Mitigating the Spread of COVID-19 Misinformation Using Agent-Based Modeling and Delays in Information Diffusion

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Abstract. The rapid spread of COVID-19 misinformation on social media poses challenges in detection and analysis. There has been extensive discussion about the roles of online and offline campaigns in spreading misinformation. Recognizing the analytical gap between online and offline behaviors during the COVID-19 pandemic, we propose a systematic and multidisciplinary approach. This approach utilizes agent-based modeling to interpret the spread of misinformation and the actions of users/communities on social media networks. Our model was tested on a Twitter network concerning a demonstration against COVID-19 lockdowns in Michigan in May 2020. We implemented the one-median problem to categorize and simplify the Twitter network, measured the response time to the spread of misinformation, employed a cybernetic organizational method to manage the process of mitigating misinformation spread in the network, and optimized the allocation of agents to reduce the response time to misinformation spread. The study demonstrates the effectiveness of our proposed approach in delaying information diffusion, thereby mitigating the spread of COVID-19 misinformation on social media.

Keywords: Systems Thinking, Organizational Cybernetics, Stochastic One-median Problem, Misinformation, COVID-19, Information Diffusion Delay.

1 First Section

During the COVID-19 pandemic, social platforms faced an "infodemic" of misinformation, increasing global risks. Millions shared COVID-19-related content online, but WHO officials warned that fake news was spreading faster than the virus [1]. President Biden and US officials criticized social media for spreading misinformation about COVID-19 and vaccines, threatening efforts to control the pandemic [2 ,3].

The spread of COVID-19 misinformation on social media can harm individuals and society [4, 5]. Efforts to combat this include collaborations and online tools for verifying news [6]. However, advanced methods and systematic approaches are needed to understand the context and intentions behind true or false information, conspiracy theories, and coordinating groups [7, 8, 9].

Many tools, like fact-checkers and automatic conspiracy theory detection tools [10], are inadequate for tracking malicious activities and influencing attempts in dynamic social networks. These tools often fail to consider information flow among communities, conspiracy diffusion over time, and the evolving network. Fact-checker applications need enhanced methodologies and systematic approaches to limit conspiracy theories, investigate influential spreaders, respond to incidents, and monitor information flow in real time. Advanced methods like game theories [11], graph theories [12], and information theory [13] are necessary to improve analysis and limit conspiracy theories' spread in real time.

In this paper, we used systematic modeling to enhance analysis in dynamic social networks. Our approach describes organizational behavior and operations in response to information spread, optimizing time and resources. We employed the Organizational Cybernetic Approach (OCA) [14] to control communications between communities and the stochastic one-median problem [15] to minimize response time to malicious information. This approach improves the operation level's response to abnormal information spread and aids better decision-making. Next, we describe the problem statement.

2 Problem Definition

Consider a social network $G = (N, A)$ consisting of the distinct node sets $N = \{1,2,\dots,n\}$ and the set of edge (links) $A = \{(i,j),(k,l),\dots,(s,t)\}$ represented by directed node pair combinations going from community i to community j. Communities i, and j are associated with numerical values representing the number of intra edges $d_{j,i}$ between communities i and j. These numbers represent the actual number of users from the community i linked to users in community j at every time window. Also, h_j means the communities' rate of the misinformation spread in the worst-case scenario, and $\left(h_j\right)$ represents the communities' malicious information spread rate of $\left(h_j = \frac{|N_j|}{N}\right)$, where (λ_i) is the proportion rate of operation level that can be monitored in the network. This research aims to develop an agent-based model that interacts with online social networks and offline environments to mitigate COVID-19 misinformation spread and tackle the complexity of social media analysis. The following research questions guide the development of the model.

- RQ1. What strategies can an agent employ to confront and overcome the challenges of curbing the spread of COVID-19 misinformation?
- RQ2. How does an agent navigate the complexities of overseeing communities and of identifying and reporting the rapid spread of unusual information in real-time?
- RQ3. What is the agent's primary objective in addressing the spread of misinformation related to COVID-19?

Next, we discuss the research methodology.

