Chapter 5

A Multi-Criteria Decision Making based Integrated Approach for Rumor Prevention in Social Networks

In the previous chapter 4, we discussed some challenges with the rumor-blocking method. Counter-rumor diffusion methods avoid the issues related to censorship, helping to keep user trust and the platform's reputation intact, while effectively reducing the impact of the rumor. These methods offer a proactive and scalable approach to rumor control by leveraging the network's inherent propagation mechanisms to disseminate corrective information.

This chapter focuses on the third contribution of this thesis, i.e., suggesting a proactive model for rumor prevention in social networks. We provide an introduction and motivation for the proposed approach in Section 5.1. Section 5.2 shows the proposed approach. This section explains the key-node selection method in Subsection 5.2.1 and the proposed rumor prevention model in Subsection 5.2.2, respectively.

Section 5.3 discusses the results and findings, and Section 5.4 concludes this chapter with a few future possibilities. Detailed related work is provided in Section 2.2.2.

5.1 Introduction

Rumor diffusion control models typically employ two main strategies. The first strategy involves blocking the nodes and edges responsible for spreading the rumor. The second strategy involves implementing a counter-rumor diffusion mechanism when a rumor is detected in the network. This is usually initiated by rumor control centers, such as authorities or influential nodes, which release counter-information to debunk the rumor. Existing research has offered solutions for controlling and preventing rumors on social networks [12, 23, 24, 89]. Although these approaches have significantly advanced research in this area, we have identified few gaps. First, most research focuses on illustrating the mechanisms for spreading and controlling rumors, with limited attention given to their prevention. Second, there is the issue of the time lag — determining when to start the counter-rumor diffusion process after the system has been infected. This timing is crucial, as starting early can push the network into a preventive state, while starting late may only bring the system under control. Finally, many researchers suggest that high trust in the government or authorities enhances the effectiveness of countering rumors. However, when public trust in these authorities is low, the effectiveness of these efforts is diminished, highlighting the problem of public distrust in authorities.

To introduce counter-rumors in the network, a few nodes are selected from the network and used to spread counter-rumors. This selection is a crucial step for rumor prevention as it determines the efficacy of the counter-rumor diffusion model. These nodes can be selected randomly or by some defined method and then used to initiate counter-diffusion. Random and strategy-based selection are known as random and targeted immunization, respectively. Many researchers have advocated that targeted immunization is a better strategy than randomization for information diffusion in a network [125–127]. So, we need to select the nodes as key nodes according to some criteria. Initially, centrality metrics were one of the most popular criteria for selecting key nodes, as they are indicators of structural information in the network. However, with time, a single criterion proved insufficient and there was a need to combine multiple criteria [128,129]. Multi-Criteria Decision Making (MCDM) based methods have become a popular means of combining various centrality criteria and selecting key nodes in the network.

5.2 Proposed Approach for Rumor Prevention

We propose an integrated MCDM based approach focused on preventing rumors in social networks. This approach is more intended towards the prevention of rumors rather than their control. Rumor prevention and control are two different concepts. A social network is said to be in a rumor control state when most of its nodes receive the rumor before receiving the counter-rumor messages. They get infected by the rumor and then after receiving counter-rumor messages, they recover from it. However, a social network is said to be in a rumor prevention state when most of its nodes receive the counter-rumor message before receiving the rumor. This ensures that nodes are alerted before they are infected with rumors. Rumor prevention can also be seen as proactive rumor control.

The idea for the prevention of rumors is to introduce counter-rumors in the system as soon as any rumor is encountered. The counter-rumors are to be spread in such a way that they reach the most number of nodes in less amount of time. So, we find the influential nodes in the social network and make them keynodes. These keynodes can be powered by artificial intelligence capabilities and work in orchestration. The keynodes will spread counter-rumor messages whenever they detect a rumor message in the network using the proposed diffusion model- Susceptible - Infected - Recovered - Prevented - Agent (SIRPA). This section is divided into two subsections that detail the proposed approach for keynode selection (subsection

5.2.1) and the proposed counter-rumor diffusion model SIRPA (subsection 5.2.2). An overall scheme of the proposed work is shown in figure 5.1. This figure illustrates our strategy for preemptive rumor prevention in social networks, selecting influential nodes and the SIRPA model-driven dissemination of counter-rumors to protect the network from rumors.

For finding the influential nodes in a social network, it is first necessary to map the concepts of the problem domain to the core concepts of MCDM. For this, social media users, represented as nodes are mapped as alternatives, centrality measures as criteria, criteria weight is the relative importance provided to different criteria over others, and models of information diffusion as the performance evaluators.

