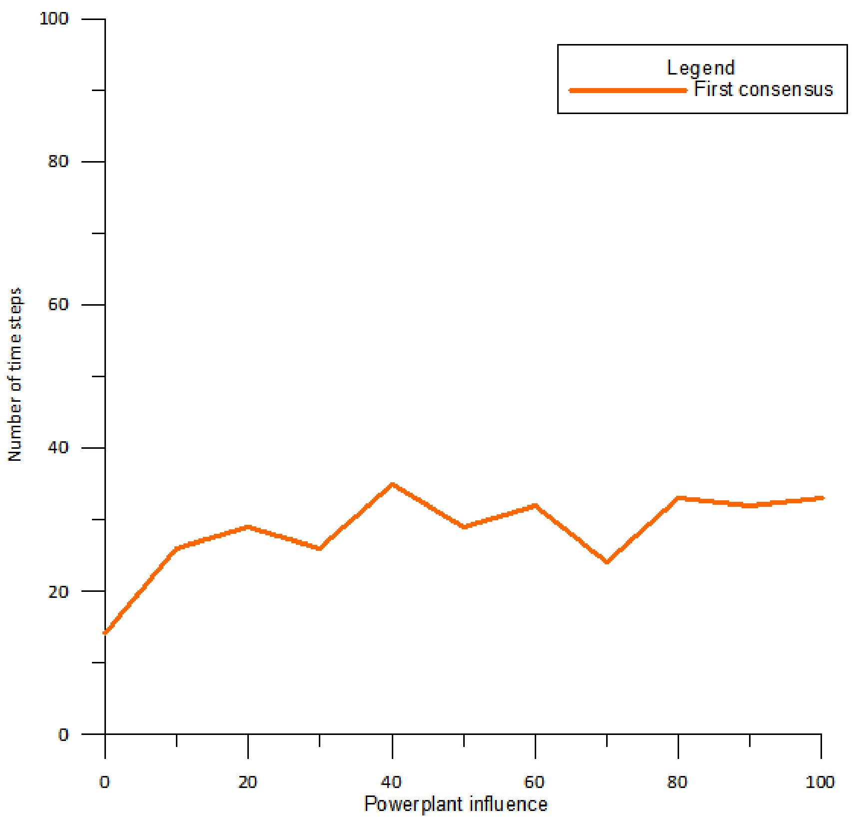

Figure 37: The number of time steps needed to form a consensus for different values for the distance of the power plant influence

The NIMBY effect

The NIMBY effect is assessed by running the model with all the parameters set to the baseline settings and the NIMBY effect turned on. The image below shows the dispersion bands bar graph and the cluster density plot of the run after 500 time steps. There is a significant difference compared with the baseline scenario (figure 25 and figure 26). As expected the NIMBY effect causes the population to have a more negative opinion. The average opinion after 500 steps is 0.8 compared to 5.0 of the zero scenario. The density of the opinion is lower, which means that the agents have more divided opinions than when the NIMBY effect is turned off. The first consensus is with 26, 3 time steps earlier than the zero scenario. The difference in the number of time steps needed is small and could be explained by the stochastic nature of the model. The NIMBY effect has an important influence on the average opinion and the dispersion of the opinions.