3 Methodology

This research aims to integrate advanced systems thinking and modeling into dynamic social network analysis. By using systems design modeling, we can visualize interactions among communities and assess social network conditions. The challenge is to develop solutions that meet agents' real-time needs and constraints. Integrating social network analysis techniques allows for a detailed examination of network dynamics, identifying key influencers and mapping information flow. This helps pinpoint intervention areas to counter misinformation effectively. Systems design modeling optimizes solutions, enhances agent performance, and analyzes causes and effects within the network, ensuring precise and impactful actions [16].

Assumptions required for the solution procedure, which are necessary for the operation level strategies, are: the operation level response time to malicious information spread is deterministic, ($V=55$) messages per hour; the time required to respond to a stochastic malicious information spread case between communities is normally distributed, ($\beta=2$) case per hours; the time of the operation level to prepare for a new stochastic malicious information spread is deterministic; communities are assumed to be active over time, including users able to link with users in other communities; and communities are assumed to be either spreading malicious information or not.

Organizational Cybernetic Approach (OCA). The Systems Thinking method manages communication between a system and its environments, flags feedback, and accounts for unexpected behaviors from users and communities. It also simplifies analyzing the system's growing complexity and referenced in [14]. The research emphasizes the operational level (system one in OCA), stressing its need for flexibility to facilitate efficient interaction with diverse environments [14]. This level ensures equitable monitoring of large communities across networks, addressing abnormal behaviors, radical posts, cyber actions, and collective behaviors [17]. Operational activities require regular reporting to management and control levels following responses to malicious posts or before initiating new actions. Processes are continually monitored to promptly address abnormal information dissemination, managing each instance in a first-in-first-out (FIFO) sequence. OCA aims to monitor, record feedback, and develop strategies to improve agents' communication with the social environment by developing and managing a plan to limit the misinformation spread; assigning agents to interact with the environment and monitoring the sources of the spread of misinformation; evaluating the performance of the agents; and developing a new strategy based on the environment's reported negative or positive feedback.

The management level in OCA ensures smooth misinformation mitigation processes, reporting these and agents' performance to the control level. The control level within OCA enhances dynamic communication through policy adjustments during urgent scenarios, rectifying feedback and adapting mitigation plans to minimize unforeseen issues in the social network. The development level integrates critical data from operational and control levels, monitoring changes in online and offline environments. Acting as a command center, it oversees the execution of misinformation mitigation strategies, ensuring coordinated efforts among agents and the broader environment. The policy level adapts the system to misinformation and environmental changes, maintaining the effectiveness of mitigation efforts and articulating the network's strategy.

Stochastic One-Median Problem. This operational method effectively tackles stochastic information spread in dynamic networks, especially in scenarios where responses to malicious information might be overlooked [18]. Using the stochastic one-median problem improves performance, optimizes operational efforts, and aids in selecting optimal community combinations for enhanced monitoring processes. This stochastic monitoring approach integrates expected response times for abnormal behaviors as detailed in equations (1) to (4).

$$Min\, TR_j(C) \qquad \forall j \in I \qquad (1)$$

$$TR(C_j) = \bar{Q}_{C_j} + \bar{t}_{C_j} \qquad \forall j \in I \qquad (2)$$

$$\bar{Q}_{C_j} = \frac{\lambda_i\, \overline{S_2}(C_j)}{2\left(1 - \lambda_i \bar{S}(C_j)\right)} \qquad \forall j \in I \quad \forall i \in M \qquad (3)$$

$$\bar{t}_{C_j} = \sum_{j=1}^{I} h_j d(C_j, I) \qquad \forall j \in I \qquad (4)$$

TR is the sum of the mean-queuing-delay $\bar{Q}$ and the mean response time $\bar{t}$ as shown in (2). Equation (3) is to define $\bar{Q}$, where C_j is the community j in the network. λ_i is the proportion rate for an agent to handle misinformation transferred between communities; for this purpose, the network will be divided into sub-networks, as discussed in the next section. $\bar{S}(C_j)$ is the mean total response time (starting from the first moment the abnormal behavior is detected), and $\overline{S_2}(C_j)$ is the second stochastic moment of the total response time to any new misinformation spread in the network. Equation (4) defines $\bar{t}$, where I is the number of communities in the network, h_j is the the rate of the misinformation spread from community C_i in the worse scenario, and $d(C_j, I)$ is the shortest path to transfer information between community C_j and community C_i.

