Effect of Segregation on the Dynamics of Noise-Free Social Impact Model of Opinion Formation Through Agent-Based Modeling

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***Abstract*— Knowing the current public opinion and predicting its trend using opinion formation models is very applicable. The social impact model of opinion formation is a discrete binary opinion model. It describes how interactions among individuals and sharing their opinions about a specific topic in a social network affect the dynamics of their opinions and form the opinion of society. The society could be an online social network. In this research, we considered the effect of segregation on opinion formation. Segregation is a phenomenon that happens due to homophily and is measured based upon network topology. Homophily is the tendency of individuals to interact with others who share similar traits. We used scale-free networks to model interactions between individuals. The social impact model includes a noise parameter, which is the stochastic part of the model, dealing with the inexplicable behavior of individuals and the effects of other influentials, e.g., mass media. Since this noise is a white noise with no bias toward any possible opinion, for simplicity, we assumed a noise-free social impact model, which is valid in equilibrium analysis we considered. The results reveal that with the same attributes for the individuals, the more segregated opinion group dominates the less segregated opinion group on average. Therefore, with the same population size and individual characteristics of both opinion groups, segregation is an overall influential factor for opinion formation. A more segregated opinion group attracts some individuals from the other group and becomes the majority opinion group of society in equilibrium.**

Keywords*— *Opinion Formation; Opinion Dynamics; Social Network; Social Impact Model, Agent-Based Modeling; Segregation

1. INTRODUCTION

The emergence of online social networks and online communities has made it possible that one user communicates with hundreds or even thousands of other people instantly, even from far away distances, and affect them [1]. This sort of communication among a vast number of users may change some opinions and gradually in some rounds of interactions result in collective behavior in, e.g., economic market, national and even international decisions and movements.

Opinion formation has been a challenge for sociopsychologists in the last few decades to explain the opinion dynamics of society due to the interaction of the society members, including face to face, online communications via the Internet and social media. Many models have been proposed for opinion formation in the last few decades. Emerging Internet and the new style of very instantly and widespread interactions via online platforms cause opinion formation to become a more exciting challenge with many applications, including word of mouth marketing [2], political election [3], and social governance [4].

In this research, we ,considered the social impact model of opinion formation [5, 6]. In this model, opinion is a discrete value with two possible values, denoted as '+1' and '-1' in the model formulation, indicating, for example, 'for' and 'against, respectively. The network of interactions is regarded as a scale-free network that has been found in many social phenomena. We used agent-based modeling and simulation to study the effect of segregation on the opinion dynamics in the social impact model. The segregation concept [7] refers to the density of intra-group links among members of a group in comparison with their links with the members of the other group. We used the segregation matrix index to measure segregation [7].

This paper investigates how segregation may affect the opinion dynamics in society using a computational framework. The study deals with the situation two opinion groups with roughly the same population size, and approximately the same characteristics from the social impact model viewpoint interact with each other. In this situation and with no influential leaders, the question is how segregation may estimate which opinion group becomes the majority opinion group in equilibrium. Similar to many other studies in computational social science [8, 9], the result from this computational framework should be interesting for the social scientist and have some applications in politics, e.g., predicting referendum trends, or in marketing, e.g., market forecasting. Very interestingly, the results could be applied to analyze online social networks and online communities.

The rest of this paper is organized as follows: in Section II we review the related literature; Section III explains the research method; the results and related discussion are presented in Section IV; and finally, we conclude the paper in Section V.

2. Literature Review

In this section, we briefly overview the main concepts of this research and the related literature.

A. Opinion Formation

According to Merriam-Webster's online dictionary, opinion is defined as a view, judgment, or appraisal formed in the mind about a particular matter. Opinion formation is a process that could be regarded as a collective phenomenon [10], which emerges as a result of repeated interactions between individuals of a group of interacting individuals. Opinion formation has attracted the attention of scientists from a wide spectrum of disciplines, including social psychology, statistical physics, mathematics, and computer science in the last few decades [11].

The first opinion formation model was a simple and intuitive discrete time model introduced by French, the psychologist, in 1956 [12]. Then many other opinion formation models were introduced, focusing on different concepts such as continuous time modeling [13], adhering to the initial opinion [14, 15], bounded confidence [16, 17], antagonistic relations [18, 19].

