Chapter 6
CELL-DEVS Modelling of Individual Behaviour Towards Influencers in Social Media

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Abstract With the exponentially rising popularity of social media, and the provided convenience of digital advertising across various platforms, individuals have found ways to sustain a lifestyle by providing companies with a personalised platform for advertising their products. These individuals are popularly labelled as 'influencers'. Determining the impact an influencer has on a product market is an important aspect in determining whether a company should invest in the influencer's platform. The model presented in this paper, namely, the influencer model employs the Cell-DEVS formalism, an extension of cellular automata that can be used to build discrete-event spaces, implemented through the Cadmium tool to simulate the reaction of individuals towards an influencer. The model simulates the rate of increase of follower count under various scenarios that exercise various reactions and employs an opinion-based approach that simulates an individual's evolving opinion state towards a subject.

Keywords CELL-DEVS modelling · Social media · Cellular automata · Behavioural modelling

6.1 Introduction

Social interactions of any kind play a role in the changing opinions of individuals and human behaviour itself. Social influence has been affected by the introduction of social media platforms. Social media has become an increasingly popular way to date, make friends, explore interests, share passions, and from certain points of view, improve our quality of life [1]. Bond et al. [2] study on Facebook message propagation determined that there was an influence of opinion in the recipients and

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their corresponding 'neighbours', which can be defined as close friends and or relatives. Such behaviour has led to the recognition of social influencers, people who are 'opinion leaders' and have the ability to affect buying habits or opinions of others by posting content (usually sponsored) on social media. From a marketing standpoint, influencers can directly reach more people than the average ad campaign and therefore have the potential to increase revenue. With the growing use of technology, more people spend time on their phones browsing social media, not only for entertainment purposes but also to connect to friends and family and explore various interests. As such, businesses have found it highly practical to employ social media and influencers to expand their global market reach, it is important to understand just how far that reach can go and how impactful the use of influencers will be to their product campaign.

The notion of evolving opinions cannot be verified or observed in real-time, as the product of the action founded by the evolved opinion would require constant supervision over unknown periods. Thus, modelling and simulation (M&S) presents itself as a useful tool that mitigates this drawback. The application of M&S allows for the prediction of future results based on events that took place in the past. Furthermore, M&S can be used to simulate certain specified events that have low probabilities of occurring in the natural environment.

This paper presents a method to simulate the evolution of opinions and the resulting events regarding following or not following an influencer as a conclusion of the influenced human behaviour. The model, referred to as the 'influencer' model, is based on the methodologies presented by Behl et al. [2], Wang et al. [3], and White et al. [4], which presented simulation strategies for opinion evolution, sentiment propagation, and the spread of COVID-19, respectively. This is a hybrid model [5] that uses multiple M&S techniques as well as different techniques to one or more stages in study [6]. The model presented in this paper combines network-based information diffusion based on a differential equation model, its definition as a cell space using the Cell-DEVS formalism, a discrete-event specification based on the DEVS formalism and spatial modelling with explicit delays [7]. The model is built using the DEVS Cadmium tool [8]. The 'influencer' model is experimented on with different scenarios to analyse the behaviour of the model and the subsequent effects of its incorporated variables/parameters. Further experiments were performed to determine the effects of changing the rate at which individuals tend to follow an influencer as well as differing personality groups.

6.2 Background and Related Work

Social interactions can be represented using a network diffusion process that allows users to understand the dynamics and propagation of the process in the network (which could represent information, infectious disease, etc.). The method of propagation can be either physical, verbal, communicated over the Internet, or planned group events, depending on the situation [9]. Network theory is part of graph theory and is a popular technique used to model the spread of infectious diseases and in the study of sociology. In a network, the individuals in a population are represented by nodes and the interactions among them as edges [10]. Network models aim to represent individuals within a population and the relationship between the identified individuals.

Diffusion is defined by Rogers [11] as a special type of communication that transmits innovation through channels consisting of individuals of a social system over a given period. Innovations can pertain to new ideas or technologies that are the result of these new ideas. Rogers first introduced such a process to explain the theory behind how new ideas and rates of innovation spread among the populous. The theory known as diffusion of innovation theory was first published in 1962 and is founded on five elements: the innovation itself, adopters, communication channels, time, and social systems, with another five stages to the adoption process: awareness, persuasion, decision, implementation, and confirmation. The theory further elaborates on techniques to achieve critical mass—the point at which enough people have adopted the innovation resulting in the adoption of the innovation to become self-sustaining with an important focus on 'top officials'.

Expanding on the idea of 'top officials' Rogers penned the term 'opinion leaders' defined as those individuals that create an informal leadership within society, and is a position earned by the individual's technical competence, social accessibility, and conformity to the systems norms—system norms are described to be the behaviour patterns present in members in a particular social system. The idea of opinion leaders is largely founded on the two-step flow of communication presented by Katz and Lazarsfeld [12], a theory of information diffusion that defines the propagation of information from *mass media* to the *opinion leaders* and finally to the *locals.* Additionally, opinion leaders are more exposed to external communications, have a higher social status, and are more innovative on average. Opinion leaders tend to be the centre of their social communication network and hold a unique influential position, while serving as a potential social model, whose behaviour can be imitated by individuals within its social communication network. However, according to Rogers, opinion leaders can lose the respect they hold in their communication network if they deviate too far from the social norm, or in retrospect, may lose credibility if they are unable to keep up with the latest trends. An opinion leader can be monomorphic—is an opinion leader in one topic—or polymorphic—is well-informed about a variety of topics.

Diffusion models are popularly used to simulate the propagation of information in social networks and the adoption of ideas by characterising the social interactions. Most diffusion models that implement social interactions as a process are extensions of the independent cascade and linear threshold models. The independent cascade model [13] focuses on the dissemination of information and interactions from individuals to their friends along a social network by considering the weak and strong ties between individuals. This is strongly correlated to the susceptible-infected-recovered (SIR) model for epidemic spread [14], which takes a similar approach to simulating disease spread through interactions between individuals based on strong and weak ties. The linear threshold model [15] describes a threshold-based perspective on influence propagation, that is, when enough of your peers have adopted a certain idea, you are more than likely to adopt it too.

AlFalahi et al. [16] evaluated different, used to measure influence probability, focusing on (1) static models, (2) dynamic models, (3) diffusion models, and (4) models based on users' behaviour. The research brought focus on how the study of social networks with the applications in graph theory while employing social network analysis to help trace sources and distribution of influence, can lead to a better understanding of the evolution of social networks, resulting in a better investigation of social structures and social influence in such networks. The research determines that the diffusion of influence can be modelled through probabilistic framework, with the probability of the individual embracing a new idea dependent on the neighbouring nodes within the network.

In an effort to model information diffusion with consideration to how information can be exchanged between individuals, various research studies have explored the similarities between epidemic and information diffusion. Goffman and Newill [17] introduced the similarities between epidemic and information diffusion processed by focusing on the aspect that the epidemic process can be defined as a more generalised abstract process of transitioning from one state to another due to exposure to an external phenomenon, with individuals susceptible to both diseases and ideas. Although epidemic and information processes are extensions of the general abstract process, there is one key difference. In the case of information diffusion, the phenomenon, in this case the information itself, is desired, whereas in the case of epidemic diffusion, the phenomenon is undesired.

Different research has explored methods of modelling social interaction and the resulting human behaviour using diffusion models as a foundation. Wang and Li [18] explored the similarities of the epidemic spread models to create the online social networks information spreading (OSIS) with the implementation of cellular automata. They discussed the nature of opinions fading over time, and the inherited aspects of the state change equations from the SIR model (susceptible-infected-recovered; a popular epidemic method). Similarly, Bouanan et al. [9] presented a method to simulate the spread of information across a network and the subsequent influence on their behaviour, with a focus on message propagation with trust factor dependencies and opinion characterisation using confidence bounds. Other social influence models focused on the strength of an individual's influence rather than the network propagation. Peng et al. [19] presented a model to evaluate social influence based on entropy, which assesses the influence of individuals based on various methods of social media interactions and designs an algorithm to characterise propagation dynamics of social influence based on the individual's entropy.

Social interaction modelling can be made more accurate by considering the opinions of the individuals. Opinions are an important aspect in predicting how an individual makes decisions, their behaviour, and how they react to information. An individual's opinions can evolve over time due to external social interactions or by new information diffused through the network. As such, it is important to define how to represent the evolution of opinion and its interactions with the social network formally. The resulting opinion calculation presented in this paper is founded on previous work done by Behl et al. [2] and Wang et al. [3].

Behl et al. [2] discussed the application of Cell-DEVS on modelling human behaviours based on social interactions, including social influence of human behaviour and its evolution considering the population size, the number of interactions, the degree of influence of each interaction, and the threshold of an individual to adopt an opinion or change in behaviour. The opinion update equation is defined as:

$$O(x) = O(x) + \sum_{y \text{ in neighbourhood } |O(x)-O(y)| \leq \text{Threshold}} \text{influence} \times (O(x) - O(y)). \tag{6.1}$$

$O(x)$ is the current opinion of the cell, $O(y)$ is the current opinion of a neighbouring cell, *influence* is the degree of influence of y on x and *Threshold* is the threshold of x that determines if x can be influenced.

An additional extension of how opinions can evolve over time was defined by Wang et al. [3], who presented a method to visualise public sentiments by analysing online posts and predicting future trends on a topic. As not all individuals contribute to the 'comments' section, a sentiment parameter was introduced. The evolution of sentiment offset is defined to be affected by:

- Social emergencies and external stimulus—an individual's interest in a topic can be influenced by an external stimulus other than neighbouring cells.
- A topic can fade over time and the sentiment offset can therefore reduce. This is represented by Wang et al. as:

$$m_i(t)' = m_i(t) \times \left(1 - \alpha^{\frac{m_i(t)}{20}}\right), \tag{6.2}$$

  where α is the fading rate and m_i represents the sentiment offset.
- Influence between neighbours.