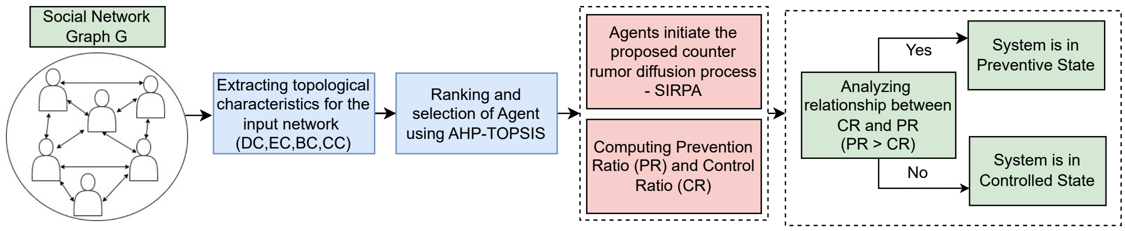


FIGURE 5.1: Overall Scheme of Proposed Work

5.2.1 Selection of Influential Nodes

They say *"Rumors stop at the wise man"*. The influential node selection task is to choose these men and make them wise by equipping them with artificial intelligence capabilities [130]. Lu et al. [130] have proposed an agent-based modeling (ABM) to show rumor diffusion in a social network. However, unlike their work, rather than hosting agents on all nodes, we are hosting agents only on the selective nodes. The reason being reduction of the overhead of providing intelligence to each node and providing targeted immunization. So, we select a few influential nodes that will be responsible for preventing rumors in the social network by faster spreading of counter-rumor messages.

The selection of keynodes resembles the influence maximization problem which is one of the well-studied and formulated problems of social networks. Currently, there is much research going on in the field of influence maximization [131] [132] that spans many simple to complex algorithms, however, addressing this problem is beyond the scope of this thesis. For such type of selection problems involving multiple criteria, MCDM methods are popularly used. These methods rank the alternatives with respect to some criteria to achieve a goal. For keynode selection, we rank the nodes in non-increasing order of preference using centrality measures based criteria. We use degree centrality (DC), eigenvector centrality (EC), betweenness centrality (BC) and closeness centrality (CC) as criteria and AHP-TOPSIS as the keynode selection method.

Since we intend to select nodes that are popular, accessible and can disseminate counter-rumor fast, a single centrality measure criterion is not sufficient. For this purpose, we use the MCDM method to find the influential nodes. We use the TOPSIS algorithm [59] to find the top k influential nodes. TOPSIS method proposed by Hwang and Yoon in 1981 [59], is a ranking-based MCDM method that selects alternatives that are closest to the ideal solution on the positive side and the farthest from the ideal solution on the negative side. This method is a popular choice among researchers for finding keynodes in social networks using the MCDM approach [60, 61, 64, 65].

However, while applying TOPSIS, we need to assign weights to the criteria depending upon the importance of each criteria. The weights to the four centrality measures criteria are assigned using the AHP algorithm [67]. In this algorithm, we first create a pairwise comparison matrix (PCM) to determine the relative importance of each centrality measure with respect to other criteria. Table 5.1 references the relative importance score that can be assigned in the AHP method and their interpretation. Table 5.2 refers to a pairwise comparison matrix created by assigning relative importance scores to the criteria for our chosen centrality criteria. The steps to calculate the criteria weight is shown in figure 5.2. The random index (RI) value for $n = 4$ is 0.90 and the threshold is 0.10. For our assigned PCM, the consistency ratio (CR) is 0.0075 which is less than 0.10. So, we accept this PCM and feed the criteria weights to the TOPSIS algorithm.

TABLE 5.1: Relative importance-score with their interpretation for AHP method

Weight	Meaning
1	Equal Importance
3	Moderate Importance
5	Strong Importance
7	Very Strong Importance
9	Extreme Importance

TABLE 5.2: Pairwise Comparison Matrix after assigning relative importance-score to each criterion

	DC	EC	BC	CC
DC	1	1/3	1/2	1
EC	3	1	1	3
BC	2	1	1	2
CC	1	1/3	1/2	1

The TOPSIS method inputs an $n * m$ decision matrix consisting of n alternatives, i.e., nodes of the network, and m centrality criteria and criteria weights(CW) obtained from AHP. A TOPSIS score is generated for each node using the steps in figure 5.3. The nodes are sorted in non-increasing order. The node having the highest TOPSIS score will be given the highest priority and are selected as the keynodes.