Thanks to the computational social science[8, 9], which has equipped the scientists with massive data based on users' posts and expressed opinions, some research has been conducted to explain opinion formation in online social networks and social communities [20]. The agent-based modeling and simulation have also been widely used to study opinion formation and opinion dynamics [21].

Several opinion formation models have been introduced in recent decades. Among them, we have focused on the social impact model of opinion formation [5, 6], a model proper for opinion formation in online communities and online social networks.

B. Social Impact Model of Opinion Formation

The social impact model of opinion formation [5, 6] is a discrete opinion model based on the social impact theory in psychology, which describes individuals are impacted by the real, implied, or imagined presence or actions of other individuals, and they, in turn, influence others.

The social impact model of opinion formation consists of N individuals or agents in the social system. Any agent i (i=1, 2, . . , N) has one of two possible opinion values, '-1' or '+1' at any time step, $o_i=\pm 1$. Any agent i is characterized by its persuasiveness (p_i) and supportiveness (s_i) strengths. The strength of p_i is the ability to persuade another agent with the other opinion to change its current opinion, and similarly, the strength s_i is the ability to persuade another agent with the same opinion to persist in its current opinion. Any individual i experiences total impact I_i from other agents interacting with. This impact is formulated in the simplest version as (1), in which d_{ij} denotes the distance between two individuals i and j, and α defines how fast the impact decreases with the distance d_{ij}. In some implementations of (1) [20, 22, 23], α have been set to 2, α=2.

$$I_i = \left[\sum_{j=1}^{N} \frac{p_j}{d_{ij}^{\alpha}}(1-o_i o_j)\right] - \left[\sum_{j=1}^{N} \frac{s_j}{d_{ij}^{\alpha}}(1+o_i o_j)\right] \tag{1}$$

The impact of the interacting agents trying to persuade agent i to change its opinion is calculated by the former summation of the right hand side of (1). Similarly, the impact of interacting agents on agent i to persist in its current opinion is calculated by the latter summation. Therefore, (1) computes the overall impact on agent i to change or persist on its current opinion. If $I_i>0$, the overall impact from the interacting agents on agent i is to change opinion.

Any agent i is affected by the impact of interacting agents, which is the deterministic part of the social impact. Moreover, agent i is affected by a non-deterministic factor, h_i, called noise which is described in the next sub-section. Therefore, the social impact model of opinion formation formulates the opinion dynamics as (2), indicating the opinion of agent i at time step t+1 regarding the impact from interacting agents at time step t and all other non-deterministic factors summarized in h_i. Meanwhile, the sign function maps negative values to '-1' and positive values to '+1':

$$o_i(t+1) = -sign\left[o_i(t) I_i(t) + h_i\right]. \tag{2}$$

C. Noise in the Social Impact Model of Opinion Formation

The noise or non-deterministic part of Equation (2), h_i, includes elements from the environment, e.g., public media, as well as the characteristics of the individuals to be influenced by others, depending on many psychological factors, e.g., emotion [24, 25]. In opinion formation models, this noise means allowing the individuals or agents to change their opinions in the whole opinion space [26].

The noise in the social impact model of opinion formation is a random behavior implemented in modeling using a random variable. The noise is usually implemented as white noise, which means it is not biased to any opinion of both possible opinions. In other words, the mean value of the distribution of the random variable is equal to zero. The noise in this model is analogous to temperature in the second order phase transition in physics, e.g., in magnetization [27]; therefore, it is also called social temperature. Higher noise levels or social temperatures result in more stochastic behavior. The noise level may reach a high level at which the next opinion of each agent is a random opinion, regardless of other influential parameters of the model.

In the noise-free social impact model, the h_i parameter in (2) equals zero. Therefore, every agent has a fully deterministic behavior, which means that the opinion of each agent in the next time step could be exactly determined according to the current values of the related parameters. The noise-free assumption in opinion formation models is not realistic, but it could be used for some purposes, including equilibrium analysis we deal with in this research.

In computational models for social science, noise is considered from various aspects, including efficiency, predictability, and diversity [28]. Effects of noise on opinion formation models have been considered, for example, on the Axelrod model [29], on the Deffuant model [26], on the

Durkheim model [30], and on the bounded confidence models [31].