Social interactions can be seen as similar to the spread of infectious diseases and thus can inherit model structures used by epidemiology studies. We designed the influencer model using an approach similar to Wang and Li [18], Bouanan et al. [9], and Peng et al. [19], which used infectious disease models to define features in social interactions. As in the case of Behl et al. [2], social interactions can be affected by differing personality traits, a subject that is applied to the influencer model. In an effort to simulate certain behaviour patterns in an attempt to assess the implications of different personality traits, research on how to create differing neighbourhoods and definitions of personality traits is needed. Research into the creation of various neighbourhoods to fulfil the requirement of simulating social divisions and different personality traits in the real world has been explored also in Khalil and Wainer [20] which included case studies on the spread of avian flu, interactions affecting the well-being of organisms, and drug usage involving individuals with different personality traits. The case studies explored boundary conditions that manipulate a cell space and various personality definitions within the cell space. The research defined various dynamic states the agents could possess as well as the transition functions.

An important foundation of the influencer model is thus the definitions of the transition functions. As previously mentioned, the design of social interaction equations can be adapted from physical interaction equations defined in infectious disease models. The influencer model was predominantly based on the state transition equations presented by various COVID-19 cellular automata models, in particular those defined by White et al. [4]. The local transition functions used to inspire the transition functions in this model are shown in Eqs. (6.3), (6.4), and (6.5).

$$I_{ij}^{t} = (1-\varepsilon)\cdot \upsilon \cdot S_{ij}^{t-1}\cdot I_{ij}^{t-1} + S_{ij}^{t-1}\cdot \sum_{(\alpha,\beta)\in V^{*}} \frac{N_{i+\alpha,j+\beta}}{N_{ij}}\cdot \mu_{\alpha\beta}^{i,j}\cdot I_{i+\alpha,j+\beta}^{t-1} \tag{6.3}$$

$$S_{ij}^{t} = S_{ij}^{t-1} - \upsilon \cdot S_{ij}^{t-1}\cdot I_{ij}^{t-1} - S_{ij}^{t-1}\cdot \sum_{(,\beta)\in V^{*}} \frac{N_{i+\alpha,j+\beta}}{N_{ij}}\cdot \mu_{\alpha\beta}^{i,j}\cdot I_{i+\alpha,j+\beta}^{t-1} \tag{6.4}$$

$$R_{ij}^{t} = R_{ij}^{t-1} + \varepsilon \cdot I_{ij}^{t-1} \tag{6.5}$$

The key points to take note of are as follows and are used in the influencer model.

- $\mu_{\alpha\beta}^{i,j}$ is the product of $\mu_{\alpha\beta}^{i,j} = m_{\alpha\beta}^{i,j}\cdot c_{\alpha\beta}^{i,j}\cdot \upsilon$, where $m_{\alpha\beta}^{i,j}$ and $c_{\alpha\beta}^{i,j}$ are the movement and connection factors, respectively, between the main cell and the neighbouring cell $(i+\alpha, j+\beta)$. The parameters υ and ε are the virulence factor and the recovery factor, respectively.
- The number of infected individuals I is the summation of infected individuals that have not recovered, susceptible individuals S affected by the infected individuals in the cell, and the susceptible individuals with the probability of being infected by neighbouring cells that have travelled to the current cell.
- The number of recovered individuals R is the addition of currently recovered individuals from the previous time step and infected individuals with probability to recover in the current time step.
- The connection factor considers various methods of transportation available to the individual that allows it to travel to other cells, whereas the movement factor is the probability of the individual moving to a neighbouring cell.

The influencer model was defined using Cell-DEVS and was implemented using the Cadmium tool [8]. A brief explanation of Cell-DEVS is defined in the following section.

6.3 Cellular Automata and Cell-DEVS

Cellular automata (CA) is the usual form of cellular modelling that uses a regular uniform *n*-dimensional lattice structure, with discrete variables at each cell. The values of the variables for each cell are synchronously calculated every time stamp and is determined by the values of the variables of a finite state of neighbouring cells from the previous time stamp. Since the calculations for the new variable values occur in a synchronous manner, CA evolves in discrete time stamps. The neighbuorhood of a cellular model can be defined using various approaches, and the most popular configurations are the Moore neighbourhood or Von Neumann neighbourhood. The Moore neighbourhood comprises of the central cell and its eight closest neighbouring cells, while the Von Neumann neighbourhood comprises of the central cell and its nearest four neighbuoring cells. Both the neighbourhoods can be extended using their respective radius, and the calculations for the number of cells based on the radius are $r^2 + (r + 1)^2$, $(2r + 1)^2$ for the Von Neumann and Moore neighbourhood, respectively. There are advantages and disadvantages of cellular automata, CA is simple enough to allow for detailed mathematical analysis while also allowing for simple mathematical calculations to be applied to the cells to create a complex mathematical system which make CA a popular method to model complex mathematical systems. However, CA does have its drawbacks, (1) performance and precision is lacking due to the discrete time-based calculations, (2) since CA is asynchronous in nature it requires the use of a synchronous digital computers, and (3) it is difficult to create time triggered events for the cells in the CA model.

The discrete-event system specification (DEVS) formalism is a discrete-event system that employs modular hierarchal formalism for modelling and analysing systems which can be described by a set of states. With regard to hybrid simulations, the DEVS formalism is a popular M&S tool since it allows defining multiple models coupled to work together in a singular model by connecting their input and output messages [21]. The DEVS formalism can be defined as either an atomic model; which defines the behaviour of a system as transition between states as a result of external events or coupled model; which defines how subcomponents of the system interconnect.

The Cell-DEVS formalism overcomes most of the limitations introduced by the CA model and is an extension if the DEVS formalism. Cell-DEVS models can be best described as an *n*-dimensional lattice of cells where every cell is an atomic model that is interconnected using the DEVS coupled formalism. Additionally, the cells within the cell space can not only interact with each other following the DEVS coupled model conventions but can also interact with DEVS models outside the cell space. When a cell receives an input, a local computation function is triggered, which calculates the future states of the cells. The output of the computation (the new states of the cell) is transmitted from the cells output port to other coupled cells after a defined delay elapses. The formalism includes a delay function and dictates when a change can occur once an external event is received from a neighbouring coupled cell, thus preventing any scheduled changes from occurring before the predefined time.

When an output is received at the cell, the external transition function is triggered. An additional duration function controls the lifetime of the cell, once the lifetime has expired an event is triggered to invoke the internal transition function to update the states of the cell. According to the formalism, before the internal transition function is triggered the output function and the output events are generated.

6.3.1 Cadmium Tool

The Cadmium library provides the necessary libraries to translate conceptual Cell-DEVS models to a computational model [22]. Cadmium is a header only C++, with the cells being defined in C++ and the cell space defined using JSON configuration files. The Cell < C, S, V> is an abstract implementation of the cell behaviour following the Cell-DEVS formalism. The local computation function is a virtual function that must be overwritten to represent the desired behaviour of the cell. If the new state is not equal to the current state, the Cadmium library adds the new state to the output queue that forwards the states to neighbouring cells. The Cadmium library uses a port-based approach when communicating state change messages between cells. Cells send scheduled state change messages that are present in the output queue to neighbouring cells via an output port and receive state change messages from external cells through an input port.

6.3.2 Influencer Model Design

The cells in the influencer model have three possible states, susceptible, influenced, and non-influenced. There are several assumptions that have been made in this model, which are listed below.

1. All cells are vulnerable to being influenced since social media is publicly available and accessible.
2. Individuals in the age group 13–40 are more vulnerable to being influenced.
3. Once an individual is influenced, there is a chance they will unfollow the influencer. Only those who are influenced can become non-followers.
4. Non-influenced individuals cannot refollow an influencer and hence cannot become influenced again. This assumption is made to demonstrate that individuals made the decision to unfollow the influencer purposefully and are unlikely to follow an influencer they have lost interest in based on the fact that there is a multitude of other influencers available.
5. The total population is static; hence, the population in each cell is always the same.
6. Individuals cannot move from one cell to another, hence cell population will never change.

7. The negative opinion can never have a probability of zero. The opinion parameter represents the probability of a positive opinion; hence, the negative opinion is the additive remainder of one. Hence, there can never be a zero probability of a negative opinion since we assume that the probability of a positive opinion will never be one.
8. The frequency of upload by the influencer affects the follower count; more regular uploads keep the audience engaged, while lower frequency values cause the individuals to lose interest overtime. This assumption does not consider the quality of the content released by an influencer.
9. There is no delay between changes in state for a given cell. The probabilistic values for each state are directly impacted on every time step and every interaction.

Following these assumptions, the model is designed to replicate the environment of social platforms and the degree of connections between individuals. The current model's configuration, however, does not simulate social groups, factions or social divisions, or types of social connections that can occur on social platforms, this would require a thorough social network analysis [22] with validated data from current social networks. The model implements a hybrid M&S approach with a combination of network-based information diffusion and agent-based modelling employed during the pre-simulation, and the Cell-DEVS formalism applied for the simulation of the model itself.

1. Pre-simulation: The conceptual model is designed to simulate how individuals (agents) connected within a social network propagate opinion and information. Thus, to illustrate such a configuration of individuals or groups of individuals connected within a network, an agent-based model integrated in cellular automata is employed with agents connected with other agents to create a network structure.
2. Simulation: To achieve results, the conceptual model is converted to use the Cell-DEVS formalism and translated into C++ to conform with the Cadmium tool. The results are analysed, and various scenarios are created to further characterise the behaviour of the model.