The four outlines in the stochastic one-median problem and the operation level that can be translated into the OCA structure and the social network analysis are – (1) The operation level is the sole system level responsible for responding to abnormal behaviors in the social network. (2) This level would record and report the interactions of the users/communities in online/offline social environments. (3) The operation level will report any changes in the behaviors of the networks to the higher levels in the OCA. (4) This level must implement the off-scene setup time to respond to any stochastic and new abnormal behaviors in the network.

Agent Level Performance. This research presents a linear multi-objective problem [19] to assess agents' effectiveness in combating COVID-19 misinformation on social media. The model considers information flow between communities, environmental feedback, and integrates an information diffusion delay to enhance agent performance in reducing false information spread. It comprises three objectives aimed at mitigating COVID-19 misinformation in the network: minimizing misinformation spread between communities (Z1), reducing the distance or nodes through which information travels (Z2), and minimizing information diffusion delay for network reliability (Z3). These objectives are supported by a set of associated constraints.

$$Min\,Z1 = \sum_{p\in O}\sum_{q\in D} w^{pq}\,Y^{pq} \quad (5)$$

$$Min\,Z2 = \sum_{u\in M}\sum_{p\in O}\sum_{q\in D} l_u\,X_u^{pq} \quad (6)$$

$$Min\,Z3 = \sum_{u\in M}\left[\frac{\sum_{p\in O}\sum_{q\in D} X_u^{pq}}{C_u - \sum_{p\in O}\sum_{q\in D} X_u^{pq}}\right] \quad (7)$$

$Subject\ To:$

$$\sum_{p\in O}\sum_{q\in D} X_u^{pq} \le \frac{Delay\,.\,\gamma\,.\,\mu\,.\,C_u}{|u|} \qquad \forall\, u \in M \quad (8)$$

$$\sum_{u\in\Gamma(i)} X_u^{pq} - \sum_{u\in\Gamma-(i)} X_u^{pq} = d^{pq} - Y^{pq} \quad if\ i = p \quad (9)$$

$$\sum_{u\in\Gamma(i)} X_u^{pq} - \sum_{u\in\Gamma-(i)} X_u^{pq} = -d^{pq} + Y^{pq} \quad if\ i = q \quad (10)$$

$$\sum_{u\in\Gamma(i)} X_u^{pq} - \sum_{u\in\Gamma-(i)} X_u^{pq} = 0 \ \ otherwise \quad (11)$$

$$X_u^{pq}\,, Y^{pq} \ge 0,\ \forall\, u\ \in M,\ p \in O,\ q \in D$$

Equation (8) ensures that X_u , the actual number of connections between two communities connected by arc u, is less than or equal to C_u (the maximum possible connections between communities connected by arc u when no delay is applied). γ is the network throughput, similar to the total number of misinformation units in the network. $\mu = 1$ is a unit of information sent from a user in community i to a user in community j, and $Delay$ is the information diffusion delay factor. Equations (9) through (11) measure the information unit conservation flow between communities in the network, where d^{pq} is the number of monitored users between the source community and destination community. Y^{pq} is the number of unmonitored users between the source community and destination community. $\Gamma(i)$ is the set of arcs whose source community is i. $\Gamma - (i)$ is the set of arcs whose destination community is i. w^{pq} is the amount of weight given to the communities p and q. l_u is the length of the path for information to transfer between communities. $p \in O$ is the source communities. $q \in D$ is the destination community setting. N is the communities set and M is the arc (link) set for the network.

4 Related Work

Several empirical studies underscore Systems Thinking and modeling as advanced methods for tackling complex social network issues [20]. The Casual Feedback method [21] identifies key variables for complex systems modeling. Muchnik et al. [22] highlight power laws in social networks and large-scale communities. Du et al. [23] discuss boundary conditions in systems thinking and modeling. Control theory [11] and information theory [13] enhance decision-making strategies based on game theory in social networks [19], providing optimized solutions for diverse agent-based complex problems. The complexities of unpredictable user behaviors, community dynamics, and rapid social network growth challenge effective analysis, limiting traditional methods.

Integrating various fields is crucial for developing strategies to examine local user interactions and inter-community communication over time. This integrated approach helps categorize online and offline user feedback. We propose a systematic agent-based approach to enhance communication between online environments and organizational operations, mitigate malicious information spread, monitor information flow among communities and users, and enable real-time responses to abnormal information.