D. Segregation

In many social relation types, links are more likely to exist between similar individuals or nodes than between dissimilar nodes, and network homophily emerges. This similarity includes many sociodemographic and behavioral characteristics, and in the context of this research, opinion similarity. Segregation is defined as "the degree to which two or more groups live separately from one another" [7]. Segregation phenomenon is related to the concept of homophily [32], more network homophily causes more segregated subnetworks.

Segregation has been introduced by Thomas Schelling in the late 1960s [33]. Schelling clarified how individual tendencies regarding neighbors could lead to spatial segregation using an agent-based model. The spatial segregation based on static demographics may result in the emergence of opinion polarization [34]. Segregation in social networks may emerge from different types of processes, e.g., gender, age, religion, or ethnicity [7]. Segregation could also be considered based on individuals' opinions on a topic, for example, segregated groups of opinions about US presidential elections have been detected using mass media on Twitter [35].

Several indexes and approaches have been proposed to measure homophily/segregation in social networks, including the segregation matrix index (SMI) [7] we used in this research. The SMI assigns a number to each segregated subnetwork. This index originally assumes two segregated sub-network, e.g., 1 and 2. Suppose an undirected network of N nodes, with m_{11} links in group 1, m_{22} links in group 2, and m_{12} links between group 1 and group 2. If m_{11+} denoted the number of all possible links in subnetwork 1, and similarly, m_{22+} denotes the number of all possible links in subnetwork 2, then the densities of links in sub-networks d_{11} and d_{22} are defined as (3) and (4), respectively:

$$d_{11} = m_{11} / m_{11+} \tag{3}$$

$$d_{22} = m_{22} / m_{22+} \tag{4}$$

Similarly, the density of between-group links, d_{12}, is calculated as (5), in which m_{12+} denotes the number of all possible links between nodes from both groups:

$$d_{12} = m_{12} / m_{12+} \tag{5}$$

If subnetwork 1 contains n_1 nodes, and subnetwork 2 contains n_2 nodes, then $m_{11+} = n_1(n_1 - 1)/2$, $m_{22+} = n_2(n_2 - 1)/2$, and $m_{12+} = n_1 n_2$. Now, segregation matrix index for both sub-networks are defined as (6) and (7) which are normalized to a quantity that varies between '-1' and '+1':

$$S_1 = (d_{11} - d_{12})/(d_{11} + d_{12}) \tag{6}$$

$$S_2 = (d_{22} - d_{12})/(d_{22} + d_{12}) \tag{7}$$

Higher values of the segregation matrix index indicate that the corresponding subgroup is more segregated.

E. Agent-Based Modeling

In agent-based modeling approach, the system is modeled as a population of interacting agents. An agent is an autonomous entity acting on its own in response to situations that the agent encounters during the simulation. In other words, agent-based modeling provides a computational framework for simulating dynamic processes that involve autonomous agents.

Agent-based modeling can make significant contributions to sociology [36]. The studies on opinion formation modeling and opinion dynamics have broadly used agent-based modeling [21, 36]. A survey article [37], published in 2015, classifies applications of agent-based modeling in several fields of sociology, including opinion formation and opinion dynamics in 20 years before its publication. A recently published survey on agent-based models for opinion formation [38] shows that the number of papers has grown at an overall annual rate of 16% over the last decade.

3. Method

To study the correlation between segregation and opinion formation in social networks, we implemented an agent-based model for the social impact model of opinion formation. Figure. 1 shows the pseudo code for one time step of the agent-based model. As the figure shows, in the 'for' loop at line 1, for every agent i, A_i, the impacts from connected supporting and persuading agents ('for' loop at line 4) are calculated according to (1) and is stored in variable I_i (line 10). Then according to (2), the agent's opinion at the next time step is determined using the values of I_i and the noise h_i (line 14). The 'for' loop in line 17 updates the agents' opinion for the next time step.

For the network of the agents' interaction, since scale-free topology has been found in many natural and social phenomena, we used the Barabási-Albert random network algorithm [39] to generate random scale-free networks of the agents' connections. The algorithm is based on two assumptions: linear growth and preferential attachment. The Barabási-Albert algorithm starts from m_0 nodes and adds every new node with m_1 edges that links the new node to previously added nodes with probability proportional to the nodes' degrees. We sat m=2 and m_0=2 in the model.