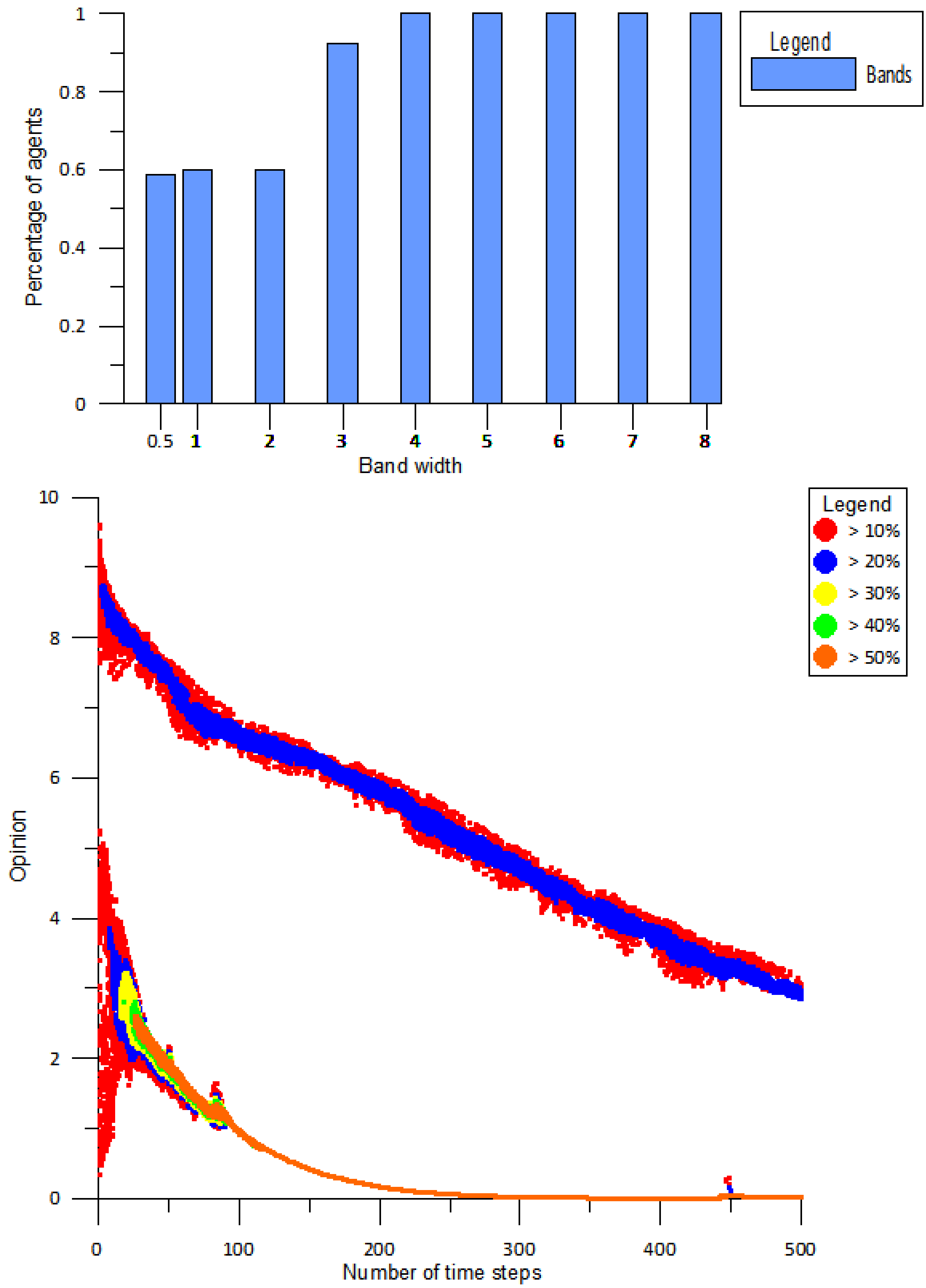

Figure 38: dispersion bands bar graph and a cluster density plot with NIMBY effect turned on. The different colours represent the percentages of agents with a similar opinion. Number of agents: 50; neighbourhood size: 15; maximum difference in affinity: 2; influence of power plant: 50 fictional units; threshold: 2

Positive feedback

The positive feedback is just as the NIMBY effect analysed with all the baseline settings and the positive feedback parameter turned on. The results are shown in figure 39. The dispersion is low and all opinions are completely in favour of the power plant. It took relatively long to reach this consensus. After 86 time steps more than 50% of the population had the same opinion. After the consensus was reached the average opinions kept on rising until it became 10.0.

NIMBY and positive feedback

Because the positive feedback and the NIMBY parameter are partly balancing out each other, they could be considered as one parameter. Both parameters have important influences on the outcome of the model. If these influences are only caused separately it will not have an added value to incorporate them together. Therefore, it is necessary to analyse their combined sensitivity. In figure 40 is shown that there is a large difference between the consensus groups. There is no dispersion band that actually reaches the 100% while all other runs have several dispersion bands including 100% of the opinions. There is fluctuation in the dispersion of the positive opinions. The average opinion is 4.1, which is less than the average of the zero scenario. The first consensus also differs from the zero scenario. The first time a consensus is reached is after 55 time steps. The combined parameter of the positive feedback and the NIMBY are causing important differences in the outcome of the model.

Moving agents

The sensitivity of the moving agents parameter is analysed in two different ways. Because of the completely different nature of the scenarios will it be compared with the zero scenario and with a scenario with the baseline settings and the NIMBY and positive feedback parameters turned on. The spatial effects of moving agents become more important if they are directly influenced by the power plant. Figure 41 shows that opinions of the agents are stable when the model is run with only the baseline settings and the moving agents parameter. The dispersion is low and the first consensus is reached after 24 time steps. The average opinion is with 4.8 also comparable with the zero scenario. The sensitivity of the moving agents is low when it is compared with the zero scenario. If it is compared with a scenario where the NIMBY and positive feedback parameters are added the results are different. Figure 41 shows the results of such a run. It took 142 time steps to reach a consensus for the first time. This consensus only held for a short time and was dispersed until more or the less 300 time steps. The figure shows a high dispersion but it reaches an equilibrium in the end. There are no dispersion bands containing 100% of the agents. Because the scenario where this run is compared with also did not contain any dispersion bands containing all agents this could not be described as an effect of the moving agents parameter. The average opinion after 500 time steps is 8.6. The sensitivity of the moving agents parameter is dependent on the other parameters. It can be concluded that the sensitivity fluctuates with settings of other parameters.

