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Enhancing Evacuation Warning Responsiveness: Exploring the Impact of Social Interactions through an Agent-Based Model Approach

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16. Abstract

Evacuations are the preferred response to human- or natural-caused disasters. The process often involves people deciding when and how to evacuate based on messages from local authorities. However, diverse opinions of the affected people may influence their decision to evacuate or to stay and see how the situation unfolds. This project applies an opinion dynamics concept to model the opinion and decision-making of people threatened by wildfire. To demonstrate how individual opinions evolve with time, the model applies an agent-based approach that includes the interaction between an agency sending an evacuation message and the affected population. There are three sources of information concerning the mathematical model of an opinion: the global broadcasting message, interaction of the agent with its social media network, and observations of neighbors' actions. The opinion value of each agent leads to a decision to evacuate if it overcomes a resistance threshold. By combining sources of information, the results show that when global broadcasting is the only information available to agents, a decision to evacuate is unanimously reached after a short period. However, when social media interactions are included, there is a delay in reaching a unanimous agreement to evacuate. Furthermore, when social media interactions are replaced by observing the actions of neighbors, there is no agreement to evacuate among the agents, and most of them decide to stay and see how the situation progresses. This research project provides opportunities for planning and management of traffic and routes when an evacuation is expected but the number of people participating is unknown. The results provide valuable insights that could be applied as part of disaster-planning and other potentially life-saving measures.

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Executive Summary

Evacuations are the preferred response to human- or natural-caused disasters. Currently, evacuation procedures in municipal areas depend upon local authorities sending a message to the affected people. However, not everyone who receives an evacuation order will abide by it. From a transportation viewpoint, knowing the percentage of people that will evacuate a threatened area may provide important insights for traffic planning and route selection. However, the diverse opinions of the affected people may influence their decision to evacuate or to stay and evaluate how the event evolves over time.

This project presents the application of the concept of opinion dynamics to model individual opinions and decision-making of people threatened by a wildfire event. To demonstrate how individual opinions evolve with time, the simulation applies an agent-based model that includes the interactions between the agency sending an evacuation message and the affected population, as well as, the interaction among these agents. There is implicit complexity and randomness in the analysis of people's opinions, and ABM has effectively proved to simulate complex interactions among heterogeneous entities considered as agents. Furthermore, the adaptation of agents arises from their rule-based interactions and may disclose emergence at the aggregate level that is not evident at the individual level. Hence, the project incorporates a python-based code that implements the ABM using the mathematical formulation of opinion dynamics concepts.

There are three sources of information concerning the mathematical model of an opinion, including the global broadcasting message, the interaction of the agent with its social media network, and the agent's observations of its neighbors' actions. The opinion value of each agent leads to a decision to evacuate if it overcomes a resistance threshold. This threshold is modeled as a random sample from a uniform distribution. By combining sources of information, the results show that when global broadcasting is the only information available to agents, a decision to evacuate is unanimously reached after a short period. However, when social media interactions are included, there is a delay in reaching a unanimous agreement to evacuate. Furthermore, when social media interactions are replaced by observing the actions of one's neighbors, there is no agreement to evacuate among the agents, and most of them decide to stay and see how the situation progresses. The model output presents a computer-interactive tool where the user can adjust the input parameters to tailor the model to different social conditions and evaluate the compliance rate of the affected people evacuating a threatened area.

This research project provides opportunities for the planning and management of traffic conditions and route design when an evacuation is expected but the number of people participating in the evacuation is unknown. The model developed in this project may assist traffic agencies in evaluating local conditions regarding evacuation opinions.

1. Introduction

Extreme weather conditions including abrupt heatwaves and prolonged droughts increase the probability of more destructive wildfires in California. These unwanted natural scenarios demand an improvement of the warning systems around evacuation processes. Currently, most warning systems depend on communication from state and federal agencies to the population about the probability of adverse events such as wildfires threatening their properties, also known as global broadcasting (Karlamangla, 2023). Once the warning is received by the population, communication between affected residents, also known as social network interactions, is among the factors that determine their course of action regarding evacuation decisions. Based on these types of communication and interactions, the call to evacuate is evaluated by the affected residents in order to reach a decision. In this research, we develop a model that determines the effects that communications from agencies and among residents have on an individual's decision of whether to evacuate from a threatened area.

As peer-to-peer communication brings complexity to mathematical modeling, this project evaluated alternative modeling tools that can handle the randomness, nonlinearity, and adaptiveness of such interactions. Agent-based modeling (ABM) of evacuation events has been applied broadly to emergencies and natural disasters (Du et al., 2017; Hassanpour & Rassafi, 2021; Jumadi et al., 2017; Liu et al., 2016; Madireddy et al., 2011; Na & Banerjee, 2019; Rendón Rozo et al., 2019; Trivedi & Rao, 2018; Wagner & Agrawal, 2014; Watts et al., 2019). Previous research has included the developed behaviors of the affected population and evacuation effectiveness strategies for situations including seismic events involving buildings and human activity (Liu et al., 2016). More extensive areas have been analyzed by integrating geographical information systems and possible routes for economic and risk management in case of no-notice natural disasters such as earthquakes (Du et al., 2017; Na & Banerjee, 2019). Additionally, ABM applications have covered behavioral elements through social interactions with evolving information (Watts et al., 2019). Despite extensive research on different types of simulations and exchanges of data, there is limited consideration of current social factors as fundamental model-drivers in the modeling. These factors, such as social media and social networks, affect the interactions of people and their ultimate decisions regarding an event. Hence, the present research aims to apply an ABM to simulate influential, modern social interactions that reflect the willingness and probability of agents (citizens) to evacuate from a defined area when an alert of a natural disaster has been issued.

Various aspects of the social influence of interacting people have been extensively analyzed. For example, an ABM to evaluate how households decide on installing energy-efficient artifacts was developed by coupling a numerical simulation with different network topologies (McCullen et al., 2013). Peer-to-peer communication and its outputs have been analyzed from an environmental side, including research on the willingness of agents to trade rainwater for irrigation purposes and defer the usage of potable water (Ramsey et al., 2020), the usage of decentralized generated electricity (Jacob et al., 2023), and the modeling of water demand at the user level (Xiao et al., 2018). The common factors of these previous ABM implementations are the granularity of the analysis and the modeling of communication strategies. Granularity refers to what an agent represents; in these applications, an agent represents a household unit. For communication strategies, placing agents on a graphical network provides the tools needed to simulate peer-to-peer interactions.

ABM represents a computing paradigm of the analysis of agents and their interactions, and most of its applications use simulation environments as part of computer modeling. Multiple software products offer ABM analysis, including the open-source MESA package in Python (Kazil et al., 2020), NetLogo (Wilensky & Rand, 2015), Mason (Luke et al., 2019), and proprietary software such as AnyLogic (Borshchev, 2014). On the one side, feasible applications of ABM could support the analysis of evacuation scenarios from an infrastructural approach around routes and the built environment. Then, the models couple the simulation environment (e.g., NetLogo and Mason) with physics-based modeling, which depends on the application (Hassanpour & Rassafi, 2021; Madireddy et al., 2011; Rendón Rozo et al., 2019; Trivedi & Rao, 2018; Wagner & Agrawal, 2014).