Since the existence of noise in the system causes a stochastic behavior of the system depending on the noise level, for simplicity, we assume the noise-free system to investigate the effect of segregation on the opinion dynamics. When the noise is a white noise, such an assumption is valid in equilibrium analysis. The noise-free system reaches an equilibrium state after a few time steps; then the simulation could terminate. One of the following two phases may occur in the network of the agents determining equilibrium condition [40]:

- Frozen phase: In this phase, the agents' opinions do not change anymore, in other words, repeating the social impact loop causes no change in the agents' opinion. Thus, the opinion of any agent is the same as its opinion in the previous time step.
- Orderly fluctuated phase: In this phase, some agents change their opinions regularly at every other time step. Figure 2 shows an example of a network of

Algorithm 1 Pseudo code for one time step of the social impact model of opinion formation

for every agent A_i **do**
  A_{i_con} = the agents connected to A_i
  $I_{i\_pers} = I_{i\_sup} = 0$ [initialize sum of persuading and supporting impacts]
  for every A_j connected to A_i **do**
    if A_j's opinion = A_i's opinion **then**
      $I_{i\_sup} = I_{i\_sup} + s_j/d_{ij}^{\alpha}$ [to calculate the sum of supportive impacts]
    else
      $I_{i\_pers} = I_{i\_pers} + p_j/d_{ij}^{\alpha}$ [to calculate the sum of persuading impacts]
    end if
    $I_i = 2 * I_{i\_pers} - 2 * I_{i\_sup}$ [Equation (1)]
  end for[every A_j connected to A_i]
  $h_i =$random value from a distribution indicating the system noise
  if $(I_i + h_i) > 0$ **then** [Equation (2)]
    A_i's next opinion = $-1*$ A_i's opinion [change for the next time step]
  end if
end for[every agent A_i]
for every agent A_i **do**
  A_i's opinion = A_i's next opinion
end for[every agent A_i]

Fig. 1. Pseudo code for the simulation algorithm

connections between six agents with two possible opinions, black and white. In the noise-free condition and equal persuasion and supportiveness strengths, due to the social impact rules, four agents change their opinions at every time step, and two agents do not change their opinions. Therefore, when the opinion of every agent is the same as its opinion in *two* time steps ago, then an orderly fluctuated phase has occurred.

Figure 3 shows the pseudo code of the algorithm we implemented to consider the effect of segregation on the noise-free system. The "for" loop at line 18 contains the social impact time step, as described for Figure 1. The time step continues in the 'while' loop at line 13 until an equilibrium phase, frozen or orderly fluctuated, occurs. The output parameters, ΔS and $\Delta\beta$, are also calculated in the while loop. Every pair of calculated ΔS and $\Delta\beta$ are collected to be used in visualizing the correlation in a scatter plot form after simulation replications (line 42).

In the algorithm of Figure 3, the parameters are set as follows:

- N = 1000, number of agents;
- β = 50, initial percentage of agents with opinion '-1', indeed every replication starts with the same number of opinion groups which are randomly selected;
- N_{rep} = 30, number of simulation replications, every replication starts with a different random seed number to generate different sequent of random numbers. The random sequence affects the topology of generated random networks, random assignments of opinions to the agents, as well as random values of persuasiveness and supportiveness characteristics of the agents.
- h_i = 0, system noise;

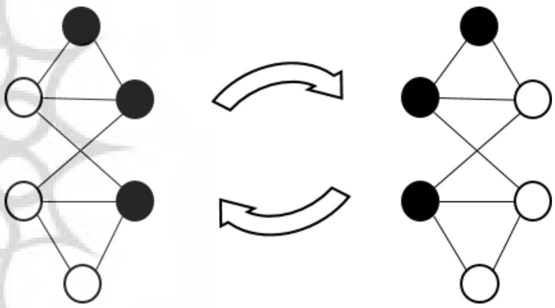

Fig. 2. An orderly fluctuated phase of agent with two possible opinions (black and white) in the social impact model of opinion formation

- p_i *and* s_i: persuasiveness and supportiveness of any agent *i*, is initialized using a random variable from Uniform(0, 100)

4. RESULTS

The noise parameter of the social impact model of opinion formation model affects opinion formation. To show the effect of noise level, various values for h_i, including 0 (without noise, or noise-free), 200, 600, and 2000, have been used in the social impact model (pseudo code of Figure 1). In every experiment, other parameters have been set the same as for Figure 3; therefore, 30 simulation replications for 1000 time steps starting from β=50%, and both p_i and s_i are initialized using random variables from Uniform(0, 100).