5.2.2 Proposed Model for Counter-Rumor Diffusion - SIRPA

The spread of rumors on social networks is influenced by many factors. These factors are node status, diffusion rate, propagation structure, etc. Our proposed model, Susceptible-Infected-Recovered-Prevented-Agent (SIRPA) is an extended variant of the classical Susceptible-Infected-Recovered (SIR) model [124]. The SIR model is a popular epidemic model that was originally proposed to study the behavior of viral disease diffusion. Rumors also spread in the same manner as viral

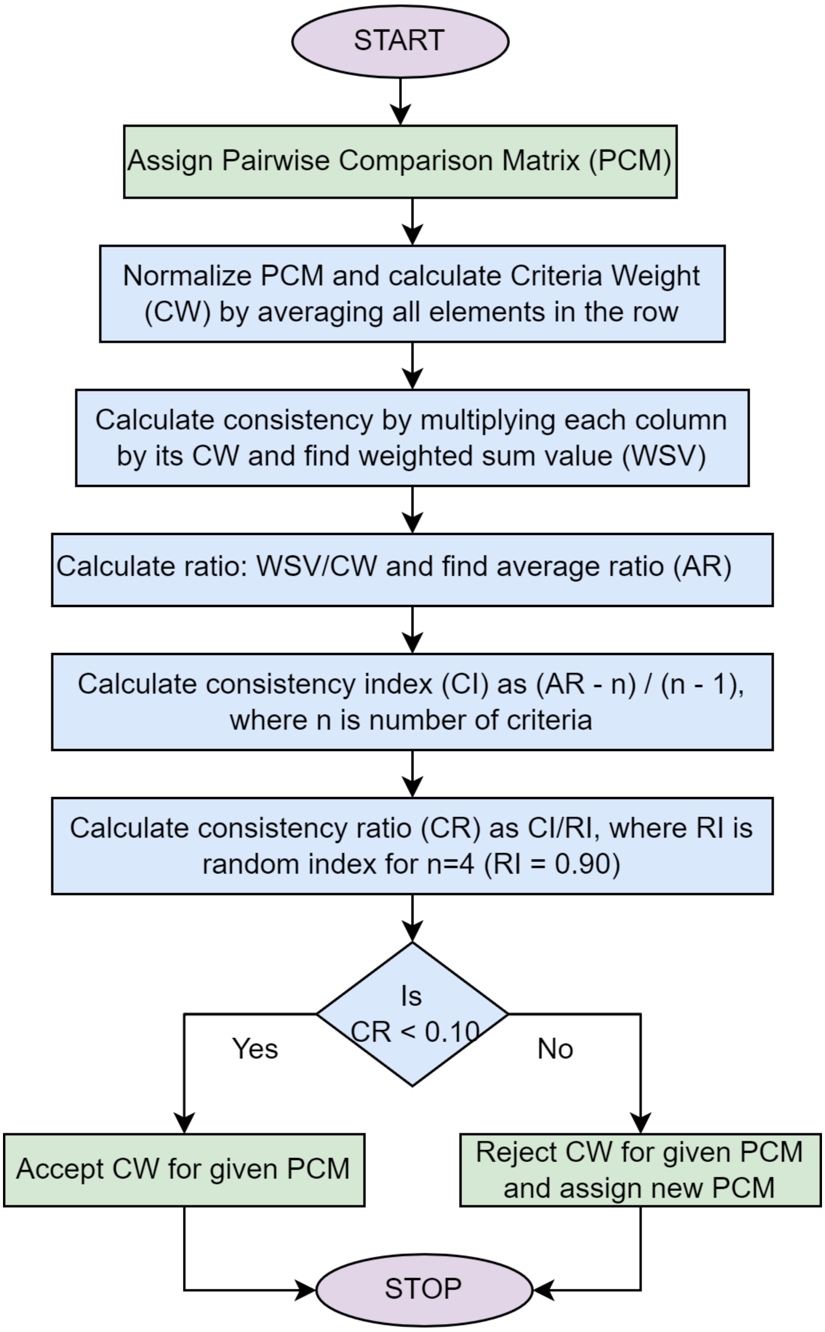


FIGURE 5.2: Steps of AHP algorithm to calculate the Criteria Weights of different Centrality Measures