To optimize real-time decision-making, various operational methods model stochastic incidents and interactions between teams and environments across different domains. Examples include enhancing fire department operations during emergencies, managing rush-hour traffic congestion, and quickly restoring telecommunication services after network failures [24]. Hakimi [24] introduced the ρ-median location model to optimize depot placement in infrastructure networks during failures, minimizing node distances and hub numbers. Patterson et al. [25] proposed a relaxed ρ-median model with overlapping service regions to reduce call losses in telecommunication networks. Love et al. [26] illustrated operational interactions using a bipartite graph representation of the ρ-median algorithm. On the contrary, Odoni [27] highlighted queuing challenges with the ρ-median model due to extended arc operations, while Chan et al. [17] noted its analytical complexity increases with multiple operation centers. Ahituv et al. [15] proposed partitioning the network into smaller, independently operating subnetworks. Our study uses the stochastic one-median problem to improve operational performance in addressing abnormal information spread within social networks.

5 Results and Findings

This section presents results from a real-world Twitter dataset used to assess the accuracy and feasibility of our proposed approach. Assumptions regarding the policy level in OCA include employing two operation levels (M=2), each tasked with monitoring less than 55% of the network. According to [4], the policy level functions akin to stakeholders, deciding on strategy implementation and adjusting operation levels based on environmental reports and feedback. The development level acts as an operations hub, executing organizational strategies, liaising with other levels, and monitoring network conditions to ensure effective strategy implementation or necessary updates.

Dataset. We collected a co-hashtag network from Twitter during an armed protest demonstration against COVID-19 lockdown in Michigan state in May 2020. Data was gathered using Twitter API for hashtags #MichiganProtest, #MiLeg, #Endthelockdown, and #LetMiPeopleGo from April 1 to May 20, 2020, resulting in 16,383 tweets and 9,985 unique user IDs. The network analysis depicted 3,632 nodes (Fig. 1), consolidating minor communities into one node [28]. The modularity analysis identified 382 communities, focusing here on the top 5 largest (C_1 through C_5) due to their user count, while smaller communities were grouped into a single node (C_6) to account for their interactions.

Experiment Results. To evaluate the performance of the agent levels in mitigating the spread of COVID-19-related misinformation in social media networks, we developed a simulation model that accounts for the misinformation spread between communities, with a maximum of 250 instances of false information being propagated across the network. In other words, the network's throughput is the number of misinformation units spread between communities. Each misinformation unit includes sets of messages transferred from the community C_i (source) to community C_j (target). For example, the misinformation units spread from community C_1 (source) to users in C_2 and C_4 (targets), where C_1 sent 100 misinformation units, fifty per target community. Likewise, 50 misinformation units spread from C_2 to C_6. Another misinformation spread was logged from C_5 to C_3. Finally, 50 misinformation units spread from communities in C_6 to target users in C_2.

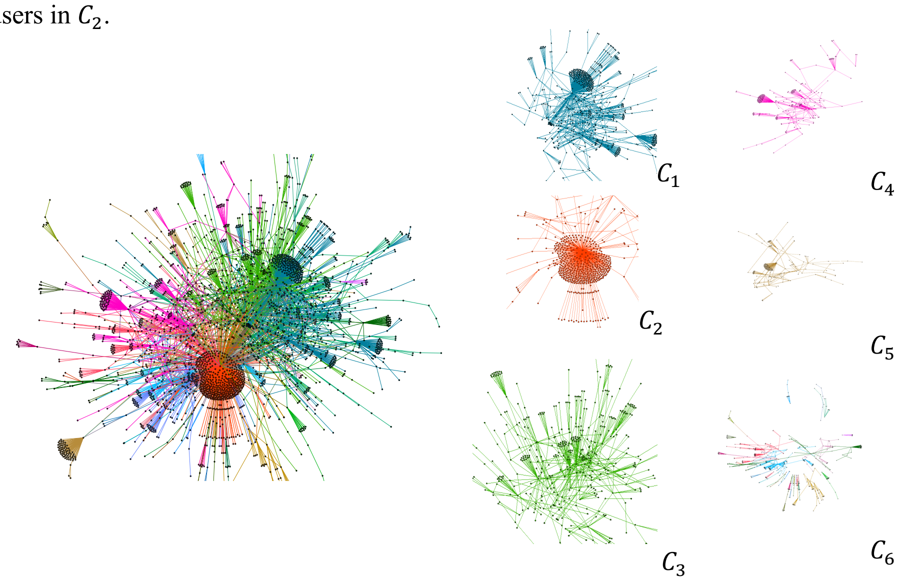

Fig. 1. Twitter network for COVID-19 anti-lockdown protest in Michigan and the six communities identified using modularity.