In accordance with the Cell-DEVS formalism cells are used to represent individuals, the neighbouring cells, and the social connections between individuals. In the model, each cell represents a static population of 100, which is subdivided into four age groups representing the different generations within the population. The four age groups used are children, 0–16 years, adults, 17–35 years, seniors, 36–50 years, and elders, 51 + years. This configuration is used to represent how in social platforms, an individual's 'friends' (the term used to represent an individual's connections on social platforms) can be vast, whether they be close or distant connections, and these connections have further multitude of connections creating an extensive network of connections. Each cell in the influencer model has four dynamic states, susceptible, influenced, non-influenced, and opinion. The model is probabilistic in nature, with the value presented for each state determined by the values of the corresponding neighbouring cells. Each state is a set of values that represent the probability of that agent being in that current state. Each cell has several static attributes assigned to it that control the personality traits as well as how susceptible the cell is to neighbouring influence, these are, extrovert factor, tech adoption, and free time. The static traits differ per age group consequently varying the probability of how likely the associated age groups are to being affected, thus the number of influenced in a cell differ between age groups and between cells. The model configuration uses a single cell to represent the influencer in the simulation, with that cell having a static population of once since there is only one influencer within the cell. The model has the simulation begin with one influencer and the primary circle of neighbours around the source being 'influenced' for two of the major age groups, which are 17–35 and 36–50.

Each cell has a neighbourhood configuration to simulate the relations and interactions between cells. The model uses a Moore neighbourhood with $r = 4$, with each layer going outward having a reduced 'connection' factor, that is, $r = 1$ having the most favorable influence on the cell in question while $r = 4$ having the least influence. For this model, an extended Moore neighbourhood is implemented to demonstrate that social media increases the range a user can impact others. The number of cells for an extended Moore neighbourhood is calculated using $(2r + 1)^2$, with r being the range of the neighbourhood. The probability of connection from the centre cell to any of its neighbouring cells is based on the Moore radius. Furthermore, to implement assumption 1, the influencer cell is included as a neighbour in every cell's neighbourhood configuration.

The opinion of an individual can vary based on many different factors, for example negative publicity, global information sharing, and influence from friends and family. An individual's opinion on a subject, in this case the influencer in question, would affect how likely the individual will choose to follow the influencer, and following that, how likely they are to unfollow the influencer. A positive opinion increases the chances of the individual becoming a follower; however, opinions can decrease over time and interest in the topic can fade, which would lead to a decreasing opinion, eventually resulting in a negative enough opinion to cause the individual to finally unfollow the influencer in which they have lost interest. There are also the rare cases that became more prominent and are widely referred to as 'cancel culture'. Cancel culture occurs when a popular figure receives a negative response to their online presence, which leads to an avalanche of negative commentary as the opinions spread between individuals, eventually leading to a popular negative opinion to diminish the online support for the influencer.

The main goal of the model is to determine the rate of influencer and non-influencer increase, as well as how other factors affect this rate change. Subsequently, the model implements state transition equations that calculate the evolution of the cells dynamic traits and updates these traits during the simulation. During each time step in the simulation, the state transition equations are used to calculate the evolution of the dynamic traits in every cell, however, if the cell is found to be an influencer, only the opinion dynamic trait is updated, since an influencer cannot follow or unfollow itself, but due to that fact that an influencer is part of every cells neighbourhood, its opinion can affect the corresponding cells opinion evolution, hence the influencers opinion must be updated in accordance with the opinion equation with respect to its own Moore neighbuorhood. This exception is implemented by adding an ‘influencer’ parameter to every cell, the parameter is Boolean and if set to true, the cell is defined to be an influencer.

The overall flowchart that illustrates the progress of the model is depicted in Fig. 6.1. At each time step, the *localComputation* function is called; the function characterises the cell behaviour for the influencer. Accordingly, if the cell is defined as an influencer, the computation function determines the change in opinion; otherwise, if the cell is a default generated cell, the three dynamic states variables are updated based on the value variables of the cell itself and its influential neighbouring cells.

Finally, in the interest of creating a model that can compare two influencers, the model was designed to work with one or two influencers defined in the environment. This was achieved by including a macro definition within the model. If the macro definition was enabled, the model followed a sequence of calculations with respect to both influencers. The model ensured that individuals were simulated to be able to follow the first influencer, the second influencer, or both influencers at the same time. This was achieved by adding a secondary set of dynamic traits with respect to the second influencer to every cell, however, it is important to note that this addition does not impact the static population of the cell, but rather the summation of each set of dynamic traits is still equal to the static population. Thus, a ratio of the population can be followers of the first influencer while still being susceptible to the second.

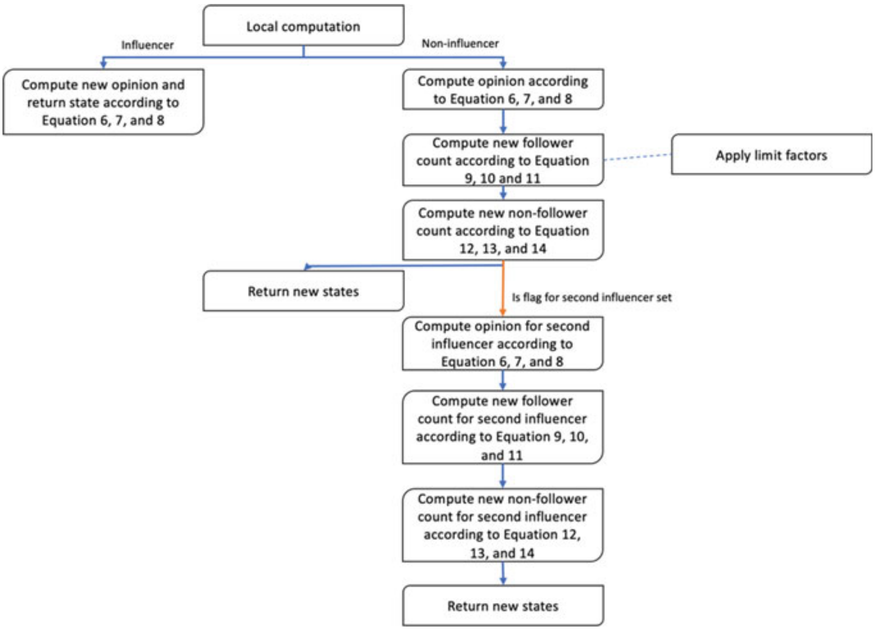

Fig. 6.1 Flow diagram for *localComputation*

Table 6.1 summarises the parameters used in the state transition equations with a brief description of their function, and Table 6.2 summarises the variables that are interdependent with state transition calculations.

The opinion Eq. (6.1) is combined with the sentiment iteration Eq. (6.2) discussed earlier. The 'new follower' calculations are based on those presented in Eqs. (6.3), (6.4), and (6.5), and are represented by the following equations. Equation (6.6) defines the value of opinion for the next time step. This number cannot be greater than 1, since that would equate to having 0 negative opinions, based on the presumption that the negative opinion ratio is calculated using $1 - o^i$.

$$\text{new}o^{i+1} = \min\left(0.999,\ \text{new}o^{i'}\right) \tag{6.6}$$

Table 6.1 Summary of parameters used in the state change equations for the influencer model

Parameter name	Symbol	Description
Follower factor	β	This value is used to vary the probability of becoming a follower
Extrovert factor	χ	This value is based on age and the individual and affects how much influence an individual has on others and vice versa
Random	γ	Random value to mimic unplanned events
Frequency	μ	This is the rate of online uploads by the influencer
Susceptibility factor	ν	Represents how susceptible an individual is to outside influence (not necessarily the influencer)
Non-follower factor	τ	The opposite of the follower factor, it controls the probability of an individual unfollowing
Population	ω	Population of the cell
Fading factor	σ	Used to reduce interest in a topic, affect the opinion on the subject
Limit factors	υ	Used to schedule changes in the environment to imitate global events
Neighbour vicinity	δ	This is the probability of connection between cells and is based on the Moore radius
Tech adoption	ε	The comfort level of individuals using social media
Free time	ϕ	The amount, on average, an individual browses social media

Table 6.2 Summary of variables used in the state change equations for the influencer model

Variable name	Symbol	Description
Global impact	α	Variable used to mimic global trends and is based on the free time and tech adoption of individuals
Opinion	o	Opinion of the individual

The first term of Eq. (6.7) calculates the influence the individual has on themselves in the evolution of their opinion, adjusted by a fading factor (decay in opinion $1-\sigma^{\frac{o^i}{\gamma}}$), the extrovert factor χ, and the random variable γ, to represent random changes in individuals' thought process. The second term determines the influence of neighbouring opinions and their additive difference $o^i - o^i_j$, while applying the extrovert factor, decay of opinion, a randomised variable, and finally the probability of connection between the cell in question and the current neighbour δ. Finally, the total is multiplied by the susceptibility factor ν, and divided by the population of that cell ω, to determine the ratio of individuals with this new opinion value. That is, the opinion propagation between neighbours depends on the difference between the current cell's opinion and its neighbours; the difference is then added to the current opinion. Additionally, the fading factor considers that with the overwhelming availability of information, the attention span on any given topic deteriorates with time (or is replaced by a more engaging topic).

$$\text{new}\, o^{i'} = \left(o^i \cdot \left(1-\sigma^{\frac{o^i}{\gamma}}\right) \cdot \chi \cdot \gamma + \sum_{\text{neighbours}=j} \left(o^i - o^i_j \cdot \left(1-\sigma^{\frac{o^i_j}{\gamma}}\right) \cdot \chi \cdot \gamma \cdot \delta \right) \right) \times \nu/\omega \tag{6.7}$$

Equation (6.8) represents the final change in the cell's opinion for the next time step.