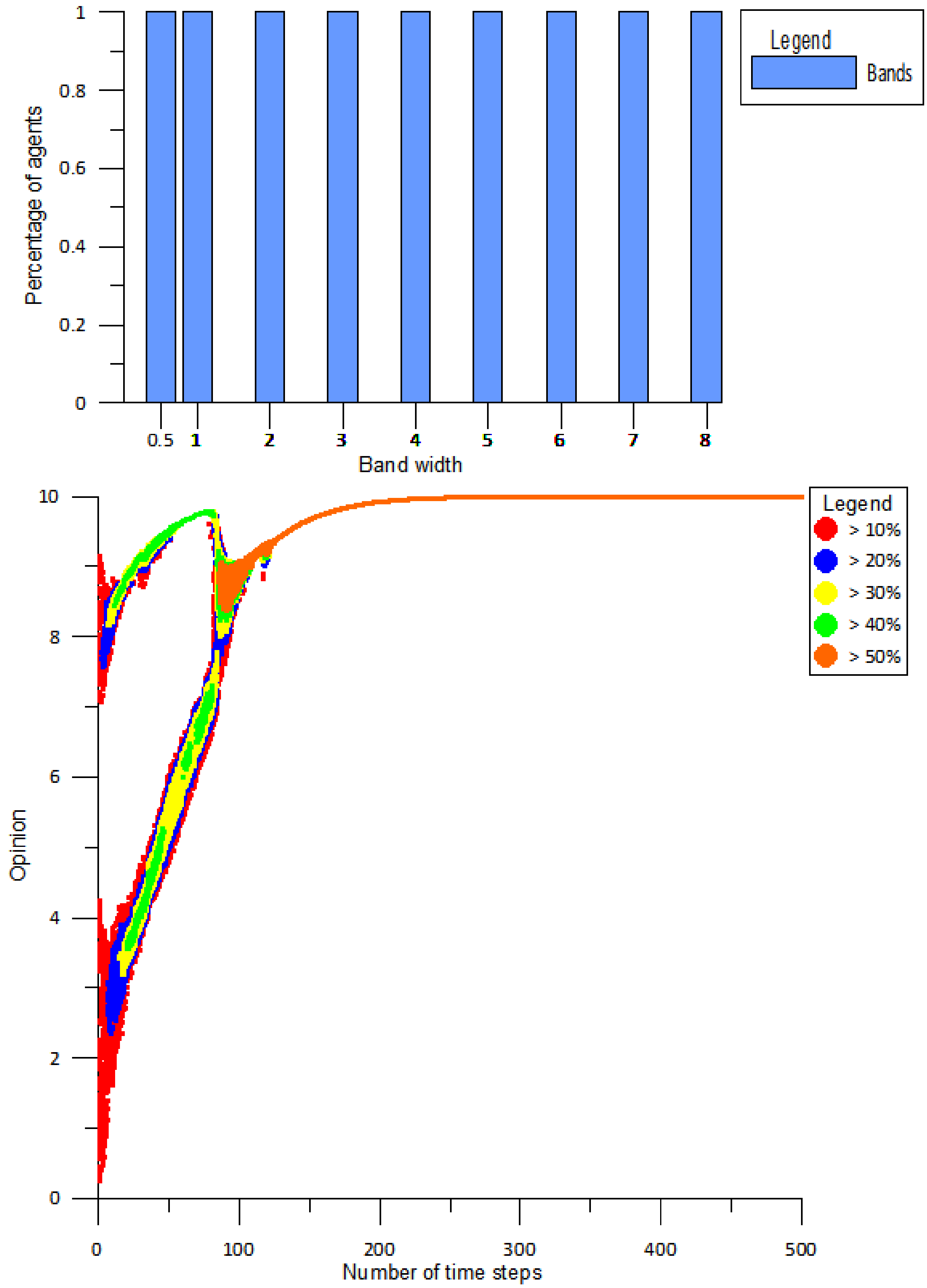

Figure 39: dispersion bands bar graph and a cluster density plot with the positive feedback turned on. The different colours represent the percentages of agents with a similar opinion. Number of agents: 50; neighbourhood size: 15; maximum difference in affinity: 2; influence of power plant: 50 fictional units; threshold: 2