Previous ABM applications support the analysis of evacuation scenarios. For example, previous research applications relate evacuation time with how agents interact with the infrastructure around them, including the area threatened by a disaster. These works analyzed how people respond to their displacement options, available spaces, and specific obstacles during evacuation processes (Hassanpour & Rassafi, 2021; Madireddy et al., 2011; Rendón Rozo et al., 2019; Trivedi & Rao, 2018; Wagner & Agrawal, 2014). Consequently, this approach has related evacuation time to how agents interact with the area threatened by a disaster in order to implement preventive actions for future evacuations.

From the analysis of agent responses, studies around transportation and risk management for disasters also integrate social-behavioral approaches around decision-making. Those studies implement concepts of evolving information and stimulated reasoning along with population density and individual assessments (Fang et al., 2016; Jumadi et al., 2017; Watts et al., 2019). The takeaways from those projects enhance the simulation of social interactions, giving them individual attributes and collective phenomena, such as grouping, crowding, and feedback loops (Fang et al., 2016; Jumadi et al., 2017; Watts et al., 2019). Consideration of the behavior of agents when exposed to variable scenarios and different channels of information has led researchers and administrators to upgrade protocols against sources of risk.

In this study, a prominent theory elucidating the impact of social influence on opinions is employed to model evacuation responses. The opinion dynamics (OD) theory serves as the theoretical foundation, explaining how the distribution of opinions among a group evolves over time (Rainer & Krause, 2002). It offers a way to simulate these changes that considers interactions and social influence. The OD model, developed for this purpose, simulates the information acquisition process as a linear combination of peer opinions. It is extended to incorporate additional information sources like social media and observations of the actions of one's neighbors (Du et al., 2017; McCullen et al., 2013). Opinions are dynamically updated through pairwise social interactions, and individuals decide to embrace innovations when their motivation surpasses a predefined threshold. The OD framework is integrated into an ABM framework effectively to capture and model decisions related to evacuating residences in response to wildfire threats.

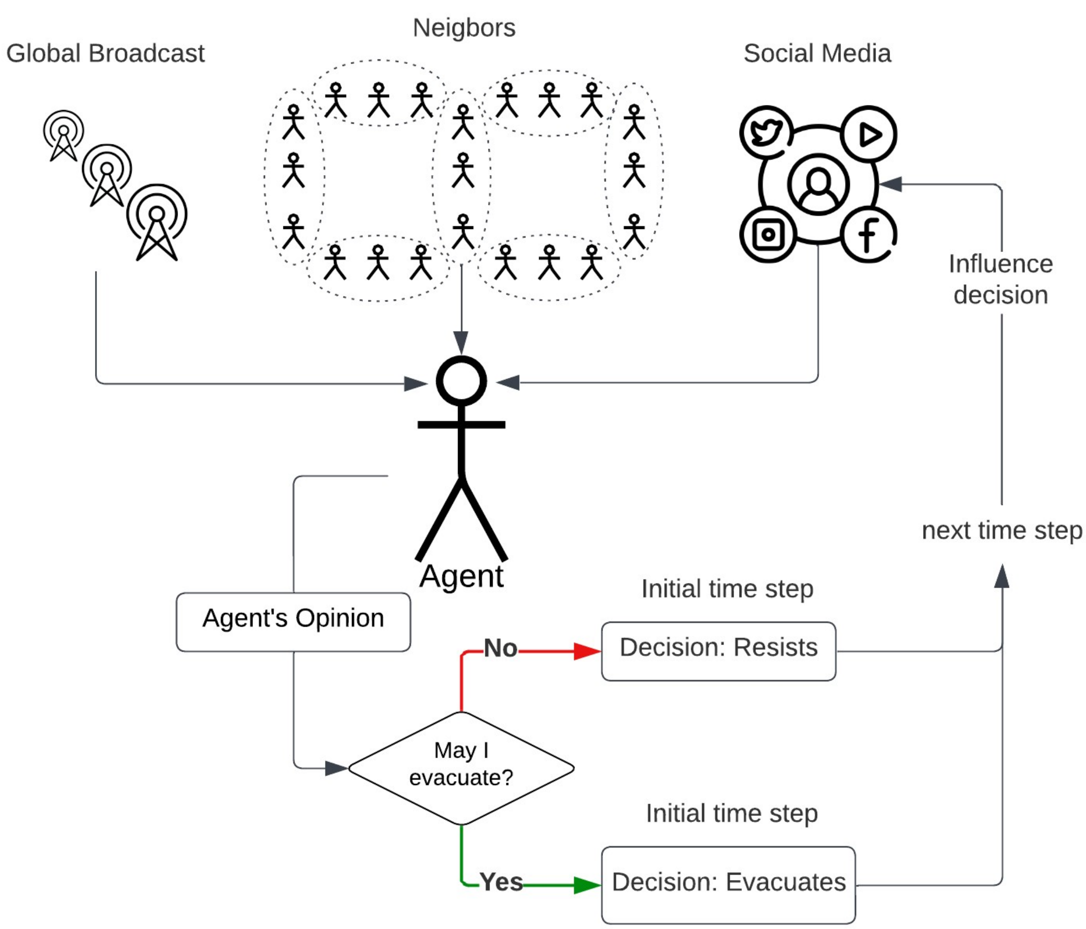
Combining the infrastructural and social-behavioral approaches mentioned above, ABM has been applied to a complex system of decisions around available resources, consequential actions, and the possibility of success (Fang et al., 2016; Hassanpour & Rassafi, 2021; Na & Banerjee, 2019). In addition to covering different disasters, previously developed ABMs have also aimed to model immediate actions in response to general communication. However, this approach limited the modeling to one-way communication, where the agent received information and responded to the agency's directions (Jumadi et al., 2017; Na & Banerjee, 2019; Wagner & Agrawal, 2014; Watts et al., 2019). Hence, more research is needed in the field of evacuation modeling on different communication techniques and different kinds of interaction among agents. This research applies an ABM to model the interaction between an agency and the agents in an area threatened by wildfire. The approach contributes to the field of evacuation analysis and modeling by providing a management tool for city planners and agencies that can be used to evaluate the level of response and traffic alternatives effectively to evacuate people from an affected area.

The rest of the report is organized as follows. The methodology section presents the mathematical formulation of the opinion dynamics model and the interaction among agents to calculate their opinions and decisions on whether to evacuate a threatened area. Then, the results and discussion sections show the trajectory of agents' opinions and decisions over the simulation period. This section also presents the number of agents that will evacuate and the number of agents that will choose to stay and see how the situation unfolds. Finally, the conclusions section highlights the effects of randomness, initial conditions, number of agents, and simulation period on the opinion and decision trajectories.

2. Methodology

This section presents the mathematical formulation of the agent-based model using the opinion dynamics theory to determine the opinion of agents over the simulation period. Our model is an application of the research project conducted by Du et al. (2017) and works as presented in Figure 1. Once the agency identifies a geographical area likely to be affected by a wildfire, the agency sends out an evacuation alert. The agents receive the evacuation alert and form an opinion about evacuating or not based on their interactions with their social networks. Social networks include the use of social media and personal communication among neighbors. The modeling framework for a population of 240 agents (agents represent households) is presented in the following sections.