The result for noise-free simulations is shown in Figure 4, which shows β at every time step. As the figure shows, the system reaches an equilibrium phase (frozen, or orderly fluctuated) in a few time steps. We focus more on this experiment; thus, more details will be described.

Algorithm 2 Pseudo code for the simulation

```
N = 1000 [Number of agents]
β = 50 [Initial percentage of agents with opinoin '-1']
N_rep = 30 [Number of simulation replications]
for i from 1 to N_rep do
    initialize rand_seed to a new seed value [to generate new random number sequence]
    B_A = Create_barabasi-albert for N nodes with m_0 = m = 2
    create N agents and randomly assign each agent to one node of B_A
    randomly assign -1 opinion to β percent of the agents, assign others' opinions to +1
    for each agent A_i do
        generate and assign p_i and s_i
    end for
    frozen_or_orderly_fluctuated = false
    while not frozen_or_orderly_fluctuated do
        S_{-1} = SMI(B_A, -1) [Segregated Matrix Index of '-1' opinion group]
        S_{+1} = SMI(B_A, +1) [Segregated Matrix Index of '+1' opinion group]
        ΔS = S_{-1} − S_{+1}
        β_1 = current_β
        for every agent A_i do
            A_{i_con} = the agents connected to A_i according to B_A [assume A_i connects to A_i itself too]
            I_{i_pers} = I_{i_sup} = 0 [initialize sum of persuading and supporting impacts]
            for every A_j in A_{i_con} do
                if A_j's opinion = A_i's opinion then
                    I_{i_sup} = I_{i_sup} + s_j [to calculate the sum of supportive impacts, d_{ij} = 1]
                else
                    I_{i_pers} = I_{i_pers} + p_j [to calculate the sum of persuading impacts, d_{ij} = 1]
                end if
                I_i = 2 ∗ I_{i_pers} − 2 ∗ I_{i_sup} [Equation (1)]
                if I_i > 0 then [Equation (2), noise is supposed zero]
                    A_i's next opinion = −1∗ A_i's opinion [change for the next time step]
                end if
            end for[every A_j in A_{i_con}]
        end for[every agent A_i]
        for every agent A_i do
            A_i's opinion = A_i's next opinion
        end for[every agent A_i]
        β_2 = current_β
        Δβ = β_2 − β_1
        save point (ΔS, Δβ)
        frozen_or_orderly_fluctuated = check_frozen_orderly_fluctuated()
    end while[not frozen_or_orderly_fluctuated]
end for
draw scatter plot for points (ΔS, Δβ) and calculate correlation
```

Fig. 3. Pseudo code for the simulation algorithm

When the noise level increases to 200, as Figure 5 shows, in every replication, a majority and a minority opinion group are formed. In this noise level, the noise level causes more segregations to break up and a majority group ('-1', or '+1') forms.

Figure. 6 shows the result for the noise level is equal to 600. The result is similar to the previous noise level, but the population of the majority group is not so much as the previous noise level. Indeed, in this case, the noise or stochastic behavior of the agents more dominates the deterministic part of the model, and more agents change their opinion randomly regardless of the impact of the connected agents.

More increasing the noise level to 2000 causes more dominance of the stochastic part of the model. As Figure 7 shows the result for the noise level of 2000, β fluctuates around 50%; therefore, no majority or minority group is formed in society.Very analogous to magnetization, this phenomenon is similar to enough increasing the temperature of a magnetic substance until it loses the magnetism property because its spins (smallest magnetic parts of the substance) disordered.