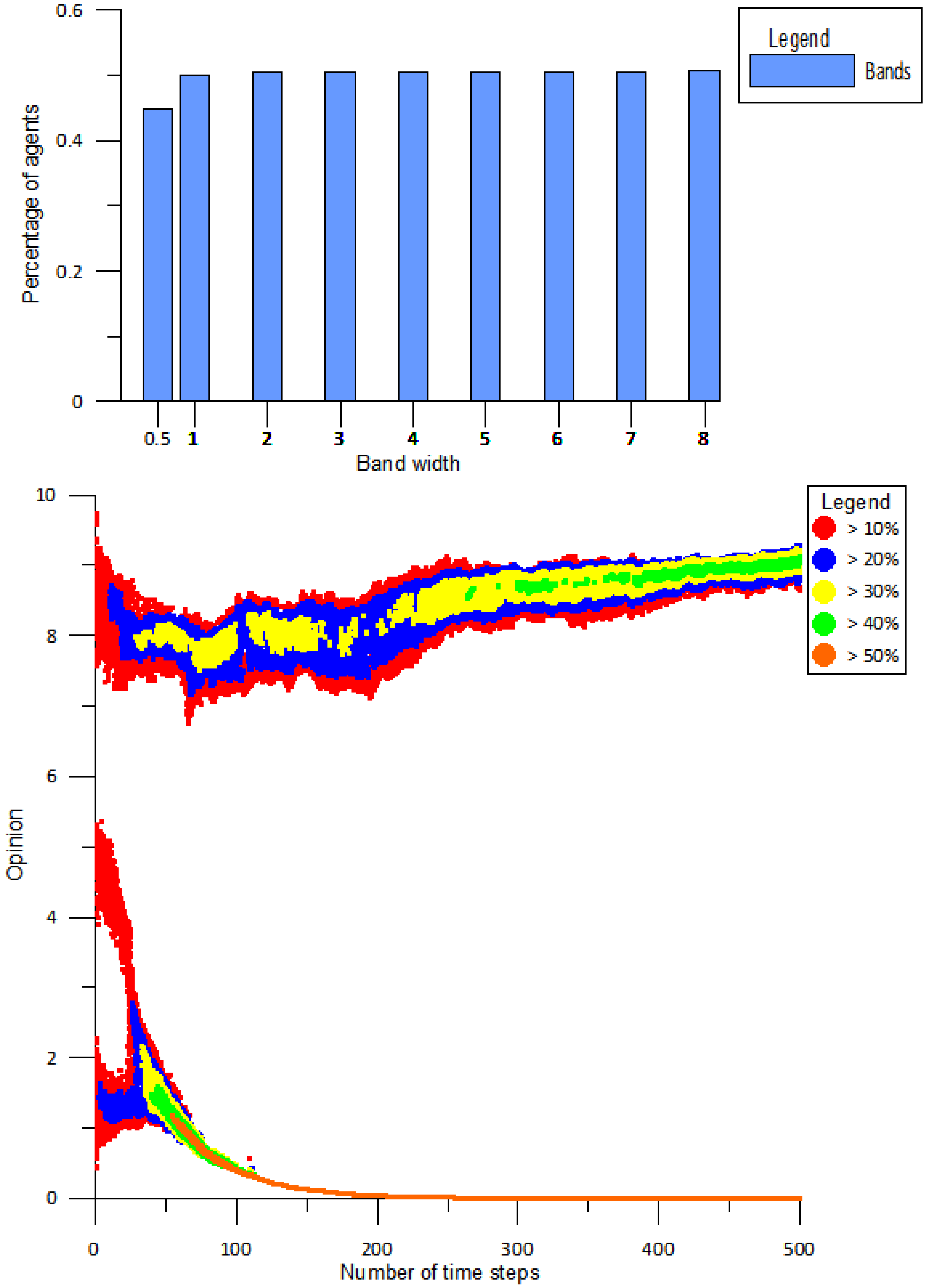

Figure 40: dispersion bands bar graph and a cluster density plot with positive feedback and NIMBY turned on. The different colours represent the percentages of agents with a similar opinion. Number of agents: 50; neighbourhood size: 15; maximum difference in affinity: 2; influence of power plant: 50 fictional units; threshold: 2

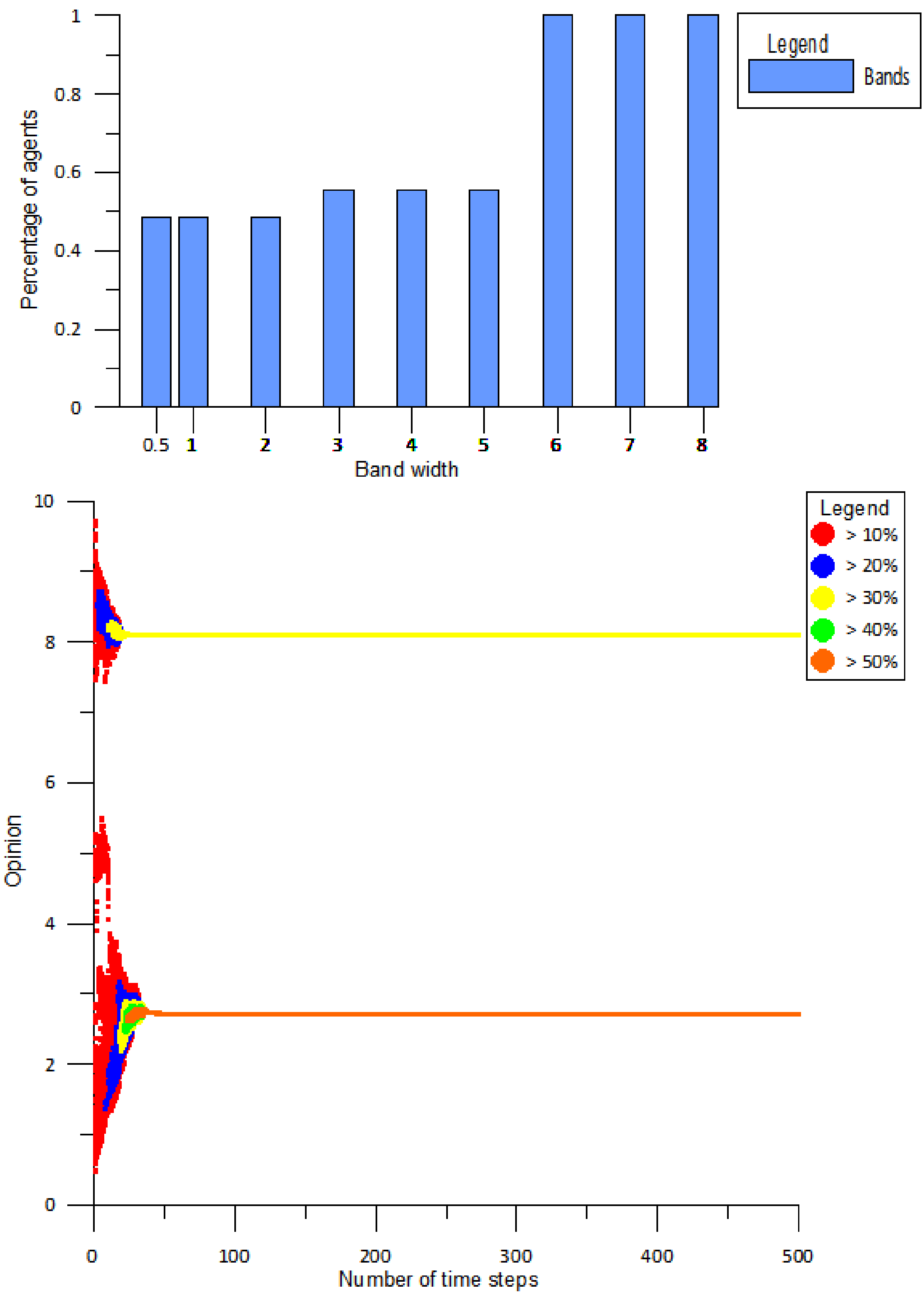

Figure 41: dispersion bands bar graph and a cluster density plot with moving agents turned on. The different colours represent the percentages of agents with a similar opinion. Number of agents: 50; neighbourhood size: 15; maximum difference in affinity: 2; influence of power plant: 50 fictional units; threshold: 2