Figure 1. Overview of the Opinion Dynamics Model to Determine the Opinion and Decision of an Agent in Response to a Wildfire Threat



2.1 Opinion Dynamics

The opinion dynamics model originates from the general rule provided by Bassett et al. (2012) to define the information state trajectory of an agent based on three sources of information: global broadcasting (G), the exchange of information through social networks (a_{ij}), and the actions of neighbors around an agent (b_{ij}). The mathematical formulation is shown in Equation 1:

$$O_j(t+1) = \left(1-\theta_j\right)O_j(t) + \theta_j \frac{\alpha \sum_{i=1}^{Nsm} a_{ij}(t)O_i(t) + \beta \sum_{i=1}^{Nn} b_{ij}(t)X_i(t) + \gamma\, u_j(t)G(t)}{\sum_i a_{ij}(t) + \sum_i b_{ij}(t) + u_j(t)} \qquad 1$$

where $O_j(t+1)$ represents the opinion of agent j at the next time step $t+1$; $a_{ij}$is a binary variable (0, 1) that corresponds to the communication of agents i and j at time step t via social media; similarly, $O_i(t)$ is the opinion of agent i at time step t. The binary representation (a_{ij}) reflects the variability of communication of agents through a social media network of Nsm agents through the simulation period. The variable b_{ij} is also a binary variable (0, 1) that represents communication between agents via a network of Nn neighbors; $X_i(t)$ is the decision value of agent i at time step t; u_j is the probability that the global broadcast message is received by agent j at time step t. G is a binary variable (0, 1), where 1 represents a warning sent by the central agency, 0, otherwise. The value of θ is the learning rate that models how some agents may update their opinion and others not, and it is defined as a random variable sampled from a normal distribution with a mean of 0.5 and a standard deviation of 0.05 (Du et al., 2017). Finally, three variables are included to evaluate the effects of each source of information on the opinion values and are weights $\alpha, \beta,$ and γ, which add to one.

The existence of any variable from the source of information is denoted with a value of 1, or 0 when non-existent. Once an opinion O_j is calculated, agent j decides about evacuating from the threatened area by comparing its opinion value to a resistance threshold, as shown in Equation 2:

$$X_{j,t} = \begin{cases} 0, & \text{if} \quad O_{j,t} < R \\ 1, & \text{if} \quad O_{j,t} \geq R \text{ or } X_{j,t-1} = 1 \end{cases} \qquad 2$$

where $X_{j,t}$ is a binary variable equal to zero (do not evacuate) if the opinion value is lower than the resistance threshold R; $X_{j,t}$ will be one (evacuate) if the opinion value is higher than R or the decision to evacuate was positive in the previous time step. When defining an adopted action of an agent i, the variable depends on R, the resistance value sampled from a uniform probability distribution with a predefined parameter U. As a result, the agent j reaches a positive decision, represented as 1, or negative decision, represented as 0, with respect to evacuating the affected area.

2.2 Scenarios

This section explains the opinion and decision trajectories when multiple scenarios are evaluated. Scenario 1 includes global broadcasting (weight α) as the only source of information, Scenario 2 includes social media interactions with global broadcasting (weights α and β), and Scenario 3 includes neighbors' interactions with global broadcasting (weights α and γ). The input data used for the different scenarios is presented in Table 1.

Table 1. Scenarios with Values for Different Sources of Information

Scenario	Sources of Information	Weight α	Weight β	Weight γ
1	Global	N(0.5, 0.05)		
2	Global + Social Media	N(0.5, 0.05)	$1-\alpha$	
3	Global + Neighbors	N(0.5, 0.05)		$1-\alpha$

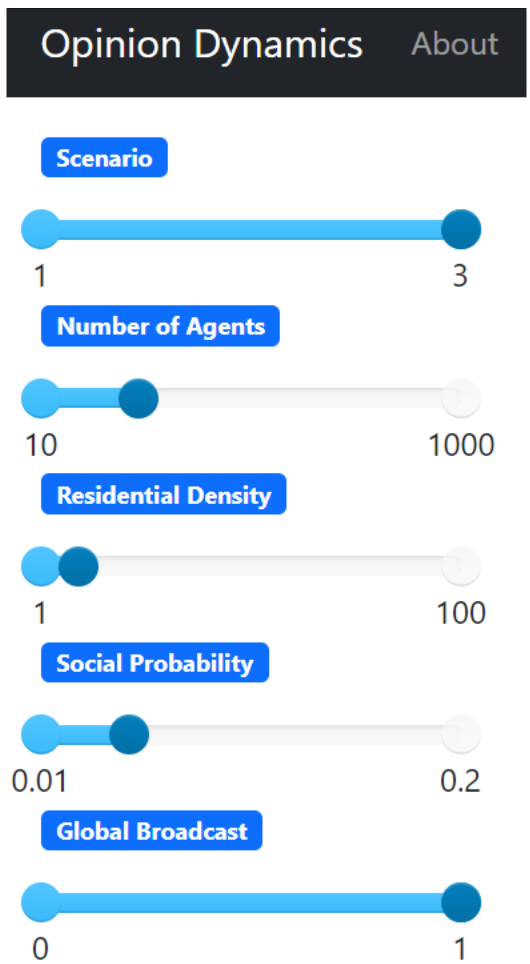
$N(mu, sigma)$: Normal distribution with mean (mu) and standard deviation (sigma).

There are two additional input values needed for the model when taking the conditions for Scenarios 2 and 3. The first of these input variables is "social probability" and refers to the interaction of agents within a social media network. The model places each agent on a network graph using the graph generator "gnp_random_graph" (McDiarmid & Skerman, 2018) of the Python package NetworkX. This feature allows the user to analyze separately an individual agent and its social media contacts with a given probability value defined as "social probability." "Social probability" is defined as 0.05 which corresponds to an agent having, on average, 20 active social media contacts, but the user may adjust this value using the slider option of the model interface. The second input value is "residential density," which refers to the interaction between the agent and its neighbors. The model places each agent on a network graph using the graph generator "complete_graph" of the Python package NetworkX. "Residential density" is initialized as 10, which corresponds to an agent interacting with 10% of the nodes representing its neighbors. This value can also be adjusted by the user using the corresponding slider in the output environment. The reasoning behind using two graphs to place an agent for social media interaction and neighborhood interaction is that social media involvement is conceived as being much more variable than observations of neighbors' actions. Hence, the "gnp_random_graph" is a random graph where an agent may interact with any agent regardless of its geographic location. However, using the "complete graph," we ensure that an agent will interact with agents within its geographic location.

3. Application

The model is applied to a network of N agents and uses a simulation period that represents daily time steps. The input variables of the model are the following: number of agents (N); scenario number (1 – 3), as seen in Table 1; residential density, which is a value from 1 to 100; and social probability, which is a value from 0.01 to 0.2. Users can adjust the input values using the sliders of the output environment to tailor the model to their local conditions. Figure 2 shows the output environment at the beginning of the simulation.