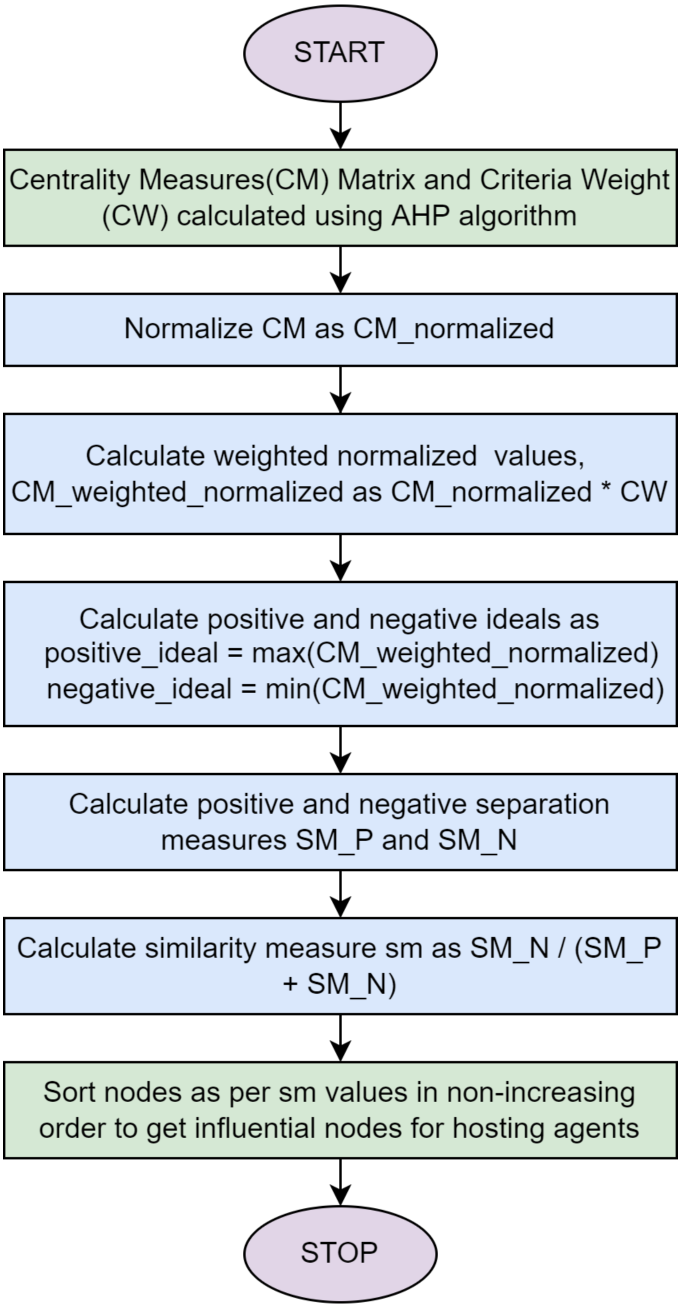


FIGURE 5.3: Steps of TOPSIS algorithm for selecting the agent nodes

diseases. However, the control mechanism of rumors is similar to its diffusion, unlike viral diseases, where vaccination has to be done for each node individually.

In the SIR model, the nodes are in one of the three states- susceptible, infected, and recovered. The susceptible nodes are the uninfected nodes that are yet to receive the rumor. These nodes become infected when they come into contact with already infected nodes. Infected nodes are responsible for the diffusion of rumors in the network. After the discovery of rumors in the social network, a recovery process starts that converts infected nodes into recovered nodes by spreading some counter-rumor message or information. The state diagram of the SIR model is shown in Figure 5.4. In our proposed model, nodes can be in two more states in addition to being susceptible, infected, or recovered. These two new states that extend the SIR model are prevented and agents. The prevented nodes are susceptible to getting infected; however, they receive the counter-rumor messages before receiving rumors. So, they do not transit to the infected state, but to prevented state. The agent nodes are the keynodes responsible for initiating the counter-rumor diffusion process in the system whenever a rumorous post is detected. Figure 5.4 presents the state transitions of the SIRPA model, showcasing how the nodes within a network evolve through the five states, and demonstrating the dynamics of rumor spread and containment.

The proposed SIRPA model makes the following assumptions:

1. The total number of nodes on the social network does not change at any time. Hence, the total number of nodes in the network remains constant. So, at any given time t, the sum of susceptible nodes, infected nodes, recovered nodes, prevented nodes, and agent nodes is equal to the total population N.

$$n_t(S) + n_t(I) + n_t(R) + n_t(P) + n_t(A) = N \tag{5.1}$$

2. During the diffusion of rumor, if the node is in a susceptible state, it accepts the rumor and transits to the infected state. If the node is in prevented, infected