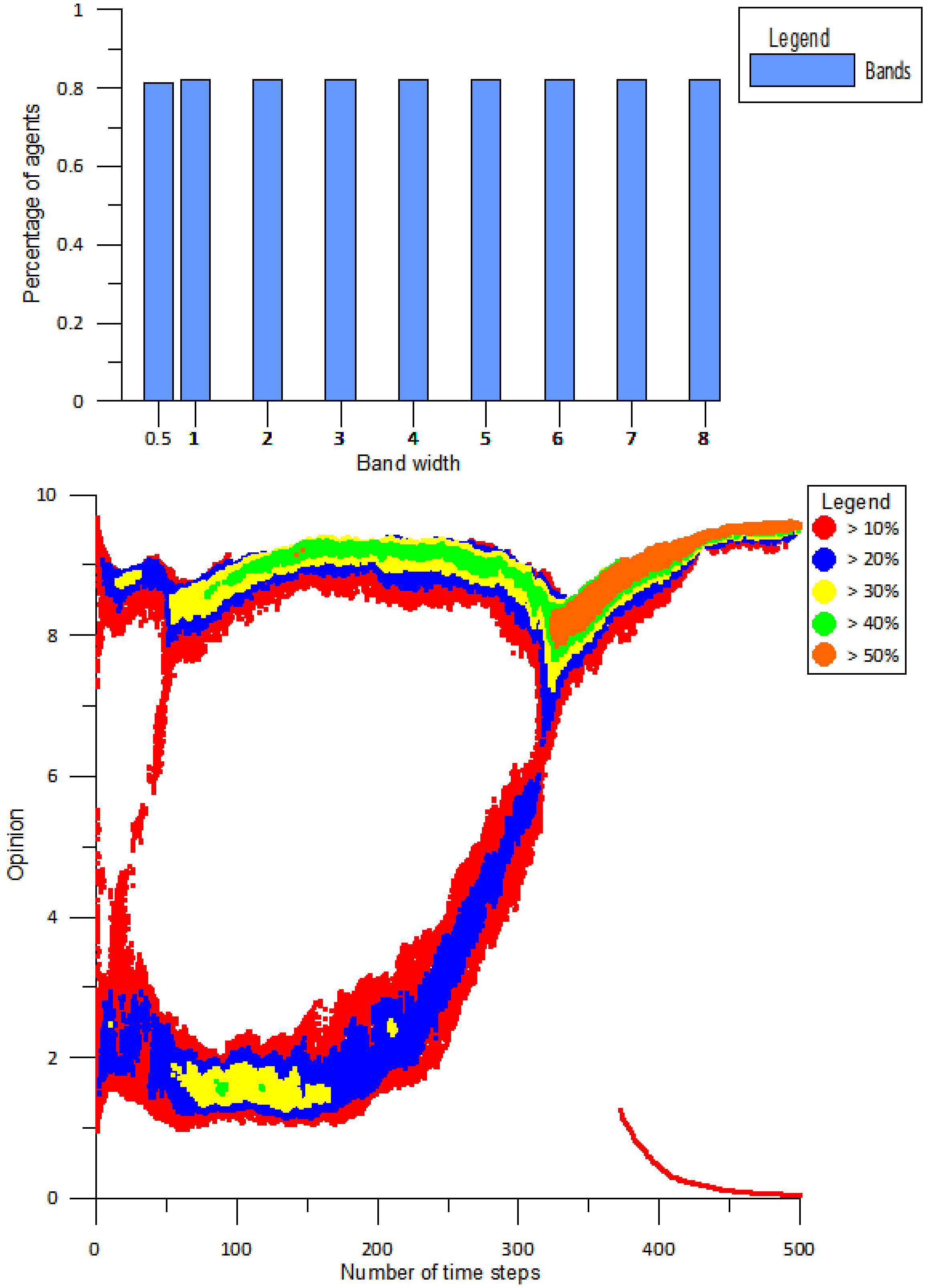

Figure 42: dispersion bands bar graph and a cluster density plot with moving agents, NIMBY, and the positive feedback turned on. The different colours represent the percentages of agents with a similar opinion. Number of agents: 50; neighbourhood size: 15; maximum difference in affinity: 2; influence of power plant: 50 fictional units; threshold: 2

Conclusions

All parameters, except for the moving agents parameter when compared to the zero scenario, show significant changes in the sensitivity measures. The sensitivity of the moving agents parameters is dependent on other parameters. The differences in the sensitivity measures of all parameters that can have a range of values are summarised in table 3 and visualised in figure 43 and figure 44. The smaller the maximum difference in the average opinion the less the parameter is influenced by the stochastic nature of the model. If there are more runs in an analysis there is also a higher change of having a large difference in the average opinion. The neighbourhood size does show highest difference in the number of time steps needed to reach a consensus. The power plant influence shows the lowest difference. It can be concluded that the number of agents, neighbourhood size, and the difference in affinity can be considered as sensitive parameters. The threshold size is also considered as sensitive because changing this parameter can result in a scenario where no consensus is reached. This will make the difference in first consensus infinite.

Table 3: Overview of the differences in the sensitivity measures of all ratio parameters

Parameter	Δ Average opinion	Δ First consensus	Average of the average opinion
Number of agents	2.0	93	5.0
Neighbourhood size	1.1	137	5.1
Difference in affinity	1.2	83	4.9
Threshold size	0.8	29	5.0
Power plant influence	0.5	11	4.9

Table 4 shows the average opinion and the first consensus of the Boolean parameters. Compared to the zero scenario the nimby effect, positive feedback and the last scenario show a significance difference in the average opinion. The positive feedback, the nimby and positive feedback, and the moving agents and power plant influence scenario show significant difference in the first consensus. Only the moving agents parameter taken separately does not show a difference in outcome. In combination with the NIMBY and positive feedback parameter it has the largest influence on the sensitivity measures. In order to fully understand the interdependency of the parameters a more comprehensive sensitivity analysis could be performed. To eliminate the stochastic aspects model, multiple runs per sensitivity analysis should be analysed. Such a sensitivity analysis did not fit within the timeframe of this thesis. It can be concluded that the model is sensitive to almost all parameters. The model is only not really sensitive to the power plant influence distance parameter. It can however be expected that this parameter has more effect if it is analysed in combination with other parameter such as the NIMBY effect and the positive feedback. For all parameters there is at least one sensitivity measure showing changes if the parameter is slightly changed. If the moving agents parameter is not being taken into account the power plant influence parameter shows the smallest differences.