Figure 2. Output Environment of the ABM-OD Model to Evaluate the Opinion and Decision Trajectory of Agents Over the Period of Simulation



4. Results

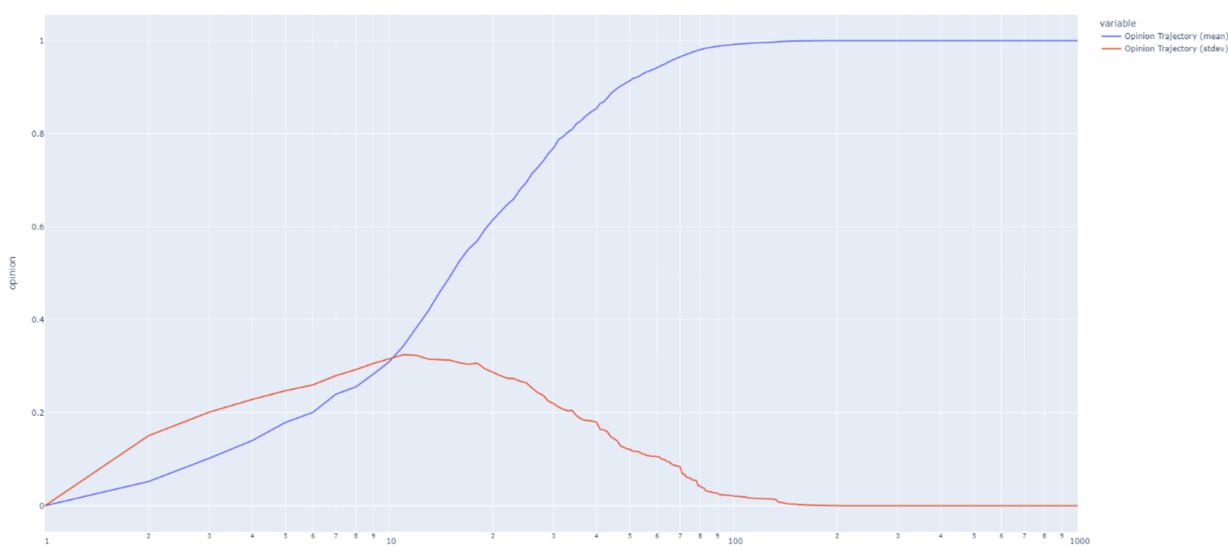
This section presents the numerical and graphical values of the opinion and decision trajectories evaluated by each scenario over the simulation period. The time steps correspond to days. The average opinion (O) and decision (X) of a set of 240 agents are presented along with their average and standard deviation values.

4.1 Opinion and Decision Trajectories

Scenario 1

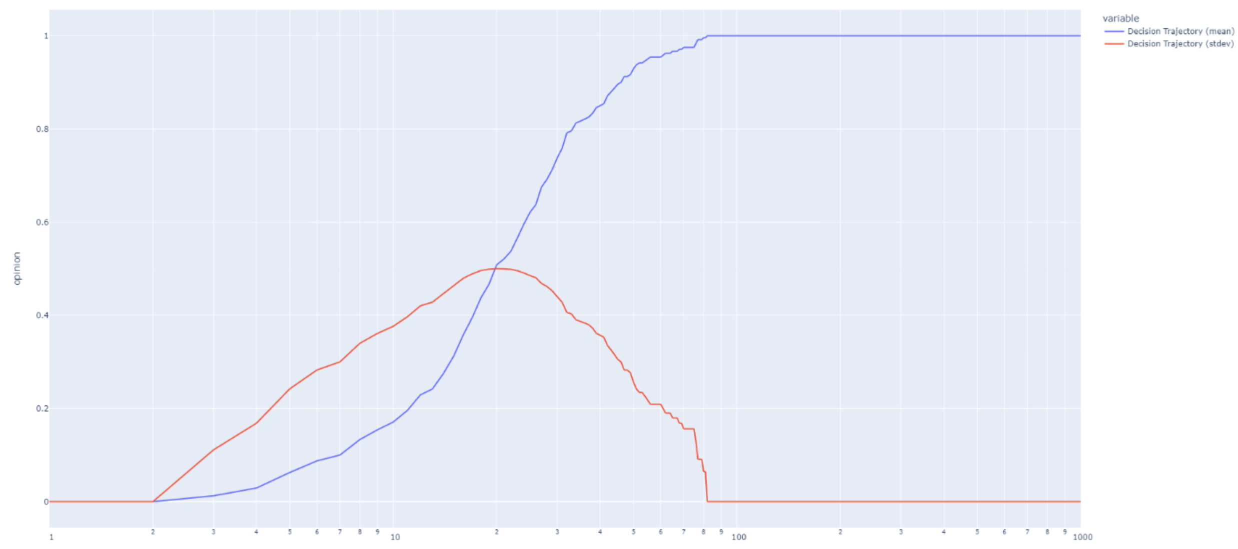
Scenario 1 includes the warning message about evacuation sent by the central agency as the only source of information for the agents. At time step one, the agents receive the warning message and form an opinion about the evacuation that will be compared to the resistance threshold to make a decision. The average and standard deviation opinion trajectory shows that initially, the agents are reluctant to evacuate with average opinion values lower than 0.5 (Figure 3). However, as time passes, the average opinion value increases to values above 0.90. (Note the x-axis has a logarithmic scale.) Furthermore, the opinion of agents reaches a maximum value of one right after time step 100 (Figure 3).

Figure 3. Mean and Standard Deviation of the Opinion Trajectory Over Time for Scenario 1: Global Broadcast as the Only Source of Information



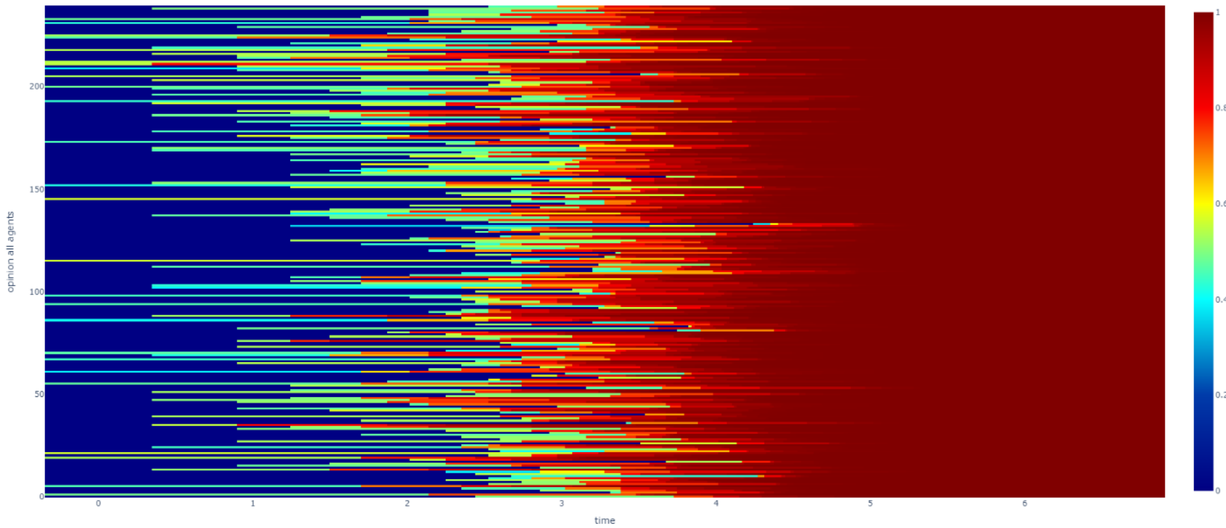
Like the opinion trajectory, the model also reports a decision trajectory, which is the result of comparing the opinion values to the resistance threshold. This project uses a uniform distribution with a range of [0.4, 0.9], including low values and excluding high values, to represent the resistance threshold of each agent. The average decision trajectory (Figure 4) shows that at time step 46, most agents decide to evacuate.