$$o^{i+1} = \text{new}\, o^{i'} \tag{6.8}$$

Equation (6.9) is the newly predicted follower count and takes a similar approach to the new opinion calculation. The current number of susceptible individuals S^i is multiplied by the influence an individual has on themselves, and the influence of the neighbouring cells on the current cell, to define a change in state from susceptible to influenced I. Both terms use the follower rate β, a randomised value that represents unobserved evolving individual behaviour, limit factors υ (if any are assigned for the phase), and the global impact defined as $\alpha = \varepsilon \times \phi$, which describes the individual's propensity towards new technology and the likely amount of time they spend on it. The total is further multiplied by the frequency μ of content release provided by the influencer and the current opinion o^i of the agent.

$$\text{new} f^{i'} = S^i \times \left(I^i \cdot \omega \cdot \beta \cdot \alpha \cdot \upsilon \cdot \gamma + \sum_{\text{neighbours}=j} I^i_j \cdot \omega \cdot \beta \cdot \alpha \cdot \upsilon \cdot \gamma \cdot \delta \right) \times \mu \cdot o^i \cdot \nu/\omega \tag{6.9}$$

Equation (6.10) takes the result of Eq. (6.9) and ensures that the new ratio of followers is not greater than the current ratio of susceptible individuals. Equation (6.11) illustrates the final predicted number of new followers for the next time step, which subtracts the updated number of non-followers to ensure that the additive ratios of susceptible, followers, and non-followers equate to the static population value of the cell.

$$\text{new}f^{i+1} = \min\left(S^i, \text{new}f^{i'}\right) \tag{6.10}$$

$$I^{i+1} = I^i + \left(\text{new}f^{i+1} - \text{newnon}^{i+1}\right) \tag{6.11}$$

In summary, the new number of influenced individuals is based on the neighbouring cells, the cells current opinion and external factors. An important consideration that is accounted for is that for any cell, the individuals that subscribe to be followers can never be greater than the current susceptible individuals. This ensures that all individuals in the cell have any of the three states, and the summation of all subclasses of individuals per state will equate to the total population of the cell, which is defined to be static.

The calculation of the final two states of the cell, the susceptible and the non-follower numbers are defined below. Similar to White et al. [4], the non-follower calculation adopts a variable that controls the rate of unfollowing an influencer τ—Eq. (6.12). Additionally, the equation includes the negative opinion of the cell by taking the additive inverse of the current cell opinion $\left(1 - o^i\right)$. This reflects how a degenerating opinion can increase the likelihood of unfollowing an influencer.

$$\text{newnon}^{i'} = I^i \cdot \left(1 - o^i\right) \cdot \tau/\omega \tag{6.12}$$

Similar to the accountability translated in the calculation for the new followers, the number of new non-followers can never be greater than the number of individuals that are currently followers—Eq. (6.13).

$$\text{newnon}^{i+1} = \min\left(I^i,\ \text{newnon}^{i'}\right) \tag{6.13}$$

Equation (6.14) defines the change in state for new non-followers and simply adds the new non-follower count to the existing number of non-followers.

$$N^{i+1} = N^i + \text{newnon}^{i+1} \tag{6.14}$$

The susceptibility number is the remainder of the ratio of individuals that are neither influenced nor non-influenced—Eq. (6.15), which can be summarised as the total population of the cell $\left(S^i + I^i + N^i\right)$ minus the new values of followers and non-followers $\left(N^{i+1} + I^{i+1}\right)$.

$$S^{i+1} = \left(S^i + I^i + N^i\right) - \left(N^{i+1} + I^{i+1}\right) \tag{6.15}$$

6.4 Influencer Model Implementation

Having defined the state transition equations and the overall flow of the influencer model, this section describes the implementation of the model in the Cadmium tool. Cadmium is a header only C++ library with the *localComputation* virtual function describing the desired behaviour of the cell which is called every time step. Figure 6.2 shows a code snippet of the actions taken during each cell's *localComputation* call.

The *localComputation* is a Cadmium method that is activated on each cell following the Cell-DEVS formalism. The model incorporates phase changes to simulate how in the real-world external factors may directly affect the follower rate

```
sfn localComputation(sfn state, const std::unordered_map<std::vec-
tor<int>,
NeighbourData<sfn, double>>& neighbourhood) const override {
    state.phase = limits->next_phase(clock, state);
    if (state.flag_inf) {
       std::vector<float> new_op_inf = new_opinion(state, neighbour-
hood);
       for (int i = 0; i < n_age_segments(state.flag_inf); i++){
                state.opinion.at(i) = new_op_inf.at(i);
}
       return state;
    }
    for (int i = 0; i < n_age_segments(state.flag_inf); i++) {
        float ratio = state.susceptible.at(i) +
               state.influenced.at(i) + state.noninfluenced.at(i);
        age_ratio.push_back(ratio);
    }
std::vector<float> new_op = new_opinion(state, neighbourhood);
std::vector<float> new_f = new_followers(state, neighbourhood);
std::vector<float> new_n = new_nonfollowers(state);
#ifdef SECOND_FOLLOWER
std::vector<float> new_op2 = new_opinion(state, neighbourhood);
std::vector<float> new_f2 = new_followers(state, neighbourhood);
std::vector<float> new_n2 = new_nonfollowers(state);
#endif
    for (int i = 0; i < n_age_segments(state.flag_inf); i++) {
state.noninfluenced.at(i) = state.noninfluenced.at(i) + new_n.at(i);
state.influenced.at(i) = state.influenced.at(i)+new_f.at(i)-
new_n.at(i);
state.susceptible.at(i) = age_ratio(i) - (state.noninfluenced.at(i) +
       state.influenced.at(i));
state.opinion.at(i) = new_op.at(i);
    }
 return state;
}
```

Fig. 6.2 *localComputation* code snippet

Cell_states: Susceptible[] Influenced[] Non-influenced[] Opinion[]	Cell_states_second_influencer: Susceptible_first_influencer[] Influenced_first_influencer[] Non-influenced_first_influencer[] Opinion_first_influencer Susceptible_second_influencer[] Influenced_second_influencer[] Non-influenced_second_influencer[] Opinion_second_influencer[]

Fig. 6.3 Cell states with one and two influencers

(economy, environment, etc.). Such phase changes are determined by *state.phase* = *limits* → *next_phase* (*clock*, *state*), a limit factor can be applied to affect the calculation of follower number based on global events. Additionally, the limit factors may affect the follower rate for a particular influencer. Then, we check if the cell is an influencer (*if* (*state.flag_inf*)); in that case, only the opinion will be computed using the *new_opinion* function. The new state of opinion for the influencer is then updated for each age segment (each cell has four distinct age groups; thus, the states of the cell must be updated per age segment) using the function *new_op_inf.at* and the state returned for the next time step. Instead, if the cell is not an influencer, the follower and non-follower counts are calculated. The *ratio* is then calculated as the sum ratio of all ratios for each age segment. This can be defined as the static population of the cell, and it represents $\left(S^i + I^i + N^i\right)$ in Eq. (6.15). The *new_opinion, new_follower and new_nonfollower* function calls implement the equations described above: Eqs. (6.7), (6.9), and (6.12) which define the state transitions using the current inputs to the cell. Additionally, if SECOND_INFLUENCER is defined (which means the model includes two influencers), the state changes are re-calculated with respect to the second influencer. To illustrate the difference between the two sets of dynamic states, refer to Fig. 6.3.

We then cycle and update the four distinct age groups. The new states for each cell are then applied for the next time step by equating *state.influenced, state.noninfluenced, state.susceptible, and state.opinion* that embodies Eqs. (6.8), (6.11), (6.14), and (6.15). The opinion calculation implements a pointer variable that is set based on whether the calculation is being done for the first or second influencer. In each case, the pointer points to the correct opinion set required at the time. The same strategy is used for any other state transition functions when required. It is important to note that the 'neighbourhood' variable shown in Fig. 6.2 does not only represent the extended Moore neighbourhood but also includes the influencer/influencers, this embodies assumption 1. An additional constraint implemented in the model is the difference of opinion between the cell and its neighbours, that is, the difference can never be negative, since the opinion of the cell can never be a negative value in this simulation.

6.4.1 The Influencer Model

In this section we show the execution of the influencer model including the previously defined transition functions, a single influencer, and an extended Moore neighbourhood with a radius of four. The neighbourhood around the influencer itself has a ratio that is predominantly influenced, assuming that close friends and families are more willing to follow the influencer. The model is used to find the initial values of the static variables and reflects a natural flow of how the rate of followers and, similarly non-followers would increase over time.

Figure 6.4 shows a spatial visualisation of the Cell-DEVS model execution within a 500-day simulation. The cells are shaded from light to dark with respect to the probability value of becoming a follower. The plot on the left depicts the simulation at the beginning with just the influencer and its closest neighbours being influenced (followers), the middle plot depicts the transition of the simulation at the midpoint of the simulation as the influence of the influencer and its followers affect susceptible cells. The final plot on the right is at the end of the simulation with almost all cells having a probability of being a follower.

Figures 6.5 and 6.6 plot the overall results of the original influencer model and the progression of the follower count within the same time scope as illustrated in Fig. 6.4. Figure 6.5 plots the total number of followers versus non-followers, while Fig. 6.6 plots the relationship between the three dynamic states.