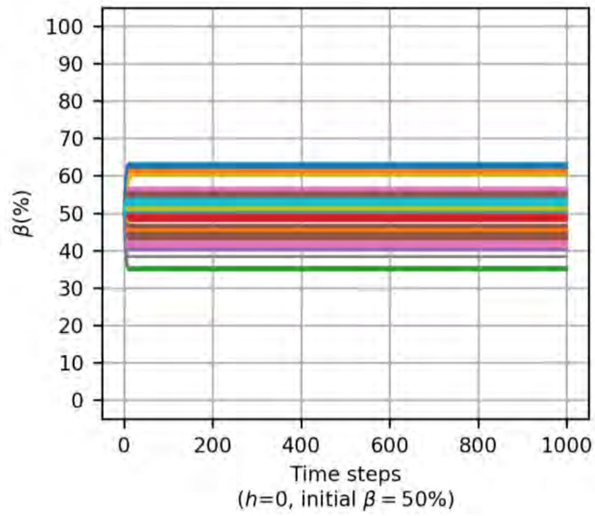

Fig. 4. Value of β in social impact simulation time steps for *h*=0

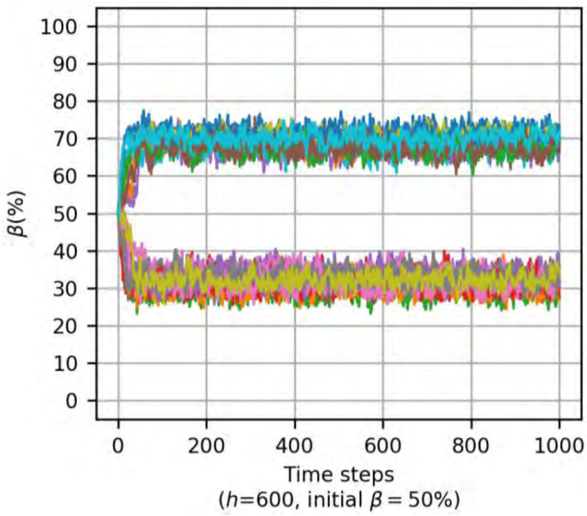

Fig. 6. Value of β in social impact simulation time steps for *h*=600

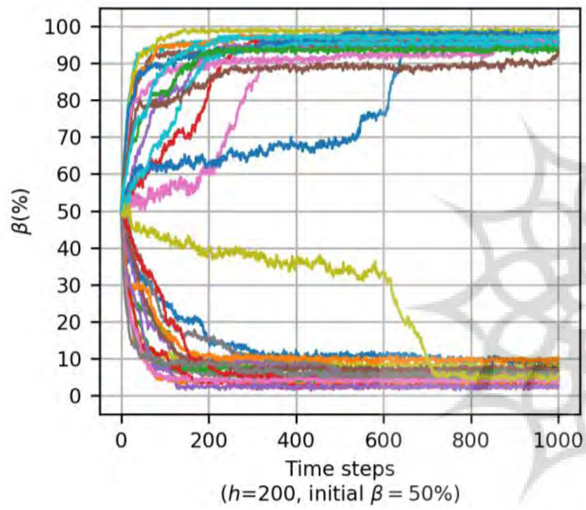

Fig. 5. Value of β in social impact simulation time steps for *h*=200

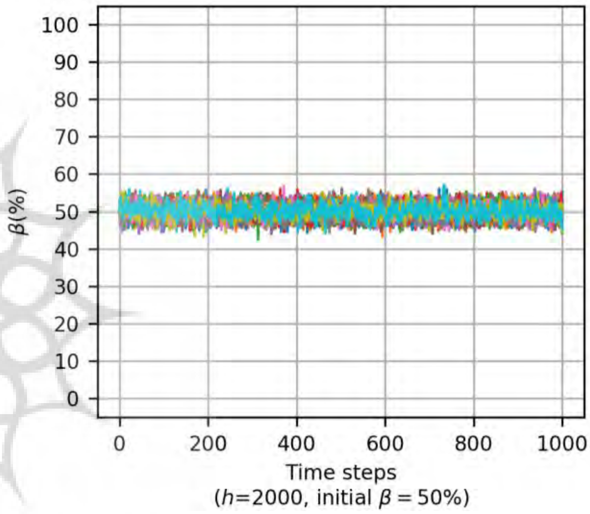

Fig. 7. Value of β in social impact simulation time steps for *h*=2000

As the results of the experiments with various noise levels show, high noise levels cause less effect from segregation. Therefore, to study the association merely between segregation and opinion dynamics, we considered the noise-free social impact model using the simulation algorithm, whose result shown in Figure. 4.

As described in the previous section, frozen and orderly fluctuated phases have been set as the termination conditions of the simulation algorithm. Figure 8 shows the initial time steps of simulation presented in Figure 4 in a high resolution. Indeed, Figure 8 shows the trend of the percentage of the population of '-1' opinion group during the simulation time steps until a termination condition occurs. As the figure shows, for the configuration we set in the algorithm, the termination condition happens in a maximum of 16 time steps, and in most cases, the orderly fluctuated phase occurs; therefore, the agents' opinions are the same at every other time steps afterward. Thus, for every replication of simulation, at most, 16 unique combinations of the agents' opinions have occurred. These unique combinations are used for finding the correlation. Some other statistics for the 30 simulation replications are also mentioned on the figure, including the minimum time steps equals to 7, the mean of time steps is equal to 10.3, and the standard deviation is equal to 2.15.