Figure 4. Mean and Standard Deviation of the Decision Trajectory Over Time for Scenario 1: Global Broadcast as the Only Source of Information



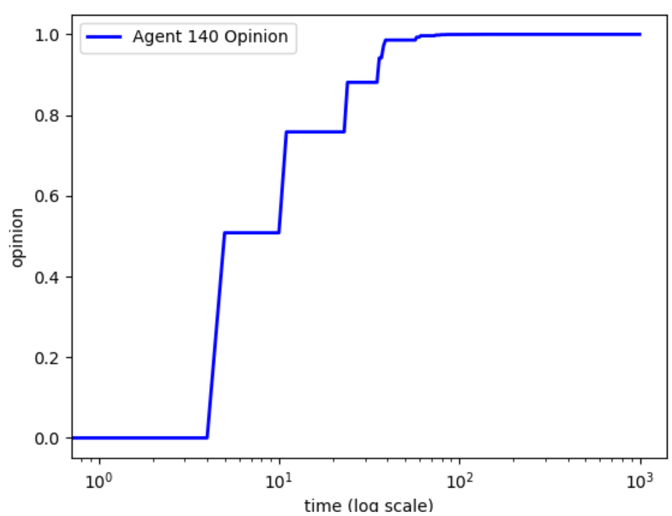
The opinion values of all agents vary over time with low values at the beginning of the simulation. However, after five days of receiving the message from the global broadcast, 100% of the agents will be evacuated as their opinion values reach a maximum of one (Figure 5).

Figure 5. Opinion of A Population of Agents Based on Scenario 1 Conditions
Over the Period of Simulation



The opinion trajectory of a randomly selected agent is presented in Figure 6. The agent's opinion is zero at the beginning of the simulation and increases to a value of one over time. However, this increment is not linear, as the opinion value of each agent is affected by the learning rate θ. The case of Agent 140 shows that the maximum opinion value is reached after two days of receiving the warning message.

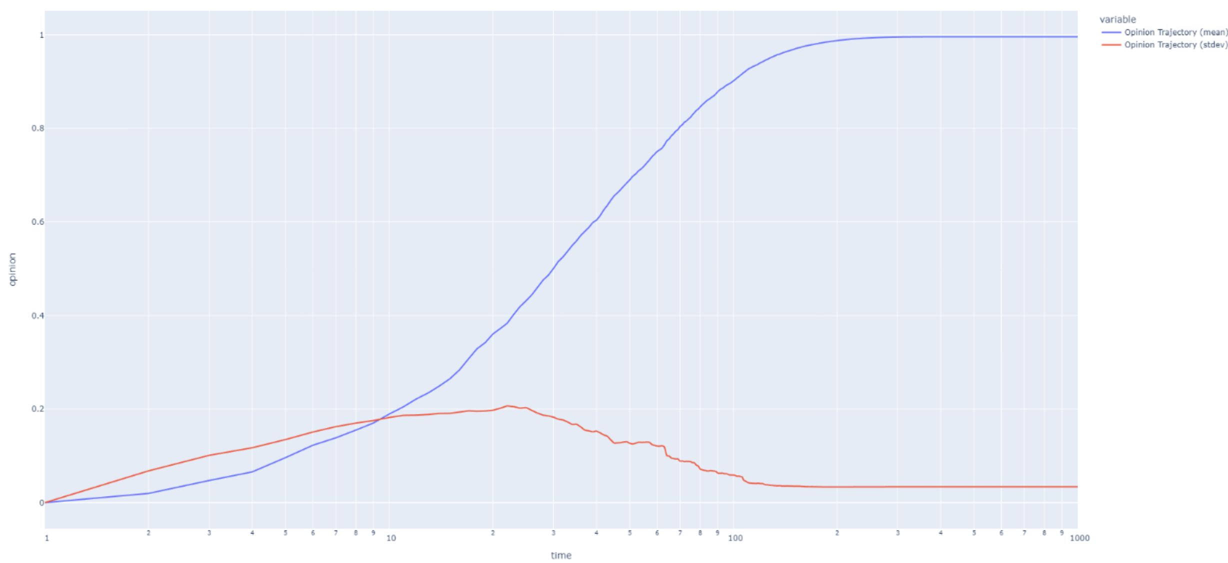
Figure 6. Change of the Opinion of a Randomly Selected Agent (140) Over
Time in Scenario 1



Scenario 2

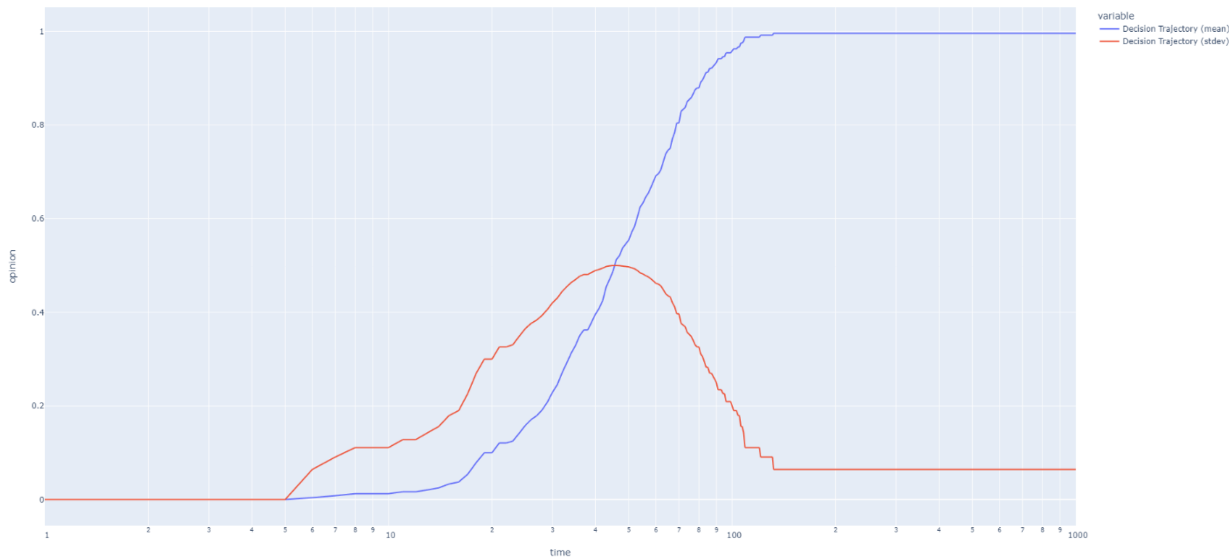
The addition of social media interactions as a source of information is analyzed as part of Scenario 2 (Figure 7). The average opinion value continues to grow over the simulation period as in Scenario 1; however, the increment is slower than in Scenario 1. At time step 100, the average opinion value is 0.90 compared to the value of one obtained at the same time step by Scenario 1. Furthermore, the variability in opinion values in Scenario 2 is lower than its corresponding value in Scenario 1, as represented by the standard deviation of the average opinion value. This would result in less frequent changes of opinion among people as two sources of information are analyzed: agency messages and social media interactions.