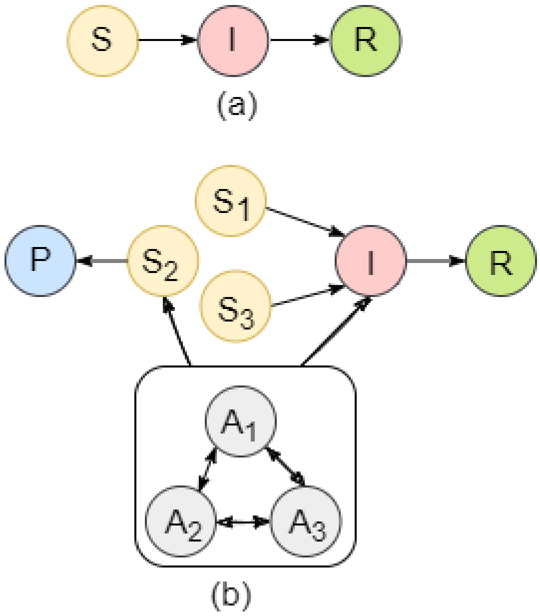


FIGURE 5.4: State Transition Diagram for (a) SIR Model (b) SIRPA Model

or recovered state, no action is performed.

$$S \longrightarrow I$$

3. During the diffusion of the counter-rumor message, if the node is in a susceptible state, it accepts the counter-rumor message and transits to the prevented state. If the node is in an infected state, it accepts the counter-rumor message and transits to the recovered state. If the node is in the prevented or recovered state, no action is needed.

$$S \longrightarrow P$$
$$I \longrightarrow R$$

4. The diffusion of counter-rumor starts as soon as any agent node detects the

rumor in the network. Then it informs other agents. All the agents simultaneously start the counter-rumor diffusion process then. Hence, for k number of agents, k simultaneous counter-rumor diffusion processes will start.

Let $G(N, E)$ be a social network of N total of users and E number of links among them. These users can be in any state susceptible, infected, recovered, prevented, or agent at any time, thus satisfying the equation.5.1. The rumor originates from a source and spreads in the system with probability of diffusion of the rumor β as long as it encounters any agent in the system. When an agent is encountered, this agent notifies other agents about the possible rumor and all agents start diffusing counter-rumor messages with counter-rumor diffusion probability γ. From this point rumor diffusion and counter-rumor diffusion process starts simultaneously, thus transiting states from susceptible to infected and then to recovered and from susceptible to prevented, respectively. If state transit is from the infected state to the recovered state, then we say that the rumor is controlled at the node. If state transit is from susceptible to prevented state, then we say that the rumor is prevented at the node. In both cases, the prevention rate and the recovery rate are the same and equal to the probability of counter-rumor diffusion γ. The rate of change in number of susceptible, infected, recovered and prevented nodes is calculated using the mean-field equations which are as follows.

$$\frac{dS}{dt} = -\beta \frac{SI}{n} - \gamma \frac{SP}{n} \tag{5.2}$$

$$\frac{dI}{dt} = \beta \frac{SI}{n} - \gamma I \tag{5.3}$$

$$\frac{dR}{dt} = \gamma I \tag{5.4}$$

$$\frac{dP}{dt} = \gamma \frac{SP}{n} \tag{5.5}$$

Using the agents in the counter-rumor diffusion process as per our proposed model results in a higher number of prevented nodes than recovered nodes at the end of the diffusion and counter-diffusion process. This ensures that the system ends up in a preventive state rather than in a controlled state.

5.3 Results and Discussion

We implemented our proposed rumor prevention model on two synthetic social networks generated using the Barabási-Albert (BA) model [91] and Erdős Rényi (ER) model [92], as well as on four real datasets from the Twitch network [93] (as discussed in Section 2.3). We conducted various experiments on these datasets to evaluate the effectiveness of the proposed model in blocking rumors within social networks. The experiments are designed to address the following research questions.

- **RQ 1:** What is the effect on number of infected nodes and prevented nodes with varying rumor diffusion and counter-rumor diffusion probability? (Answered in subsection 5.3.1)
- **RQ 2:** How number of agents effect rumor prevention process in the network? (Answered in subsection 5.3.2)
- **RQ 3:** How MCDM based approach (AHP-TOPSIS) for selecting agents perform than single criterion for rumor prevention? (Answered in subsection 5.3.3)
- **RQ 4:** How number of initial infectors effect the rumor prevention process? (Answered in subsection 5.3.4)
- **RQ 5:** How is the proposed variant SIRPA different than classical SIR model in preventing rumor? (Answered in subsection 5.3.5)
- **RQ 6:** How does AHP-TOPSIS perform in comparison to TOPSIS for rumor prevention? (Answered in Subsection 5.3.6)

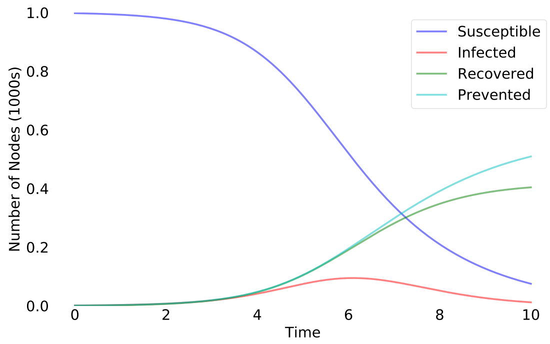
To overcome the randomness in the results, we performed each experiment 1000 times and averaged the results. The following subsections describe the experiments that we performed.