The question of this research could be rephrased regarding Figure 8. Considering this figure, is there any correlation between these two parameters: "segregation of opinion groups in the current time step" and "changing of β in the next time step comparing to β in the current time step".

To visualize the correlation between the segregation of opinion groups and the change of opinion population, the scatter plot of Figure 9 has been generated as an output of the simulation algorithm of Figure 3. As Figure 9 shows, 304 points are on the scatter plot, which means that in the 30 replications of the social impact simulation, 304 opinion combinations of the agents have occurred before meeting termination condition, frozen or orderly phase.

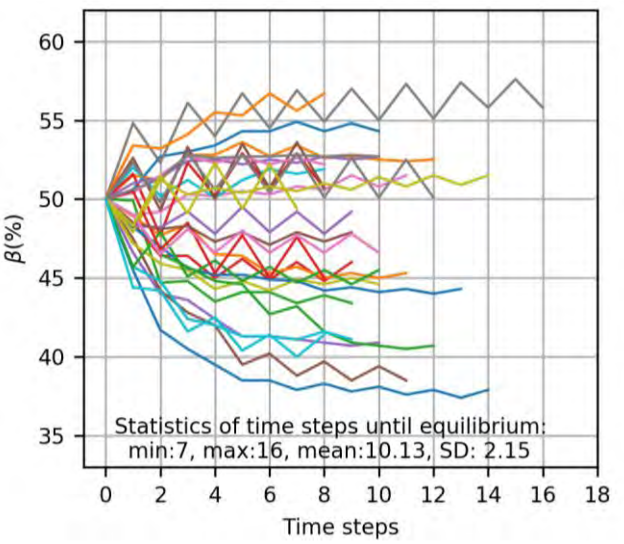

Fig. 8. Percentage of the '-1' opinion group for simulation replications until the termination conditions, frozen or orderly fluctuated phase

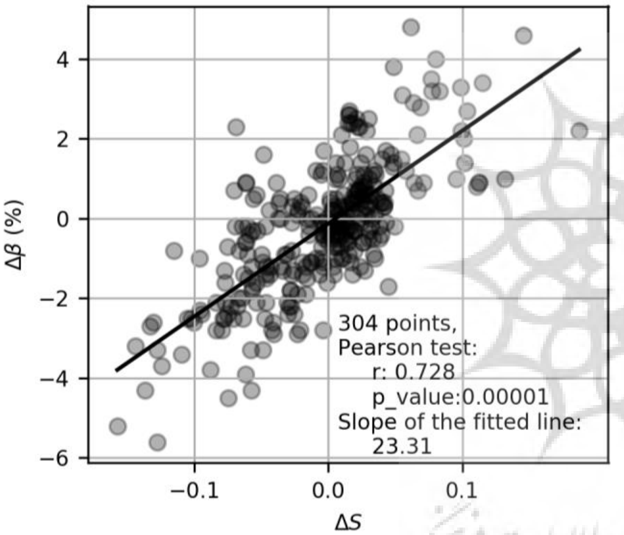

Fig. 9. Correlation between difference of the segregation of opinion groups and difference of percentage of the more segregated group after one time step

It is also notable that with the same percentage of '-1' opinions, there may be two different combinations of opinion assignments to the agents. Therefore, in some cases in Figure 8, it is observed that the same values of β are repeated in every time steps or every other time steps, but it is not an equilibrium state, and the simulation continues.

As Figure 9 shows, ΔS and $\Delta\beta$ are strongly correlated, which is the mose important finding of this research. The Pearson correlation coefficient has been calculated, which is equal to 0.728 (with p_value < 0.01), implying a strong correlation. The conditions for the Pearson test, including normality and homoscedasticity of both ΔS and Δβ dimensions, have also been tested and passed. For the normality test and homoscedasticity test, we used the D'Agostino-Pearson method [41] and Levene method [42], respectively. We also used implementations of both methods from the SciPy library of Python. The line fitted on the scatter plot has been drawn using the least-square line fitting method. As shown in the figure, the slope of this fitted line is 23.31.