Analysing Figs. 6.5 and 6.6, there is a slight increase in the number of followers in the first days from 0% to 0.1%. During the initialisation of the simulation, several cell ratios are already configured to be influenced (followers) within the Moore neighbourhood of radius $r = 1$ around the influencer cell. This is achieved by setting the 'follower' state of the neighbouring cells to a positive value in the model configuration file. This is purposefully done to model that individuals closely connected to the influencer are far more likely to become a follower. Next, we see a gradual increase in the number of followers, and the non-follower count increases at a slower rate (but parallel to the rate of follower increase). This is an expected feature, as the non-follower count cannot be larger than the current number of followers, thus

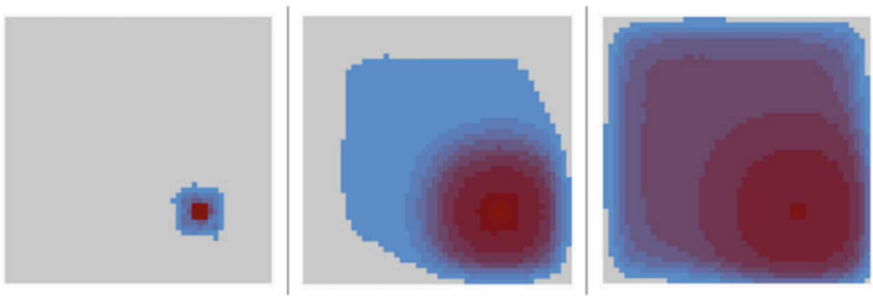

Fig. 6.4 Spread of influence using the DEVS viewer

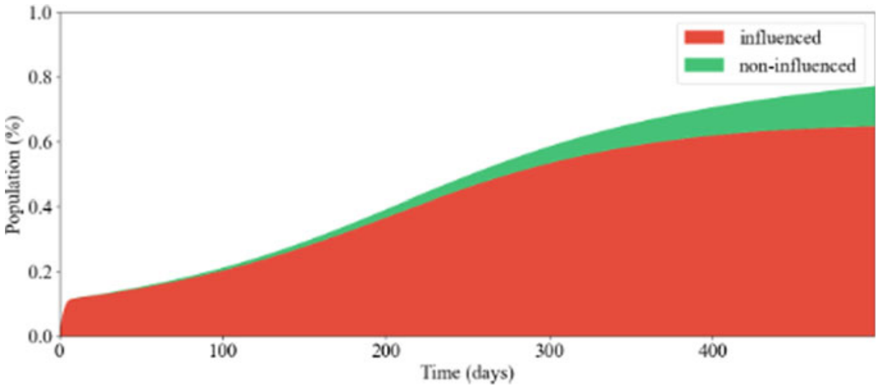

Fig. 6.5 Follower rate increase

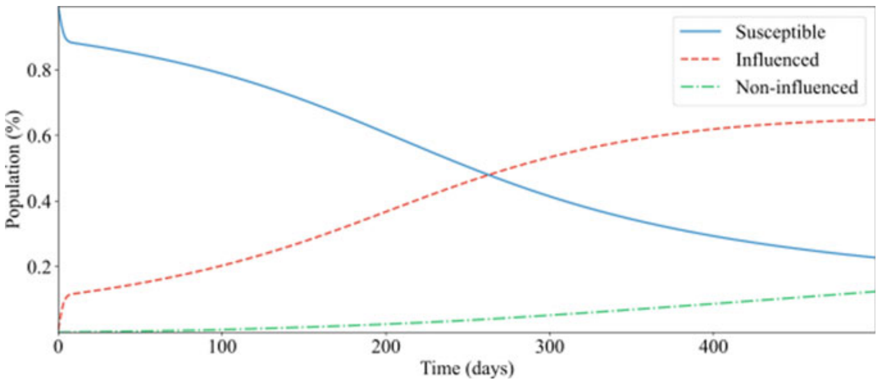

Fig. 6.6 Relationship between susceptibility and follower rate for the default influencer model

a rate of increase in non-followers can only occur when there is a viable number of followers. Furthermore, the susceptibility count is inversely proportional to the number of followers, showing that the current susceptible ratio is determined by subtracting the follower ratio and non-follower ratio from the cell's population.

Although face value validation of the model is not feasible (as data about influencers is not available), we conducted a formal analysis of the design of the model by comparing the behaviour with White et al. [4]. The transition functions for the influencer model and those in Eqs. (6.3), (6.4), and (6.5) are related; the influencer model follower, non-follower, and susceptible can be seen as similar to the infected, recovered, and susceptible for infectious disease (where the state 'deceased' is excluded). The main characteristic in White et al. [4], illustrated in Figs. 6.7 and 6.8, is that as the number of infected increases so does the number of recovered, with the susceptibility being inversely proportional to that of infected + recovered. This is similar to the behaviour represented in Figs. 6.5 and 6.6.

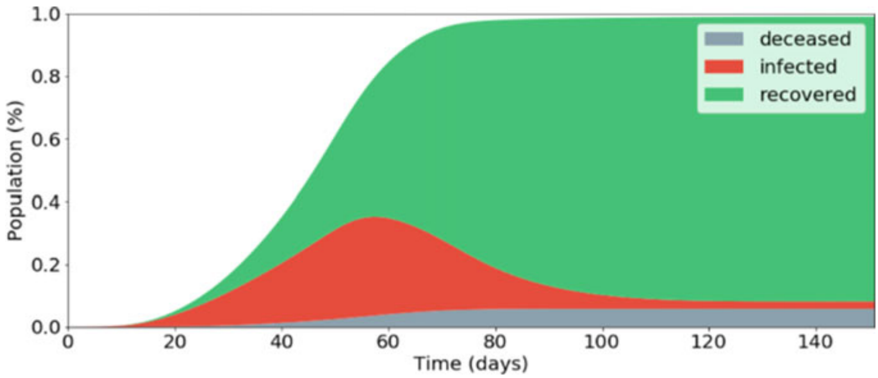

Fig. 6.7 Results for White et al. [4] model

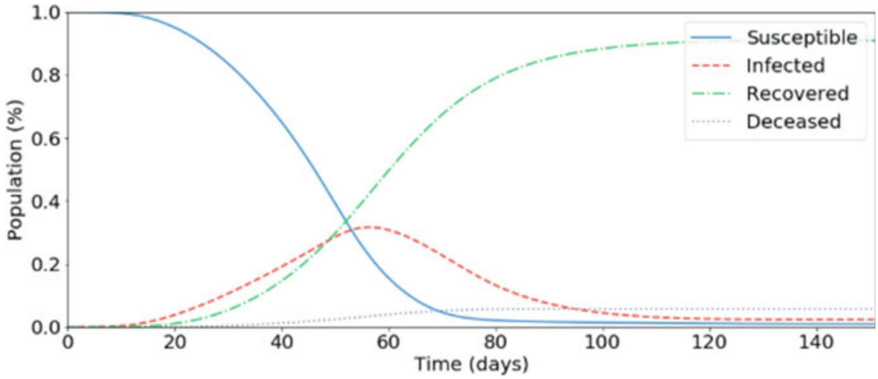

Fig. 6.8 Relationship between susceptibility and infection rate for the White et al. [4] model

Firstly, there is a gradual increase in the number of followers as there is an increase in those infected. Secondly, as the number of followers increases, there is also a gradual increase in the number of non-followers as can be seen in Fig. 6.5 with the increase becoming more prominent after 200 days have elapsed; the same can be said about the number of recovered individuals with respect to the number of infected. As observed in the White et al. [4] model, there is a gradual decline in the number of infected as recovered individuals become immune. However, this behaviour is not present in the influencer model. This is because the influencer model observes a relatively slower growth in the number of non-followers—White et al. [4] model has a 0.9% recovered rate at 70 days, whereas the influencer model does not reach this value even after 500 days, since the influencer model has a lower non-follower rate when compared with the recovered rate in the model presented by White et al. while also taking into account negative opinions, an additional factor that is not included in White et al. model, which results in the number of susceptible cells still being higher than the number of non-followers, hence follower numbers can continue to rise until such a case occurs.

When simulating the model for a longer time (Figs. 6.9 and 6.10), we can observe a gradual decrease in the number of followers at the intersection of the number of susceptible and non-followers depicted in Fig. 6.10. This behaviour is similar to the White et al. [4]: the number of infected also decreases once the number of susceptible intersects with the number of recovered.

The final similarity between the models is the decrease in followers/infected once the number of susceptible has intersected with non-followers/recovered. Furthermore, since the influencer model and the White et al. [4] model have a shared assumption—the influencer model assumes that once an individual has become a non-follower, they can never become a follower again; White et al. [4] assumes that once an individual has recovered, they can no longer be infected—the number of followers/infected cannot increase again once the number of susceptible is lower

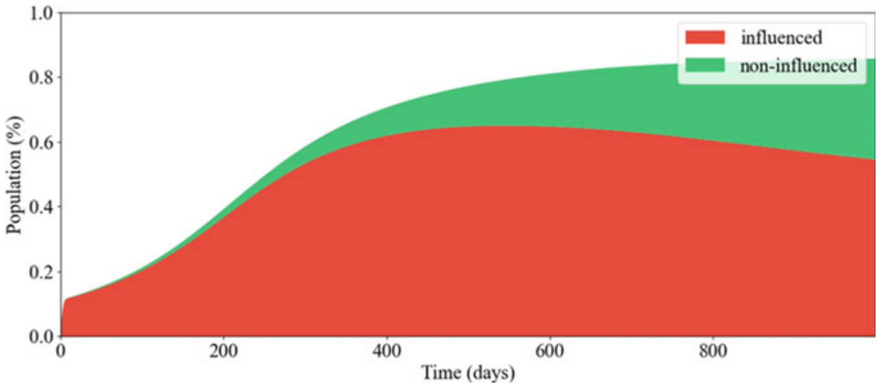

Fig. 6.9 Rate of increase of follower rate and non-follower rate during a longer simulation time

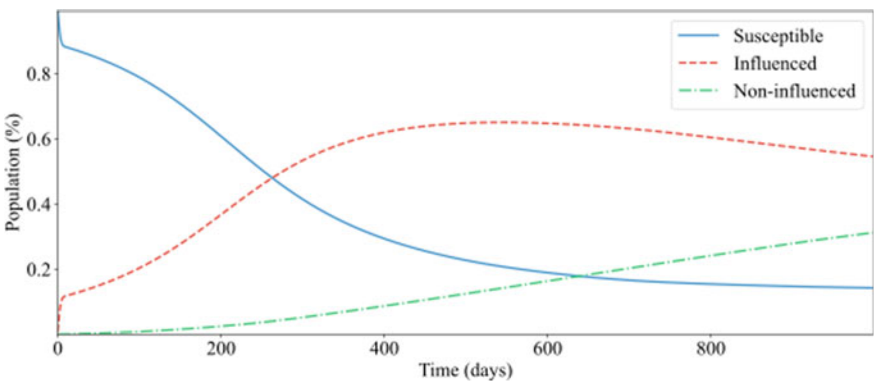

Fig. 6.10 Relationship between susceptibility and follower rate during a longer simulation period

than the number of non-followers/recovered. It is also safe to assume that if the influencer model 'non-follower rate' variable and the calculation for the number of new non-followers identically matched White et al. [4] recovery factor and number of recovered calculations, the rate at which the number of non-followers increased would be extremely similar to the rate at which the number of individuals recovered.