Table 4: Overview of the sensitivity measures of all Boolean parameters.

Parameter	Average opinion	First consensus
Zero scenario	5.0	29
Nimby effect	0.8	26
Positive feedback	10	86
NIMBY and positive feedback	4.1	55
Moving agents	4.8	24
Moving agents and power plant influence	8.6	142

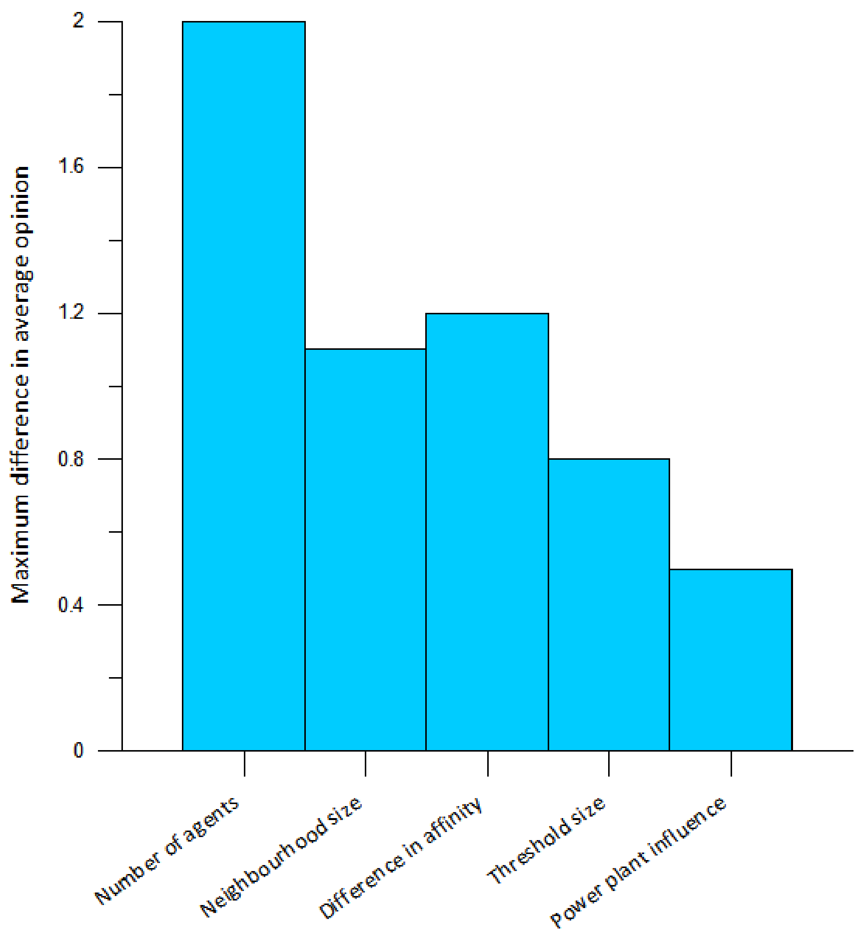

Figure 43: The maximum difference in average opinion for all ratio parameters.

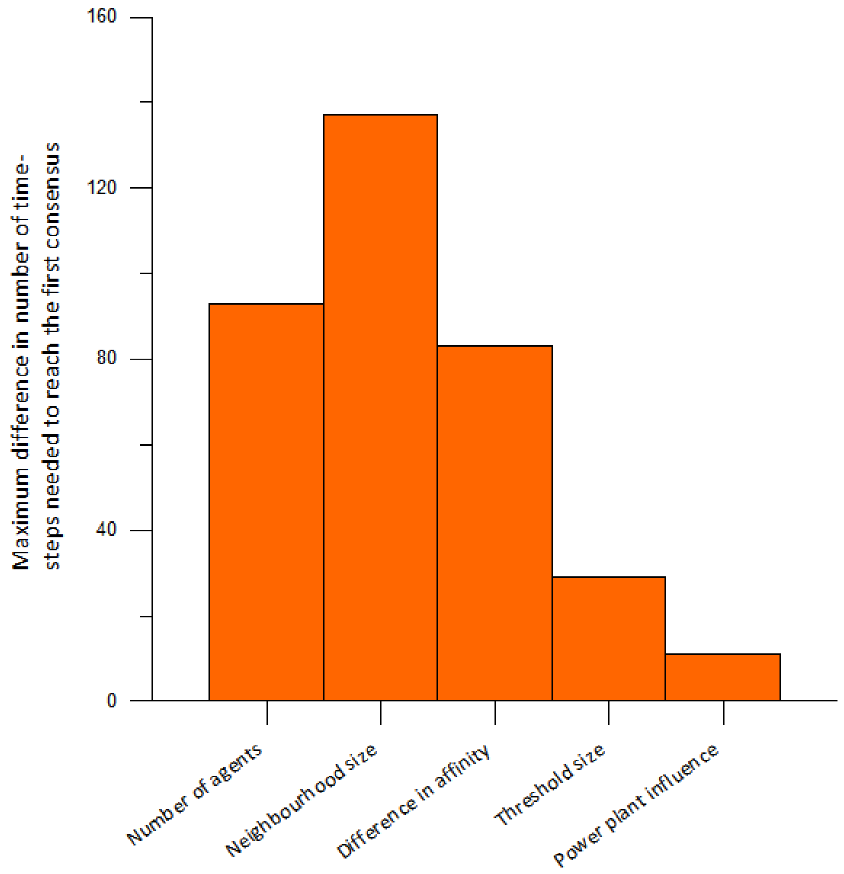

Figure 44: The maximum difference in number of time steps needed to reach the first consensus for all ratio parameters.