5.3.1 Varying Rumor Diffusion and Counter-Rumor Diffusion Probability

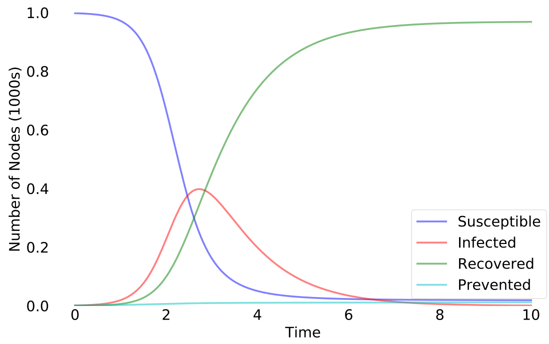
In this experiment, we have analyzed the effect of varying the probability of rumor diffusion β and the probability of counter-rumor diffusion γ on the prevention and control of rumors. We assume that the recovery and prevention rate for the nodes is the same as they both are outcomes of the counter-rumor diffusion process. For analysis, we have run the SIRPA model for a 1000 node network having a number of agents = 4, considering a single rumor initiator for different values of β and γ starting from 0 to 0.5, increasing by a factor of 0.05 each time. The simulation results show that when $\beta \leq \gamma$, the system halts in a preventive state. This means that when counter-rumor diffusion probability is greater than and equal to rumor diffusion probability, the system has more number of prevention nodes, which is obvious. When $\beta > \gamma$, we observe two cases. When $\gamma \geq \beta/2$, the system always halts in a preventive state i.e. the number of prevention nodes exceeds the number of control nodes. However, when $\gamma < \beta/2$, that is, the probability of counter-rumor diffusion is less than half of the likelihood of rumor diffusion, the system ends up in a control state. In conclusion, we can say that the social network system ends up in a preventive state whenever $\gamma \geq \beta/2$, that is, the probability of counter-rumor diffusion should be at least half of the probability of rumor diffusion. Figure 5.5 shows the snapshots of the SIRPA model run on the social network for different probabilities of rumor diffusion and counter-rumor diffusion.

5.3.2 Effect of Number of Agent Nodes

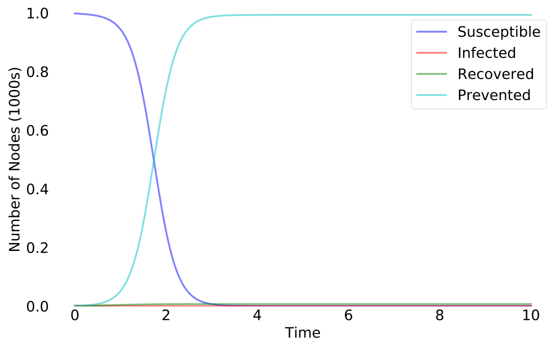
The number of agent nodes determines whether the system will halt in a preventive state or in a control state. We have simulated the SIRPA model for agents



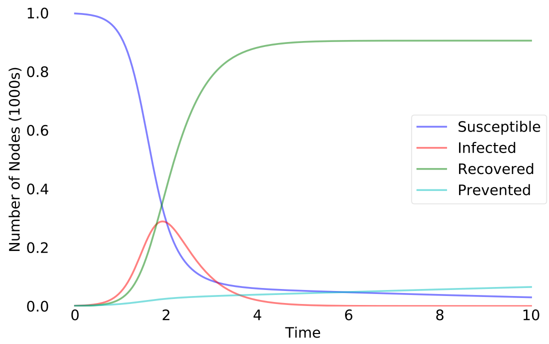
$\beta = 0.10, \gamma = 0.05, \gamma = \beta/2$



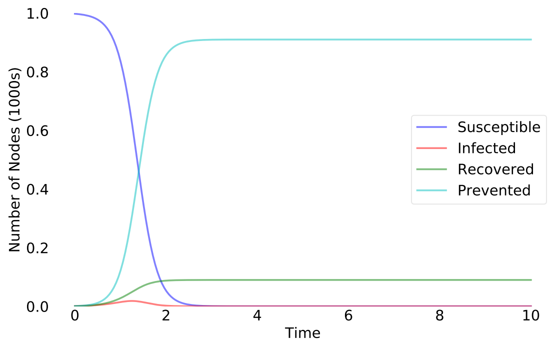
$\beta = 0.20, \gamma = 0.05, \gamma < \beta/2$