6.4.2 No Opinion Model

To verify that the opinion of an individual plays a key role in determining whether the individual will become a follower or not, a modified 'influence' model was tested in which the new follower evaluation was adjusted to not be dependent on the individual's current opinion. Equations (6.16) and (6.17) illustrate the difference in how new follower and new non-follower count is evaluated without consideration of the opinion.

$$\mathrm{new}f^{i'} = S^i \times \left(I^i \cdot \omega \cdot \beta \cdot \alpha \cdot \upsilon \cdot \gamma + \sum_{\mathrm{neighbours}=j} I^i_j \cdot \omega \cdot \beta \cdot \alpha \cdot \upsilon \cdot \gamma \cdot \delta \right) \times \mu \cdot \nu / \omega \tag{6.16}$$

$$\mathrm{newnon}^{i'} = I^i \cdot \tau / \omega \tag{6.17}$$

The resulting rate of increase in follower count can be seen in Fig. 6.11. It is evident that disregarding the opinion of an individual would automatically create a scenario in which any individual would become a follower without the slightest inclination to think otherwise. Hence individuals will assuredly and without thought follow an individual once they are made aware of them. This resolves the importance of having an opinion-based model to interpret the probability of an individual becoming a follower.

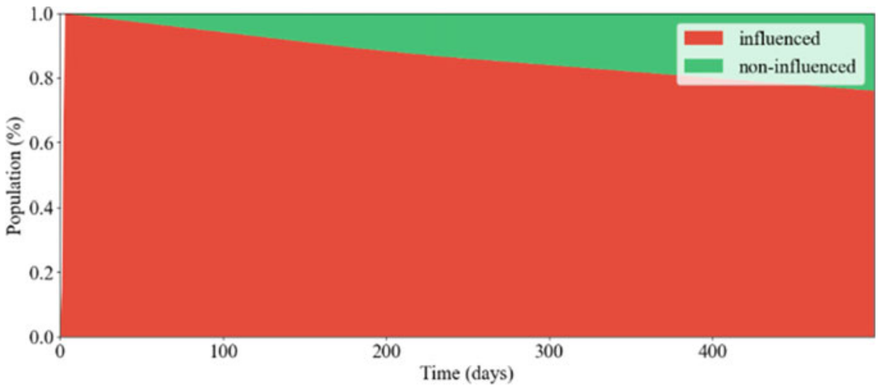

Fig. 6.11 Result of removing the opinion-based calculations from the model

6.5 Varying the 'Follower Factor' Variable

Using the original influencer model the value of the 'follower factor' variable is varied to determine the behaviour of the model in response to this change. A total of five different sets of the follower rate were tested, in each case, each set was randomly generated and simulated. Table 6.3 defines the different sets of follower rates used.

Based on the results obtained using the random variables, the number of new followers is directly proportional to the 'follower rate', this does not come as a surprise, however, the behaviour resulting from the relationship between 'follower rate' and susceptibility can also be observed from this experiment. Building on this point, we must note that for this model, the susceptible ratio of the population per age group is defined as [0.1, 0.61, 0.22, 0.07], which implies that the most susceptible age group is between the ages of 17–35 years. If the follower rate augments the correct age group—in this case the adult age group—there will be a healthy growth in the number of new followers' overtime. However, in the case the follower rate does not augment the age group that is the most susceptible, the rate of increase in the number of followers is less in comparison. We can observe this effect by comparing the results of the random sets 3 and 4 depicted in Figs. 6.12 and 6.13, respectively.

Table 6.3 Random values used for determining the effects of follower rate

	Values
Random 1	[0.269979, 0.745675, 0.227634, 0.26146]
Random 2	[0.587839, 0.777752, 0.724959, 0.336366]
Random 3	[0.009422, 0.777854, 0.252165, 0.614234]
Random 4	[0.713371, 0.468194, 0.774718, 0.647773]
Random 5	[0.23911, 0.214832, 0.274497, 0.512304]

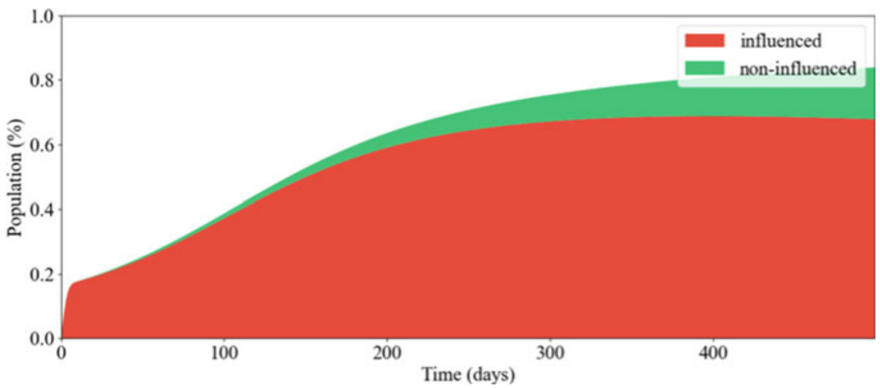

Fig. 6.12 Results of using random set 3 for follower rate

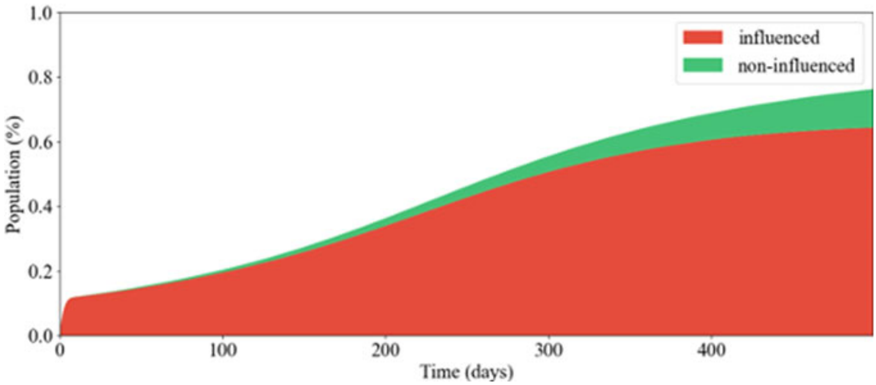

Fig. 6.13 Results of using random set 4 for follower rate

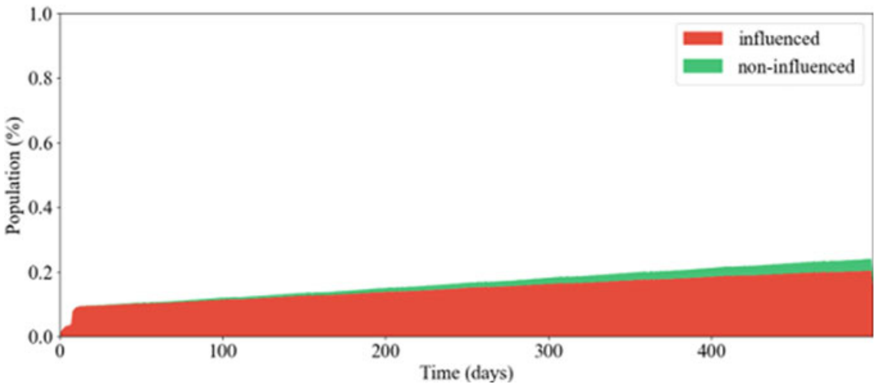

Fig. 6.14 Results for using random set 5 for follower rate

In general, a low 'follower rate' in all age groups results in a weak increase in follower count, and this can be observed in the results of random set 5 visualised in Fig. 6.14.

6.6 Introverts Versus Extroverts

The goal of these tests is to determine whether a particular personality type is more vulnerable to becoming a follower or not. The experiment is carried out using two different methods, the first being two small groups of cells being defined as either introverted or either extroverted, while the second involved having all cells—except from the influencer cell and its Moore neighbourhood—being either introverted or extroverted. Both methods involve changing the 'extrovert factor' of the cell by randomising the values based on a particular range to simulate an introvert or an extrovert personality. For example, in the case of an introvert the randomisation range is set to 0–0.2 while for an extrovert the range is 0.6–0.9.

For the first method, a group of cells was designated as introverted, while in the same configuration file, a secondary group is designated as extroverted. This method was tested three times, each with a random generation of values for the 'extrovert factor'. Based on the results gathered from this first method, there is no definite proof that personality affects the increase in follower count. There are three reasons that could explain why this is the case, the first is that the two groups created were too small to observe a definitive behaviour and thus, the overall behaviour of the other cells overshadowed any relevant behaviour. The second reason could be that the cumulative behaviour of the cells simply results in an increase in the rate of number of followers, overshadowing any observable patterns that would result from different personalities. The final reason could be that personality differences have no effect on the rate of increase in follower count, however, to investigate whether there is a foundation to this reasoning the second method was implemented.