Chapter 5: Discussion on the plausibility of the model

Introduction

The sensitivity of the parameters does not yet explain whether the model is valid or not, but it does help analysing the plausibility of the parameters and the model. In order to be able to draw conclusions on the plausibility it must be determined if the observed results could have been expected when they are compared to reality. In order to do so the results of the sensitivity analysis will be used to elaborate on the preliminary results of the model. The model can be influenced by five ratio parameters. Four of the parameters can be considered to influence the model significantly.

The number of agents

The first parameter, the number of agents, controls the density of the population. The area does not change, and therefore, the number of agents within a certain distance from each other becomes smaller. This results in more intense interactions between agents. The time needed to reach a consensus is smaller in larger populations. It is difficult to say if this is realistic or not. The neighbourhood size becomes relatively larger, which result in the logic outcome that there is less time needed to reach a consensus due to the higher percentage of connections. Increasing the number of agents without altering the neighbourhood size cannot simply be compared to a sparse population in an agricultural area and a dense city. This can only be done if it is assumed that people living in a denser populated area know proportionally more people than people in a sparsely populated area. In this thesis it is not assumed that people living in denser populated areas know proportionally more people than people in a sparsely populated area. Increasing the number of agents without altering the other parameters will result in a scenario where the population is dense, but do all know each other. An example could be a nomadic population that is temporary settled in a small area. In such a scenario it is more logical that a consensus is reached more quickly. If the population density becomes too low, no consensus is reached because most of the agents do not interact with each other. Taking the interaction with the neighbourhood size into account the results can be considered to be plausible. Because the concept of a neighbourhood is variable it must be taken into account that the scenario represented by the model changes when the number of agents changes.

Neighbourhood size

As explained in the previous paragraph, the neighbourhood size is strongly connected to the population density. If the neighbourhood size is being changed without altering the number of agents, it has a strong influence in the time needed to reach a consensus. This only counts for the lower values, because from a certain distance and longer the fastest time to reach a consensus is reached. This is due to the fact that from a certain distance the whole population is already indirectly connected to each other in two steps. From this point every agent has at least one relative in each neighbourhood. Increasing the neighbourhood size results in a shorter time to reach a consensus and a denser scatterplot. A larger neighbourhood size implies that people are more connected to people living close by. An example in the difference in neighbourhood size could be a neighbourhood with many gates and protected properties where people feel unsafe compared to a neighbourhood where people feel save and do know a larger proportion of their neighbours. The neighbourhood size has a direct proportional relation with the time needed to reach a consensus until the population is no longer influenced by the number of connections. These results can be fully explained and can be considered to be plausible.

The difference in affinity

The difference in affinity defines just as the neighbourhood size the number of connections per agent. If there are more connections per agent the opinions are less dispersed and there is less time needed to reach a consensus. For the maximum difference in affinity there is also a maximum value from where the time needed to reach a consensus is no longer influenced because the whole population will be indirectly connected. The difference in affinity represents sizes of families or other social institutions in comparison to the whole population. It could for example be argued that a community centre would result in less dispersed opinions. The difference in affinity can be considered to be plausible because the results can be fully explained rationally.

Threshold size

The threshold size has completely different influences on the model than the previous discussed parameters. A threshold causes the population to have more dispersed opinions and it takes longer to reach a consensus. In many cases there is not one consensus, but groups of opinions that are too different to influence each other. The smaller the threshold size the less opinions are averaged. A small threshold size results in different patterns with several groups of opinions. Without a threshold the outcome of the model does not represent the dispersion of opinions in a population. In reality the dispersion of opinions is more complex than one or two groups. The threshold size is a way of making the dispersion of opinions more realistic. It is still a simplification of the complexity, but does show more realistic patterns of opinion development. It can be debated whether the threshold size is plausible or not. There is not yet a better alternative to model the diversity of opinion dynamics. Without the threshold size the results will be unrealistic. Adding a threshold makes the outcome of the model more plausible than not adding a threshold.

Power plant influence

Without adding any scenarios the influence of the power plant is limited. It does make the agents close by the power plant less susceptible to influences. Because there is no difference in probabilities of the initial values, the only result is that it takes a little longer to reach a consensus. The results could only be applied to situations where the power plant represents a facility that is not always considered to be negative for people living close by. An example could be a parking lot. Some people could be happy to be able to park their cars, while others could prefer to have a playground. In either case the power plant does not have a large influence on its surroundings. The parameter is without adding a scenario not a useful addition to the model because of the small influence on the result. Despite this small influence it can still be considered to be plausible.

NIMBY and positive feedback

The two parameters NIMBY and positive feedback are the most interesting when they are considered together. Separately they either cause the population to have a negative opinion or a positive opinion. A feedback is needed to prevent the model to result in completely unrealistic results. With a feedback it is still possible that there is consensus against or in favour of the power plant, but these are often less extreme and show a more sophisticated pattern than without a feedback mechanism. It sometimes happens that the negative opinions of the people living next to a power plant are taken over by the rest of the population. An example of such a scenario could be an underground CO_2 storage. The scenarios in where there is no consensus, but only a thick band of opinions where on both sides agents are 'pulling' the population into a direction, could be considered as a comparison with reality. In reality it never happens that everyone has the same opinion and there will always be a range of different opinions. The two scenarios combined give the most plausible results from all the parameters combined, because they show complex patterns of opinions that are constantly interacting. Separately the results of the parameters are unrealistic and cannot be considered as plausible.