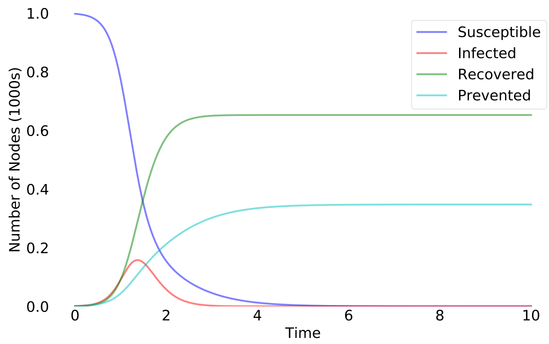
$\beta = 0.20, \gamma = 0.20, \gamma = \beta$



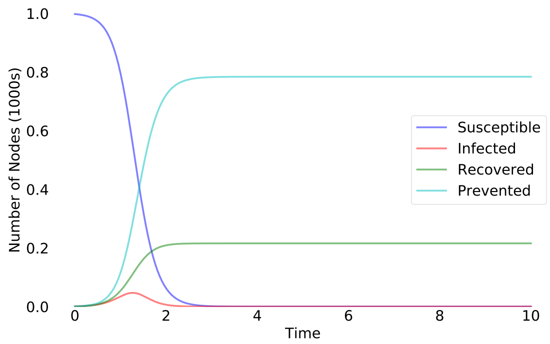
$\beta = 0.30, \gamma = 0.10, \gamma < \beta/2$



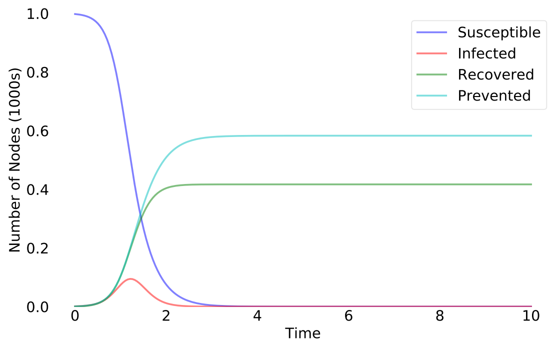
$\beta = 0.40, \gamma = 0.25, \gamma > \beta/2$



$\beta = 0.45, \gamma = 0.20, \gamma < \beta/2$



$\beta = 0.45, \gamma = 0.25, \gamma > \beta/2$



$\beta = 0.5, \gamma = 0.25, \gamma = \beta/2$

FIGURE 5.5: SIRPA Model Implementation Results for different β and γ where N=1000, number of agents = 4, and a single rumor initiator

numbered 1 to 15 for a random single infector. The results for BA and ER networks are shown in figure 5.6 and figure 5.7 respectively. For the BA network that behaves like a real social network, when the number of agent nodes is 4 or greater than 4, the system enters the preventive state as the number of prevention nodes exceeds the number of recovered nodes. This is 0.4% of the total number of nodes. Similarly, for the ER network, which is more a random network, the least required number of key nodes to bring the system into preventive mode is 7 i.e. 0.7% of the total population. For Twitch datasets, the minimum number of agents required for putting the system in preventive state is 37 for EN network, 41 for ES network, 15 for PT network and 42 for RU network, respectively. Table 5.3 shows the minimum number of agents required for each dataset to place the system in a preventive state. From the table, we conclude that the SIRPA model helps to prevent the rumor for a number of agents $< 1\%$ when there is a single infector. Increasing the number of agent nodes above the threshold increases the difference between the prevention nodes and the control nodes. So, one can choose the number of agent nodes that they want to consider. However, this difference becomes constant after a certain number of agent nodes. So, introducing a small number of agent nodes in the network is enough to prevent rumors. When the number of agents is less than the minimum requirement, the system halts in a rumor-controlled state.