As can be seen in Figure 9, when ΔS=0, which means both opinion groups have the same value of segregation measure, as expected, that none of both groups dominate the other one. In other words, the number of members of both opinion groups does not change; therefore, β does not change in the next time step, and $\Delta\beta$=0. A positive value for ΔS means that the group with opinion '-1' is more segregated than the group with opinion '+1'; thus, as the figure shows, it is expected that the opinion '-1' becomes more dominant, and some agents from the other group change their opinion to '-1'. It means that β, the percentage of the population of agents with opinion '-1', increases and consequently, $\Delta\beta$>0. Similarly, when ΔS<0, a $\Delta\beta$<0 is expected, as the figure implies.

In the experiment explained to measure the correlation, ΔS is the independent variable, and $\Delta\beta$ was measured for each value of ΔS that occurred in the network. The resultant correlation explains a causal relation that implies how ΔS causes $\Delta\beta$ effect.

5. Discussion

The most remarkable result to emerge from the simulation experiences in this research is that there is a strong correlation between segregation and opinion formation. In other words, in the same or similar situations for both opinion groups of society, the more segregated opinion group becomes the dominant opinion of society in equilibrium. If some parameters of opinion groups change and/or some changes occur in the environment, we expect the results change according to the new conditions. Some examples of changes are mass media supporting one of the opinion groups or influential leaders with high connections and high persuasion strengths decide to support one of the opinions.

The reason for the strong correlation between segregation and opinion formation revealed in the results could be explained as follows. Both opinion groups have the same population with similar agents from the opinion formation viewpoint. On average, any agent from the more segregated group is connected to more agents from its opinion group than the other group. Thus, the probability of changing opinion is low. On the other hand, in the less segregated opinion group, some agents are attracted to the more segregated group due to less connection with the agents of its opinion group and some connections with the other opinion group. Of course, some randomness nature in the model should be considered in explaining the model behavior. The random behaviors include random assignments of supportiveness and persuasiveness strengths to the agents and randomness nature of the interaction network. When segregation measures of both opinion groups are (roughly) the same, no dominance of one opinion on the other is expected, as the results reveal.

In this research, we reported the results for a simulation with a specific initial state. However, we have run several other simulations with various settings and the similar results generated. Therefore, we believe that the discussed hypothesis of the effect of segregation on opinion formation is valid for similar conditions.

6. Conclusion

In the social impact model of opinion formation, both segregation and noise level affect the opinion dynamics. We have presented how increasing noise level causes no majority opinion form, regardless of segregation. In low noise levels, segregation plays an essential role in opinion formation. Using agent-based modeling, we considered a noise-free social impact model to study the effect of segregation and possible correlation between the segregation of opinion groups and the dominance of the more segregated opinion group on the less one. The results lead us to conclude that there is a strong correlation with the Pearson correlation coefficient of 0.728 between the difference of segregation of the opinion groups and increasing the population of the more segregated opinion group in one time step.

Therefore, in a society of individuals partitioned in two equal population size opinion groups, the more segregated opinion is expected to become the majority opinion. This conclusion could be rephrased that the group with denser links among group members becomes the dominant or majority opinion after interacting with connected agents after a while.

In the social impact model of opinion formation model, the persuasiveness and supportiveness strengths of the agents are randomly assigned using a uniform distribution random variables. This case is analogous to the case when the connected people chat about a topic with no outstanding or well-connected charismatic leader, and no majority opinion forms. Therefore, assigning the persuasiveness and supportiveness proportional to the structural positions of the agents, e.g., their centrality, could be more compatible with the real-world cases in which one or more influential leaders influence the individuals' opinions. It is the case that has occurred in many social movements, and its modeling could be considered in future works.

Furthermore, to simplify the social impact model and eliminate other factors to consider the effect of segregation, we assumed a noise-free condition for the social impact model in our implemented simulation. By this assumption, we ignored the stochastic part of the model. Considering the correlation in the presence of the stochastic part with various noise levels needs more studies. Moreover, the research considered the social impact model of opinion formation, other opinion formation models could also be studied in future studies.

In this research we used a computational approach to study a concept in social socience. More studies in real world environments regarding social science aspects could validate the results and probably reveal some more affecting parameters.

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