Moving agents

Separately, the moving agents parameter does not show much difference in the results. It does only change the concept of a neighbourhood because it becomes variable when the agents are moving around freely. The concept of location changes even more when the NIMBY and positive feedback parameters are active. Agents crossing the border of the power plant influence area are taking their opinions with them and are influencing the agents around them. In the current form the moving agents parameter does not represent a real situation, but could be a first step to a more complex model to represent opinion dynamics. Letting agents moving around on an actual map and letting them travel from their home to places such as work, relatives, school, and the church and back could give more realistic results. The moving agents scenario cannot be considered as plausible because it does not represent a real situation.

Conclusions

In this chapter is tried to combine the results of Chapter 4 and 5 to draw conclusions about the plausibility of the model. In general the model can be considered as plausible because all outcomes and patterns can be explained by reason. Not all scenarios could be considered as realistic, but they do explain the influences of the parameters that are excluded. The most plausible results are caused by the combination of the NIMBY and positive feedback parameters. Letting the agents moving around freely does in the current model not give plausible results. The moving agents scenario could be the basis for a more realistic opinion dynamics model.

Chapter 6: Conclusions and discussion

Introduction

During this thesis it was tried to couple spatial and social networks in an opinion dynamics model. In the previous chapters is explained how the model was developed and what the results of the model are. In this final chapter the conclusions of this thesis will be discussed. Because the model is explorative many different conclusions could be drawn from running the model. In this paragraph will be tried to structure the results and emphasise the most important results from all previous chapters. The final conclusions are followed by a discussion about the scientific contribution of this research.

A summary of the findings

This thesis started with answering the first sub-research question "*What concepts are still missing in the scientific literature to couple social- and spatial systems in models of opinion dynamics?*" From the literature study could be concluded that there is much literature available about the opinion dynamics. There are many different methods available for modelling opinion dynamics. Few of these models are using a developed social or spatial network. None of the models combined a spatial and social network. The answer of the first sub questions can be summarised as follows.

- The distance between agents is not based on measureable locations
- Geographical locations are not used together with an ABM
- Opinions about an area are only represented as CA models
- Social networks are often based on location only
- The position within a social network is only based on connections and not on initial values
- Initial values are often dependent

The second research question "*Which types of models are useful for modelling the spatial opinion dynamics within a social network?*" is answered in Chapter 3. The model is based on the theory of Latané (1981). The basic interactions are based on the model by Deffuant et al. (2000) and the model by DeGroot (1974).

In the same chapter is demonstrated how an opinion dynamics model can be developed that is coupling social and spatial networks. The model results are diverse and they show many different patterns. Most of these patterns look different than the patterns observed by Deffuant et al. (2000). In Chapter 5 the plausibility of the model is discussed. The research question "*How plausible is the developed model?*" was answered. In general can be concluded that the developed model is plausible given the patterns it generates. Not all parameters give plausible results, but they help understanding the importance of the other parameters. The most plausible scenario is the scenario where agents living close to the power plant receive a negative opinion each turn and agents living far from the power plant receive a positive opinion each turn.

The main research question "*How can social networks be coupled to spatial networks in a model of opinion dynamic?*" is answered in this thesis by developing, demonstrating and analysing a model in which a spatial and social network coexist simultaneously. The model was created by using the basic concepts of Deffuant et al. (2000) and placing the agents on a fictional map based on coordinates. The coordinates define the spatial network. The social network was added by randomly assigned values to the agents which determine the social network. The sensitivity analysis shows that both the parameters show significant difference in outcomes when the values are changed. The described scenarios prove the importance of using a spatial as well as a social network.

The additional value of the model

The existing models of opinions dynamics have shown similar patterns of reaching a consensus. The threshold concept of Deffuant et al. (2000) also shows similar results in the existing models. In the simplest scenario the addition of location and a social network does only control the number of connections and, thus, indirectly the time needed to reach a consensus. The social network and the location of agents become more important when other parameters are added to the model. It creates possibilities to model and study concepts such as the NIMBY concept. The locations and the social network play an important role in the distribution of opinions and their influence can be studied by changing the parameters controlling the spatial and social network. The model developed in this thesis proves the possibilities of coupling social and spatial networks in opinions dynamics as well as the importance of adding location to such a model.

Discussion

This thesis is an explorative research in the field of opinion dynamics. Because of the nature of the research there are some remarks that can and must be made on the validity and the repeatability of the research.

In order to perform such an explorative research many assumptions must be made that are difficult to verify with empirical data. Therefore is tested whether the model is plausible or not instead of whether it is realistic or not. The current model is a representation of a number of archetypical processes which are assumed to be important in spatial opinion dynamics. It cannot be used yet in an operational model social decision making.

Choices had to be made on which results should be discussed because of the high number of possible outcomes. Because of time restraints and to keep a clear overview a selection is made from all possible outcomes. It can be debated whether the results shown are the most important results or not.

The choices for the sensitivity analysis are for a large part based on time restraints. Ideally, the sensitivity analysis should be more comprehensive than the performed sensitivity analysis. In order to fully validate and understand the current model all scenarios should be analysed on their sensitivity. Such a sensitivity analysis could be a useful addition to this research.

Discussing the plausibility of the model could contain many subjective choices. It must be noted that the conclusions could be dependent on the researcher performing the analysis.

Future research could focus on improving the social and spatial network. The current model could be improved by adding a road network or more realistic social relationships. The social network is based on randomly assigned values. By studying social networks more thoroughly a more realistic social network could be added to the model.

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