Figure 7. Mean and Standard Deviation of the Opinion Trajectory Over Time for Scenario 2: Global Broadcast and Social Media Interactions as Sources of Information



For the decision trajectory of Scenario 2, which depends on the comparison of opinion values and the resistance threshold, even though the opinion does not increase as fast as in Scenario 1, it is high enough to make people evacuate (Figure 8). Therefore, social media interaction does not change the number of people evacuating.

Figure 8. Mean and Standard Deviation of the Decision Trajectory Over Time for Scenario 2: Global Broadcast and Social Media Interactions as Sources of Information



As in previous analyses, the total number of agents reaching a value of one decreases in scenario 2 (Figure 9). The agents take longer to reach high decision values, as the graph in Figure 9 shows the blue color covering more area than the corresponding case in Scenario 1. However, as mentioned above, there is a consensus about evacuation decisions with most agents reaching high opinion values after five days of interacting with their social media contacts and receiving the evacuation alert.

Figure 9. Opinion of a Population of Agents Based on Scenario 2 Conditions
Over the Period of Simulation

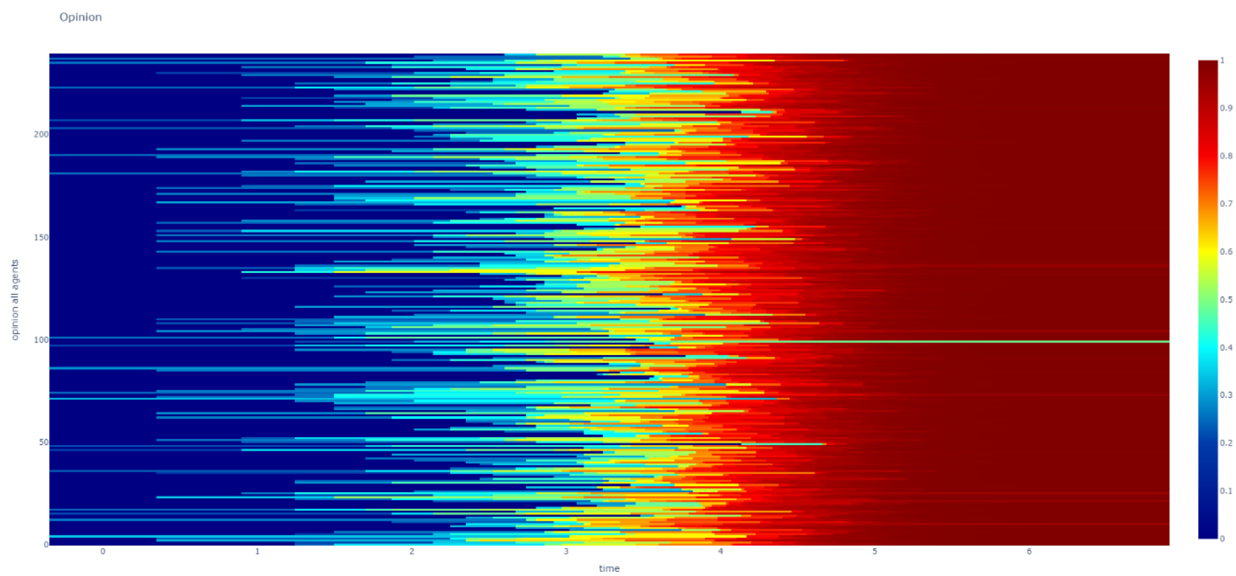
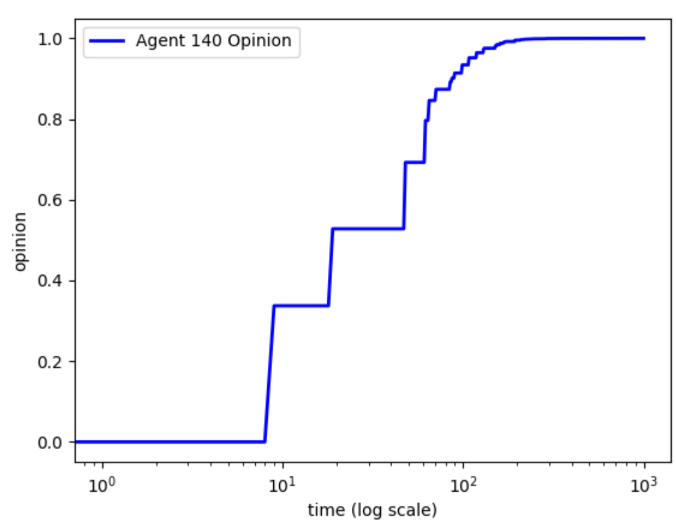


Figure 10 illustrates the opinion evolution of an agent chosen at random. The agent's initial opinion starts at zero and gradually rises to a value of 1 throughout the simulation. As in Scenario 1, the rate of this increase is non-linear, influenced by the learning rate θ and the additional source of information. For instance, Agent 140 exhibits a notable surge in opinion value after the second day of receiving the warning message.

Figure 10. Change of the Opinion of a Randomly Selected Agent (140)
Over Time in Scenario 2

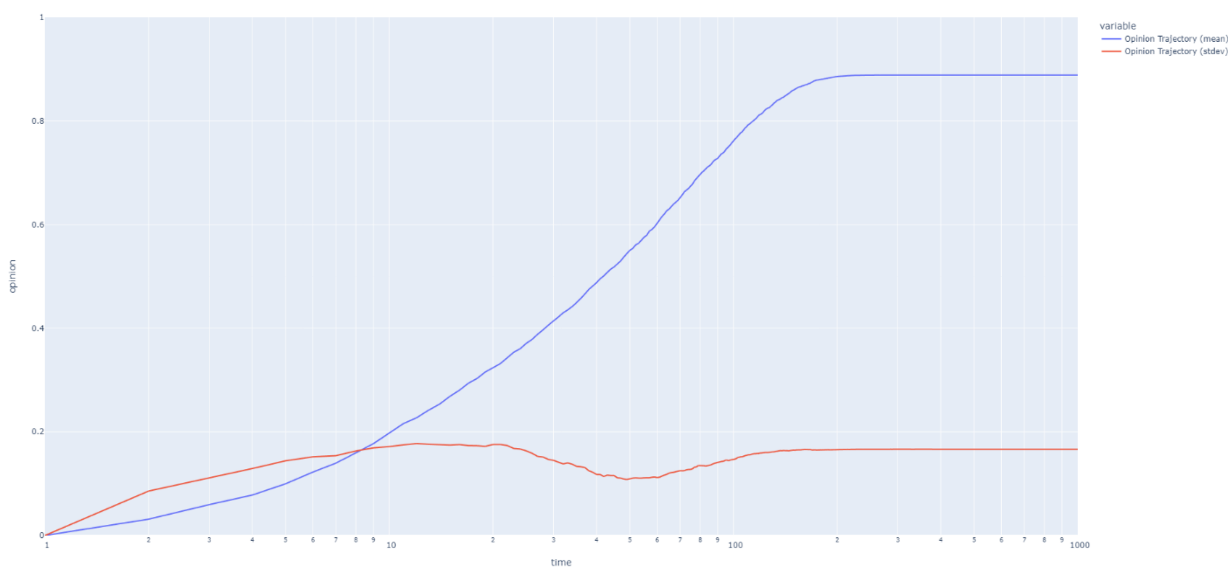


Scenario 3

The last scenario is the inclusion of neighbors' communications as a source of information in addition to global broadcasting. The main difference between Scenario 2 and 3 is the number of agents that can interact and how the opinion at the prior time step is used to calculate the effect of these sources of information (see Equation 1). Scenario 2 places agents on a random graph, and there is no need for geographical proximity for two agents to interact with each other because of social media networks. Scenario 3 does require that agents be geographically close to each other as they are placed on a complete graph. Hence, the analysis of Scenario 3 provides insights into the effect of peer-to-peer communication of agents located in proximity to each other.