The second method randomises the 'extrovert factor' for all cells, with once scenario having all cells set as introverts, while the second scenario has all the cells set as extroverts. Both scenarios randomly generate the 'extrovert factor', with three different sets, and both scenarios are simulated separately. In both scenarios, no discernible difference was observed in the rate of increase in follower count. Thus, the third reason introduced still holds, and based on these results different personalities do not seem to affect the rate of increase in follower count.

6.6.1 The Pandemic Scenario

Having defined the behaviour of the influencer model, the model is further experimented with by applying it to realistic use cases. This section presents the application of the influencer model towards a scenario with a society that has been affected by pandemic regulations.

The original influencer model is applied to a scenario that has been extended to include limit factors to simulate three general scenarios that appeared to occur during the pandemic. The three phases for this specific model can be described by the assumptions as follows.

1. Before the pandemic—individuals have an active social life, reducing the free time they must have to browse social media. This results in an average interest on influencers, with an average rate of follower increase.
2. During the pandemic—individuals have a reduced social life, with lockdowns in effect and limited physical activities. This results in an increase in free time as individuals try to find more relevant and entertaining forms of digital diversions. With the increased free time, individuals may also engage in personal growth activities, by finding hobbies and influencers that share their interests. Based on

these assumptions, the model is designed to increase the follower rate during this phase to simulate the higher probability of becoming a follower.

3. After the pandemic—as lockdowns and restrictions are lifted, individuals can be assumed to try to make up for the time they lost outdoors. Thus, individuals are more likely to engage in physical and social activities. This assumes that individuals would be mentally exhausted by the lockdown rules and regulations and would be anxious to get back to a sense of normalcy. Based on these statements the follower rate would be lower when compared with during the pandemic phase.

The limit factors and phase change factors are implemented using an incrementing simulation clock. During each cell iteration the simulation clock time is used to calculate which phase the simulation is currently in. Based on the calculated phase, the respective limit factor is applied to the state calculation, which directly impacts the rate at which the follower count increases.

The importance of this model is to demonstrate how external environmental changes can affect how an individual responds to the influencer presence.

The result of the pandemic scenario demonstrates how the follower count can drastically change due to changes in the global environment, as can be observed by the sudden spikes—at time 100 days—and drops—at time 400 days—in the follower count increase presented in Fig. 6.15. Figure 6.16 shows the dynamic behaviour of the states over the shared rate of time.

The pandemic model is controlled by the limit rates and the scheduled phase changes, in this case the phase changes occur at timestamp 100 and 400. If a phase change is scheduled the corresponding limit rates are applied for that phase until the next phase change. For the first phase of this scenario, (time stamp 0–100), the limit factor is 0.5, for the second phase, (time stamp 100–400), the limit factor is 2, and finally, for the last phase the limit factor is 0.5. The effects of the limit factors can be observed in the simulation, in timestamp 100, there is a sharp spike in the rate

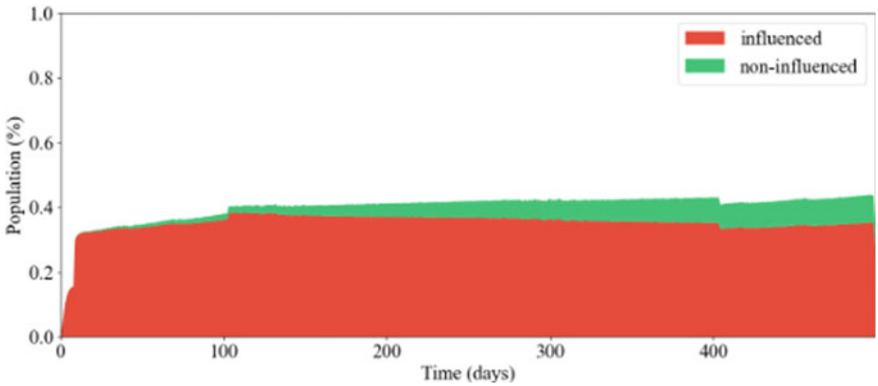

Fig. 6.15 Rate of increase for follower and non-follower rate for the pandemic scenario using the influencer model

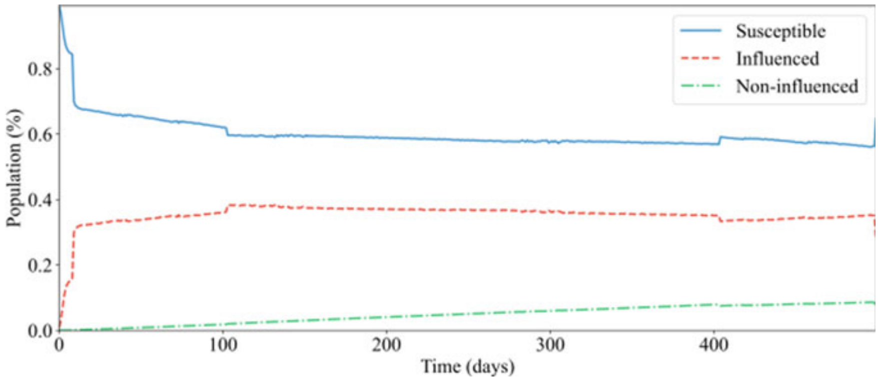

Fig. 6.16 Line plot comparing susceptibility and follower rate for the pandemic scenario using the influencer model

of increase in number of followers as the applied limit factor transitions to 2, and a sudden drop is observed at time stamp 400 as the limit factor transitions to 0.5 illustrating the expected behaviour during each corresponding phase change.

The limit factors are set to simulate the three phases defined for the pandemic scenario. Based on the results, the expected behaviour can be observed for each phase. However, these results only strengthen the assumptions made about social behaviour during a pandemic. This predefined behaviour may not occur and there may be other factors at play. It could be said that after the pandemic (third phase) there was never a drop in interest towards social media, and the effect of remote working further strengthened the attitude individuals had towards pursuing their personal growth objectives and hobbies, thus leading to a continued increasing follower count. It could also be said that during the pandemic individuals have created the habit of following influencers and browsing social media, and this trend continued even after the pandemic. There are several factors that can affect the follower count rate, hence this scenario does not fully represent the reality of the situation but demonstrates how the model can be used for such scenarios if more realistic data is present to corroborate the simulation.

The DEVS simulation for the pandemic model is shown in Fig. 6.17. The affected cells are comparably not as many as the original influencer cell, this is because the pandemic scenario implements limit factors, that is, a reducing limit factor is applied during the first and last phases of the simulation.

6.6.2 The Academy Awards Scenario

This scenario further extends the pandemic scenario applying the limit factors while simulating individual behaviour towards two separate influencers simultaneously.

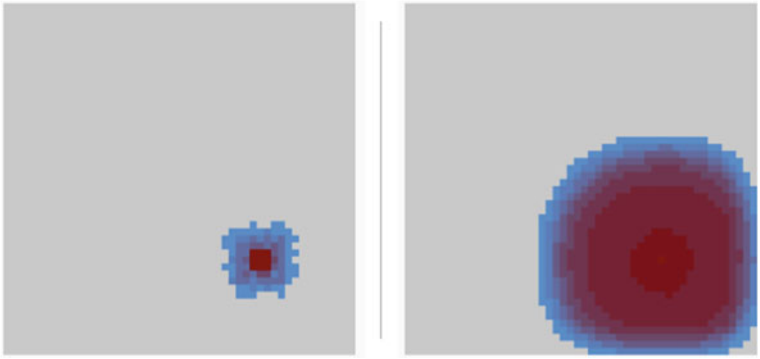

Fig. 6.17 Spread of influence across the cell grid using DEVS viewer

This scenario exemplifies how certain global changes can affect one influencer public status while having no effect on another. As in the case of the Academy Awards, by nominating a certain actor or actress, that influencer in question will be globally publicised, however, other artist may not receive the same amount of attention due to the lack of publicity. This is the reason using two influencers in the simulation is important to compare the differences certain factors that can have on the follower count, and how trends affect the probability of following an influencer.

The scenario will have three phases as described below:

1. Before the Oscars—it is assumed that both influencers in this case have a similar popularity rating, with low public recognition. The rate of increase in follower number will be muted but present.
2. During the Oscars—this statement can be vague without specifying that range of time this takes place. This assumption made here is that the period is between announcements of the nominations to the end of the award ceremony. During this phase, the influencer publicised by the annual awards will experience a spike in follower rate, while the second influencer will continue to observe the same rate of increase.
3. After the Oscars—once the Oscars are over, the promotion and movement to raise recognition for the first influencer loses traction. However, the popularity of the first influencer is still higher than the second. This assumes that, once a popular public personality has gained some amount of global awareness, their presence is widely spread through social media and social interactions.

Overall, this scenario demonstrates how external factors can affect a single influencer instead of all current influencers.

The implementation of this scenario was slightly more complicated when compared with the previous scenarios. Although the state transition equations do not change, the limit factors are applied based on the phase changes as described in the pandemic scenario. However, the possible state for each cell is doubled. Each cell in this case has eight dynamic states, the first four states, influenced, non-influenced, opinion, and susceptible remain unchanged, and four additional states are added to depict the states of the cells with respect to the second influencer, hence the four states added are influenced_second, non-influenced_second, opinion_second, and finally susceptible_second. The first four states are specifically for the first influencer and represent the ratio of individuals in the cell that are influenced/non-influenced by, susceptible to, opinion on the first influencer, while the last four states are equivalent to the first four states but with respect to the second influencer. Furthermore, the calculations applied during each iteration is dependent on if the new state being calculated is for the first influencer or the second influencer.

For the implementation to work on both the first and the second influencer without requiring additional duplicate code for the second follower, the base code is reused, and pointers are applied. The data the pointers point to change based on if the calculation is for the first or the second influencer. During each iteration, all eight new states of the cell are calculated starting with the first influencer and followed by the second influencer. After the states of the first influencer is calculated, a flag is set to ensure the pointers used to point to the state data points to the states for the second influencer. The state transition equations then calculate the new states using the new data that is being pointed to.