The model assesses how agents respond to the spread of information over time, incorporating an information diffusion delay factor into equations (8) from section 3, with data delay thresholds set at 0.01–0.1 per hour. This approach gauges agents' effectiveness in curbing misinformation propagation across the network. Increasing the delay threshold enables agents to manage more users and misinformation units exchanged between communities. Optimizing this delay factor hinges on network throughput, user connections between communities, and message transfers among them.

Table 1. Information Diffusion Delay Factor.

C_i	C_j	Information Diffusion Delay Thresholds						
		None	**0.01**	**0.02**	**0.03**	**0.04**	**0.05**	**0.1**
1	5	8	1	2	4	5	7	13
1	4	8	1	2	4	5	7	13
1	6	25	4	8	12	17	21	42

1	2	59	10	19	29	38	50	98
1	3	74	12	24	37	48	62	123
3	2	40	7	13	20	26	33	67
3	5	13	2	4	6	8	11	22
3	4	18	3	5	9	11	15	30
3	6	42	7	13	21	27	35	70
2	6	125	21	41	62	82	104	208
4	6	8	1	2	4	5	7	13
5	6	25	4	8	12	17	21	42
4	5	4	0	1	2	2	3	7
2	5	13	2	4	6	8	11	22
2	4	29	9	9	14	19	24	48

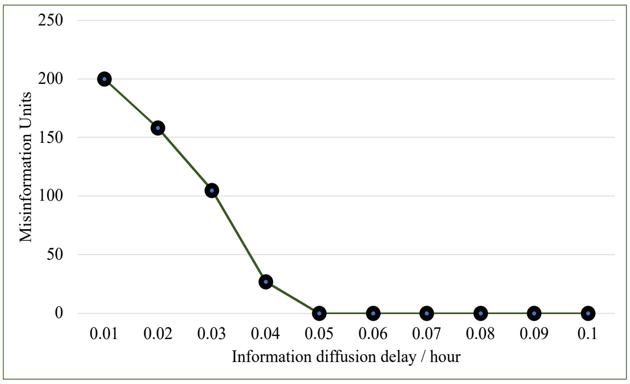

Fig. 2. Agents' performance in mitigating misinformation.

Table I compares the handling of misinformation units in the network with and without an applied delay factor. Various thresholds for the delay factor were tested to assess agents' effectiveness in mitigating misinformation spread. Fig. 2 illustrates the efficient frontier resulting from these tests. Our findings show that implementing a delay factor did not effectively reduce misinformation spread when the threshold was below 0.05 hours. However, we observed a notable improvement in agents' performance when the delay threshold was set to 0.05 hours or higher. This strategy can enhance the performance of agents in handling the maximum number of misinformation units spread between different communities on social networks.

6 Conclusion

This research tackles COVID-19 misinformation on social networks using multidisciplinary methods like Systems Thinking and operational techniques. It employs cybernetic strategies to counter misinformation with practical front-end and back-end solutions. A systematic agent-based model is introduced to simplify social network complexities, reduce misinformation, and optimize performance using real-world feedback.

By applying an Organization Cybernetic Approach (OCA) and the one-median problem, the model enhances resource efficiency, comprehends network structures, and boosts agent effectiveness. Evaluations demonstrate effective mitigation of COVID-19 misinformation on Twitter, highlighting the value of agent-based modeling, delay factor methodology, and Systems Thinking. This approach allows for real-time communication control, community behavior monitoring, agent performance measurement, and dynamic strategy adjustment. It handles complex social network analysis efficiently, regardless of network size or user count, using minimal resources (two agent levels). Managers can optimize resource allocation based on network size, community metrics, and real-time environmental feedback. In the future, we intend to examine whether the spread of disinformation is increasing or decreasing in dynamic social networks and evaluate the OCA's strategies to mitigate misinformation spread after considering different approaches, such as reinforcement learning and training maze-agent.

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