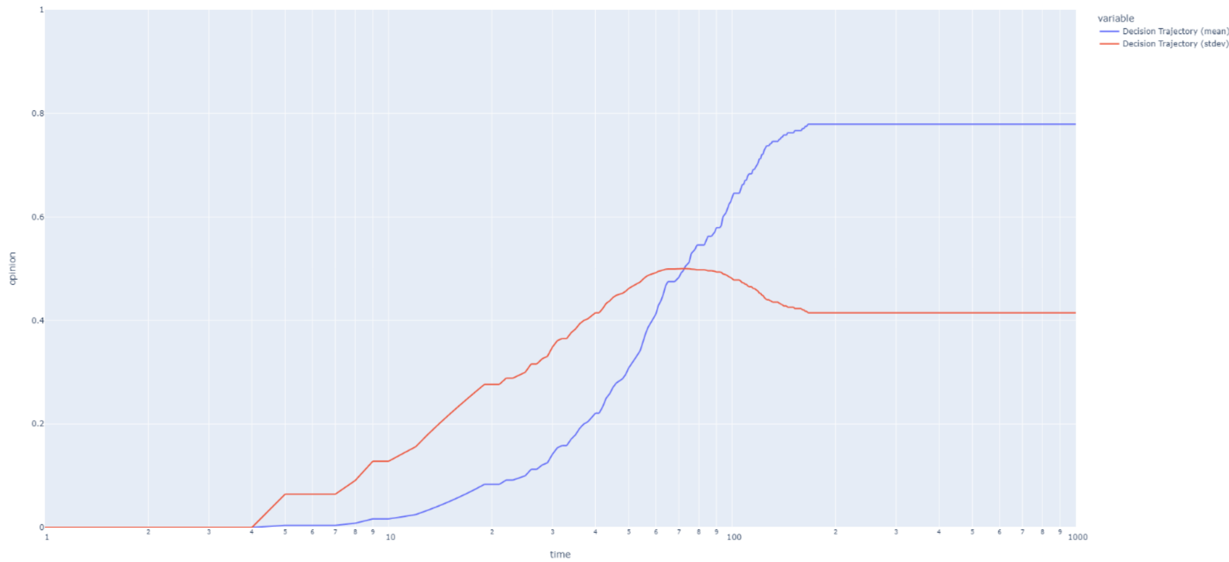
The average opinion trajectory for Scenario 3 differs from the previous two scenarios (Figure 11). There are no agents reaching the maximum value of one at the end of the period of simulation. After 200 days, the maximum value of the average opinion is 0.88. The variability of the opinion value is low, which indicates that adding neighbors' interactions to the global broadcasting may result in low opinions about evacuation practices.

Figure 11. Mean and Standard Deviation of the Opinion Trajectory Over Time for Scenario 3: Global Broadcast and Neighbors' Interactions as Sources of Information



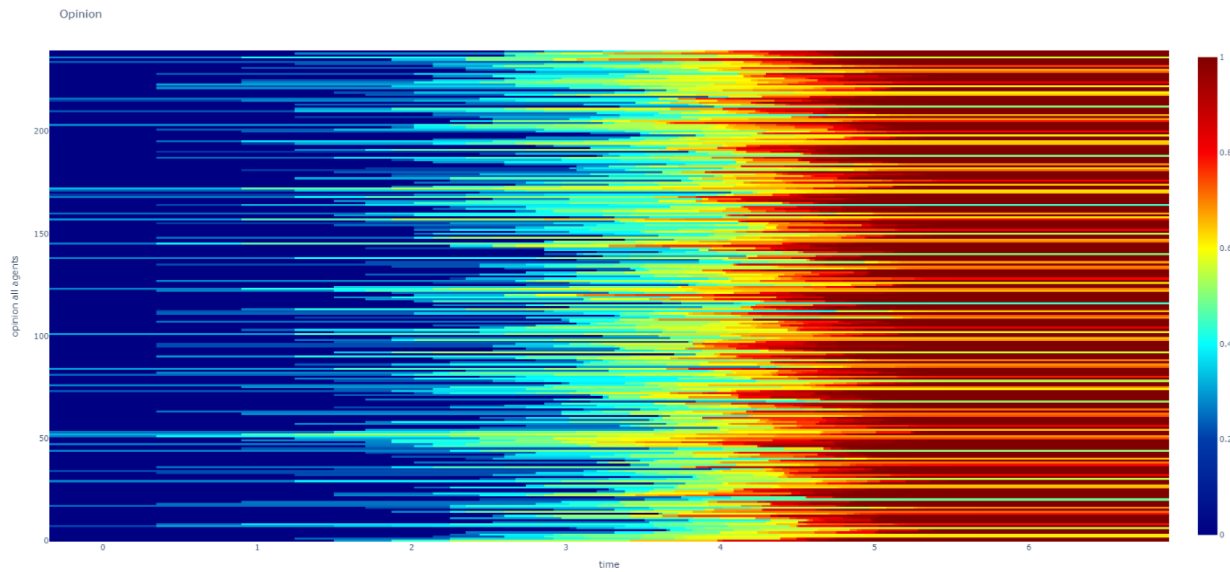
With low opinion values, Figure 12 shows an even lower rate of agents deciding to evacuate. The variability in the decision trajectory shown by the standard deviation significantly increased when compared to the previous values. Hence, interactions with neighbors that mainly focus on peer-to-peer communication and observation of actions may slow down the rate of people evacuating from the threatened area.

Figure 12. Mean and Standard Deviation of the Decision Trajectory Over Time for Scenario 3: Global Broadcast and Neighbors' Interactions as Sources of Information



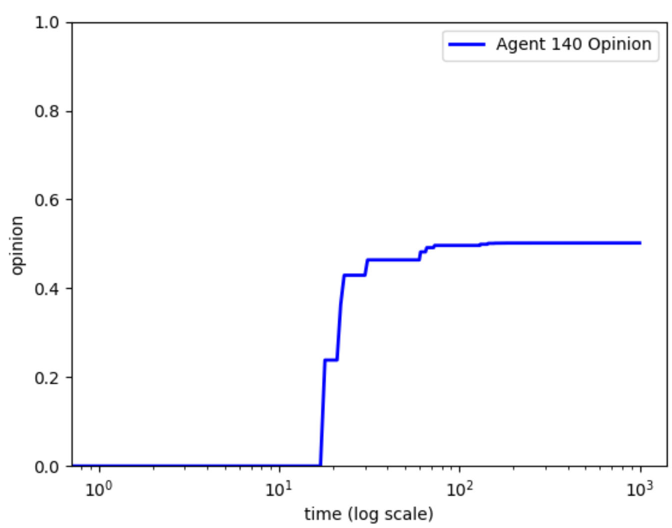
In Scenario 3, the number of agents that reach high opinion values is lower than the ones reported by the previous scenarios (Figure 13). Here the agents take longer to reach high decision values, and some of them do not reach high values at all. The main difference with the previous scenarios is that Scenario 3 does not present a consensus among the agents about evacuating the threatened area.