This scenario's main goal is to demonstrate that it is possible to simulate two influencers in the same scenario while also demonstrating that it is possible that the attitude of individuals towards different influencers are distinct.

The plot for each influencer is separated and it can be observed that the behaviour of individuals towards the two different influencers are disparate. For the first influencer there is a sharp spike at the beginning of the second phase—100 days—and a progressively increasing follower count after the third phase—400 days, whereas for the second influencer there are no predominant spikes and a mostly stable follower count growth. As previously done with the pandemic scenario there are three phases, and the values of the corresponding limit factors are 0.5 for the first, 2 for the second, and 0.8 for the third to simulate an average following before the Oscars, an increasing popularity during the Oscars after being widely recognised for their accomplishments, and a continued vehemence for the influencer after the Oscars. The third phase assumes that individuals that adore the influencer will continue to propagate awareness of the influencer and endorse their future projects. Additionally, during the second phase the probability of connections between the general population and the influencer is doubled as individuals purposely look for the influencer in question on social media, and news circulations—relevant news associations would want to advertise the Oscar candidates and explore their lifestyle to participate and emphasise the significance of the Oscar's—increase the probability of individuals becoming more aware of the influencer.

Figures 6.18, 6.19, and 6.20 illustrate the expected behaviour during such a global event, however, as mentioned with the pandemic simulation, this behaviour was predetermined and does not reflect the reality of the situation. There are certainly other possible outcomes that can occur, for example the influencer being nominated for the Oscar could suddenly be impacted by negative publicity during the second phase of the scenario, and instead of having an enlarging limit factor, could see a sharp drop—or paradoxically a sharp increase as individuals become absorbed into the scandal—in popularity instead with a reducing follower count after the Oscar's as popularity drops and the scandal fades away.

In conclusion this scenario does accomplish its goal of illustrating how two influencers can have different follower count patterns and are individually impacted by certain scenarios.

The DEVS simulation of the scenario can be seen in Figs. 6.21 and 6.22 for both the influencers. As with the pandemic scenario the cells are shaded from light to dark with respect to the probability value of becoming a follower.

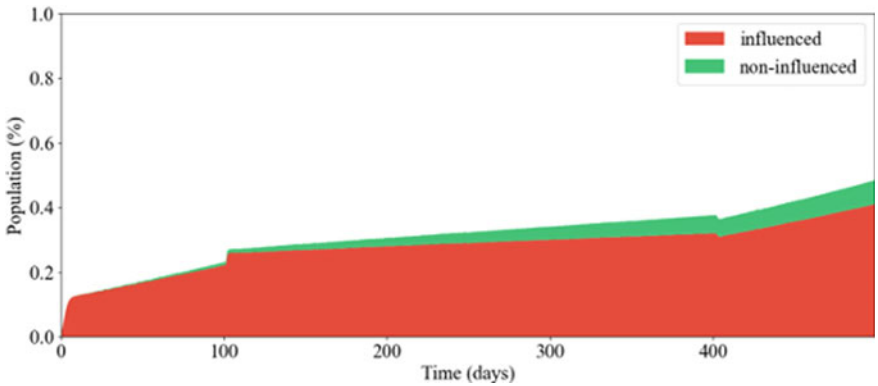

Fig. 6.18 Increase in follower and non-follower rate of the first influencer in the Oscar's scenario using the influencer model

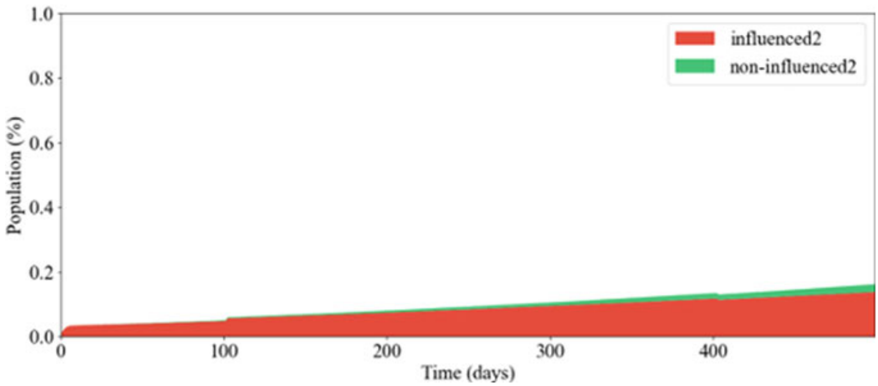

Fig. 6.19 Rate of increase for follower and non-follower for the second influencer in the Oscar scenario using the influencer model

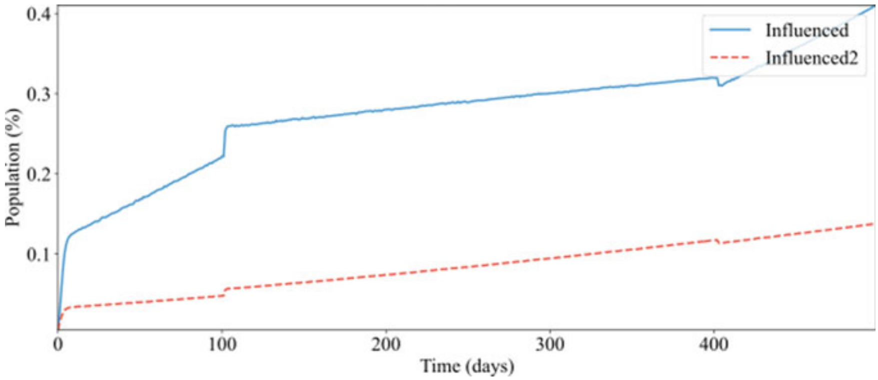

Fig. 6.20 Line plot comparing the rate of increase of the follower rate for the first and second follower in the Oscar scenario

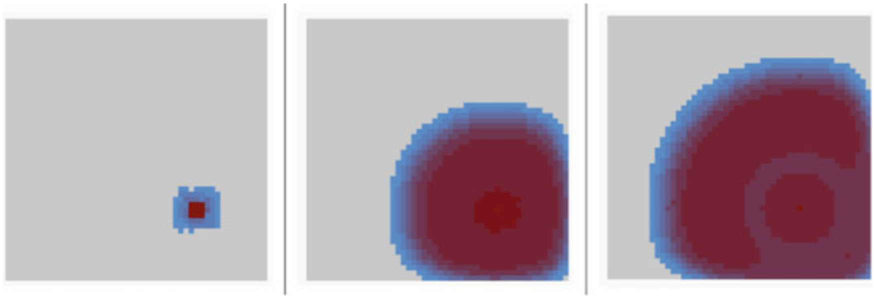

Fig. 6.21 Spread of influence with respect to the first influencer across the cell grid using DEVS viewer

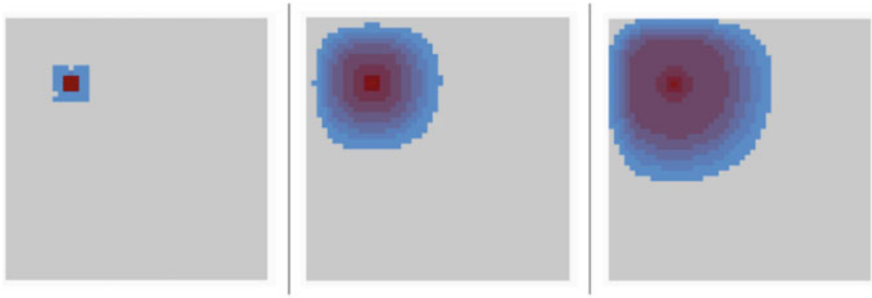

Fig. 6.22 Spread of influence with respect to the second influencer across the cell grid using DEVS viewer

6.7 Conclusion and Future Work

We presented a model that defines a network-based approach with an opinion evolution calculation. This is an important aspect of the model that predicts an individual's opinion towards the influencer, the effects of the opinion towards the individuals' actions, and the impact of the present individual's opinion on its close susceptible neighbouring persons. The evolution of opinion ascertains that the rate of increase in follower count occurs in parallel to the rate of increase in the individual's positive opinion, that is, as the probability of a positive opinion increases, the probability of the individual following the influencer increases. The model also takes into consideration the convenience/accessibility of social media platforms and the constant availability of influencers. Thus, influencers are treated as constant companions to the individuals in the model. Additionally, we provided a relevant example on how the model can be applied to real-world scenarios.

We employ the Cell-DEVS formalism, which has proved to be useful for simulating the spread of infectious diseases, to create a working model that is capable of simulating the rate of increase in follower count pertaining to a certain influencer under various scenarios and possible timed events.

In the future, we hope to extend the influencer model to use a threshold-based approach in determining the impact of neighbuoring agents on the opinion evolution of an individual. Furthermore, a quantitative approach could be taken to explore the real-time validation of the model, by collecting and mining for data that represents the rate of increase in follower count with respect to an influencer under certain conditions and available events. Another interesting approach would be to apply sentiment analysis in combination with machine learning to gather data from various social media platforms that can be used in the real-time validation of the model. By applying sentiment analysis machine learning techniques, we can further refine the behaviour of the opinion simulation in the influencer model. This could be useful—although not an abstract simulation—to further study the impact of influencers on social media.

Finally, modifications can be made to the assumptions taken for this model, for example, removing assumption 4 by modifying the current model to have an additional transition function to determine the count of non-followers that transition to becoming susceptible again with a timed wait period. This would represent individual behaviour that occurs on social platforms, where individuals constantly contradict their previous decisions and are thus likely to refollow influencers given various reasons, such as a change in popular attitude towards the influencer or correcting a previous mistake.

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