Figure 13. Opinion of a Population of Agents Based On Scenario 3 Conditions
Over the Period of Simulation



The final comparison shows the opinion of one agent selected randomly (Figure 14). As expected, the opinion of Agent 140 does not reach a high value, and at the end of the period of simulation, its value is 0.5, which will turn into a negative decision about evacuating.

Figure 14. Change of the Opinion of a Randomly Selected Agent (140)
Over Time in Scenario 3



4.2 Outcome Environment Analysis

Figure 15. Opinion Dynamics Mesa Visualization of Evacuation Scenario 1 Over 30 Days

Figure 16. Opinion Dynamics Mesa Visualization of Evacuation Scenario 2 Over 30 Days

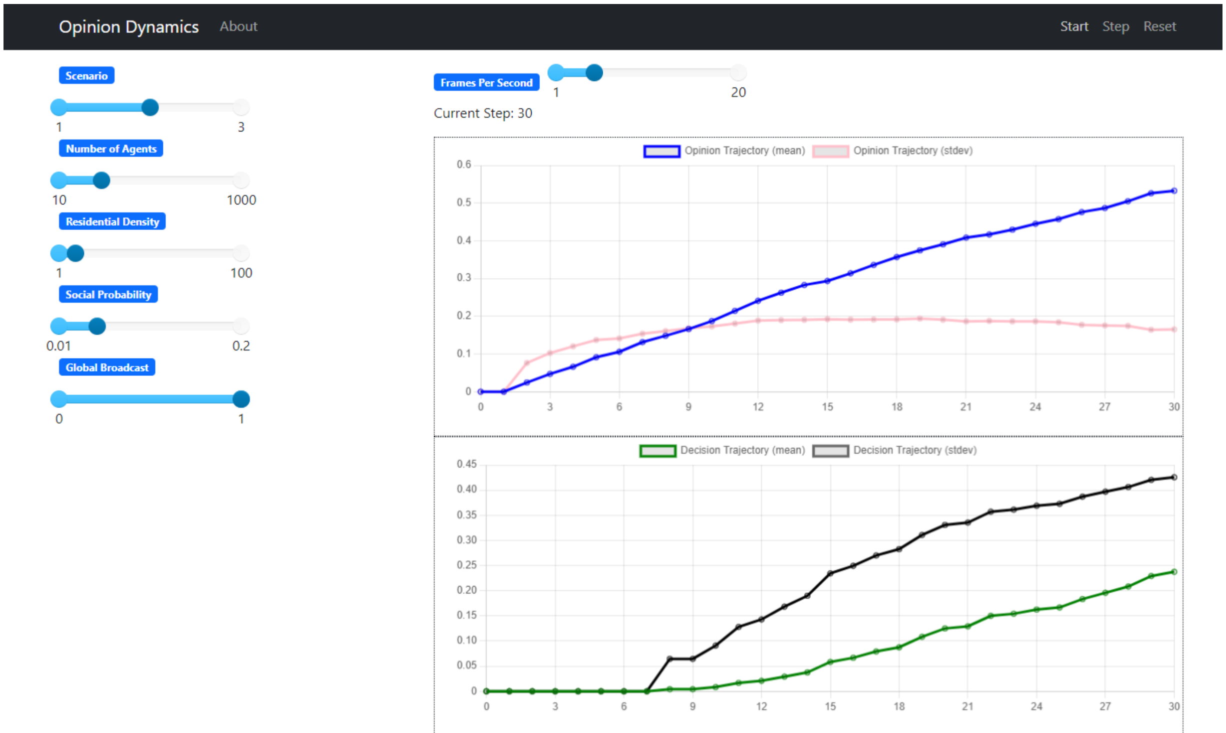


Figure 17. Opinion Dynamics Mesa Visualization of Evacuation Scenario 3 Over 30 Days

5. Conclusions

This research explored the use of an opinion dynamics model using agent-based modeling to simulate the interaction between a central agency and affected people when facing the threat posed by a wildfire event. The research model was based on previous opinion dynamics frameworks from the literature (Du et al., 2017; McCullen et al., 2013). Agents are entities that represent a central agency within the affected population. The central agency sends out a warning message recommending people evacuate from the area, which is the first source of information to the agents living within the affected area, called "global broadcasting." The affected agents communicate with each other by means of two additional sources of information modeled as social media and the interaction of neighbors. Then, each agent forms an opinion about evacuating the affected area as a function of the source of their information and their corresponding parameters. Agents will decide to evacuate the affected area if their opinion value overcomes a resistance threshold; otherwise, agents will stay and see how the situation unfolds.

Results indicate that when global broadcast is the only source of information, all agents reach a consensus to evacuate the affected area after a short period of time. This indicates that evacuation routes and traffic planning may be necessary for the safe evacuation of the affected area. Also, the individual opinion of a randomly selected agent is a steep ascending curve, meaning that some agents start evacuating as soon as they receive the warning message. However, it is worth noting that specific communication strategies were not discussed in this manuscript. Furthermore, the simulation assumes that global broadcasting is continuous and that evacuation orders will be received by the agents as soon as they are broadcast.

The opinion of agents differs when including a second source of information such as interactions within social media. A random graph with probability represents how agents may interact with each other using any social media platform. In Scenario 2, the agents' opinions decrease in comparison to the ones in Scenario 1. However, most agents reach high values later in the period of analysis. Hence, traffic planning will also be necessary to evacuate the affected area.

When the second source of information is the interaction between agents located in proximity (e.g., neighbors), there are agents that do not reach opinion values that overcome the resistance threshold. Therefore, evacuation routes may see a decrease in the number of vehicles on them, and rescue and traffic entities may need to plan their actions accordingly. The variability of the opinion values also differs among the scenarios, as Scenario 3 reports the highest variability in opinion.

To simulate diverse information sources, this study demonstrates that incorporating an opinion dynamics approach can lead to a more variable and realistic result in the population's opinions regarding evacuating from an area threatened by wildfire. The rising prevalence of social media plays a pivotal role in enhancing communication strategies, particularly in promoting safe evacuation procedures. Additionally, with the ongoing advances in digital communications, simulation models offer a valuable tool for local agencies and researchers to assess the efficacy of strategies before implementation.

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Alessandro Toledo is a Civil Engineering undergraduate student at California State University, Fresno. He has participated in multiple research projects around civil infrastructure, optimization, modeling, and data analysis. Under the guidance of Dr. Jorge Pesantez, he worked on the agent-based model to simulate the opinion dynamics of a population threatened by a wildfire event.

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