Table 5.3: Effect of number of agents on Rumor Prevention using SIRPA model

Dataset	#Nodes	#Agents	Percentage	
BA	1,000	4	0.40	$< 1\%$
ER	1,000	7	0.70	$< 1\%$
EN	7,126	37	0.52	$< 1\%$
ES	4,648	41	0.88	$< 1\%$
PT	1,912	15	0.78	$< 1\%$
RU	4,385	42	0.96	$< 1\%$

5.3.3 AHP-TOPSIS vs Other Centrality Measures

We have used the AHP-TOPSIS method to select the agents that start a counter-rumor diffusion process to prevent rumors. The AHP-TOPSIS method considers

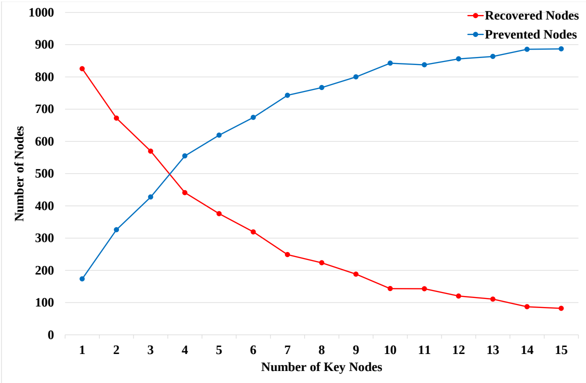


FIGURE 5.6: Effect of Number of agent nodes on BA Network

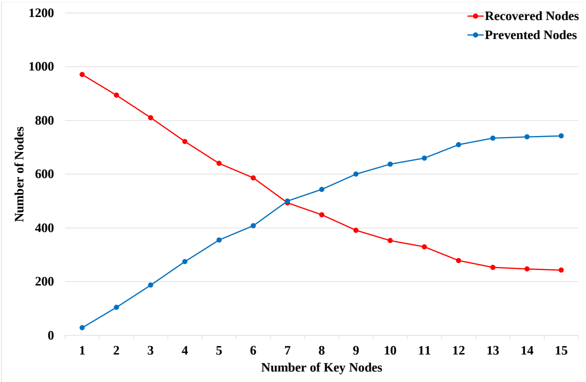


FIGURE 5.7: Effect of Number of agent nodes on ER Network

multiple centrality measures in order to select capable agents from multiple perspectives like popularity, accessibility, and faster dissemination of counter-rumors. Figure 5.8 and figure 5.9 show a comparison of number of prevention nodes obtained using SIRPA model when run using selected agents through AHP-TOPSIS method vs other individual centrality measures for counter-rumor diffusion for BA and ER models respectively. For both networks, AHP-TOPSIS outperforms in most cases. Also, the mean of all prevention nodes when agents selected in range 1 to 10 using AHP-TOPSIS is 617.21 whereas 609.23, 605.63, 610.45 and 596.88 for CC, EC, BC and CC respectively for BA network. For ER network, the mean of all prevention nodes when agents selected in the range 1 to 10 using AHP-TOPSIS is 366.60 and 362.45, 355.09, 344.19 and 363.39 for DC, EC, BC and CC respectively, considering that rumor prevention starts when agent nodes are 7 or more for ER network. Table 5.4 compares the percentage of agents required for rumor prevention from AHP-TOPSIS and other individual centrality criteria for different datasets of Twitch social network. The average result of four datasets shows that AHP-TOPSIS method requires less number of agents than DC, EC, BC and CC and thus performs better than the individual centrality criteria.

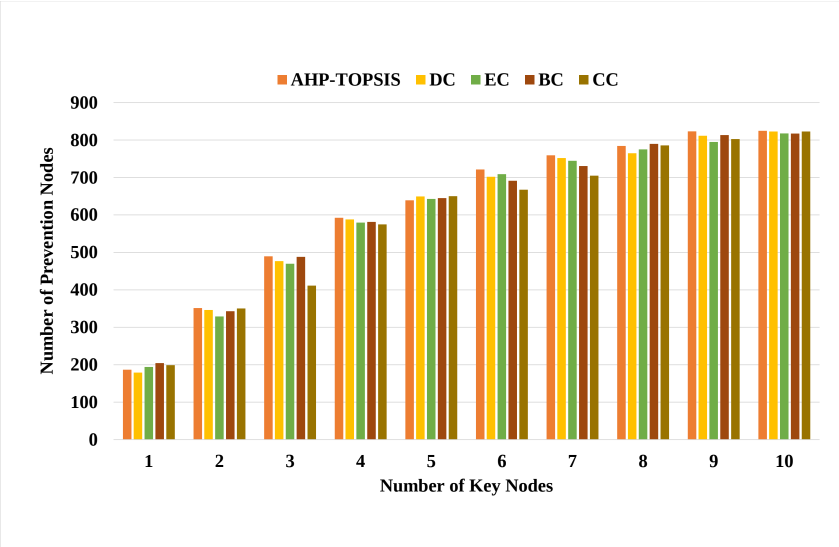


FIGURE 5.8: AHP-TOPSIS vs other centrality measures for BA model

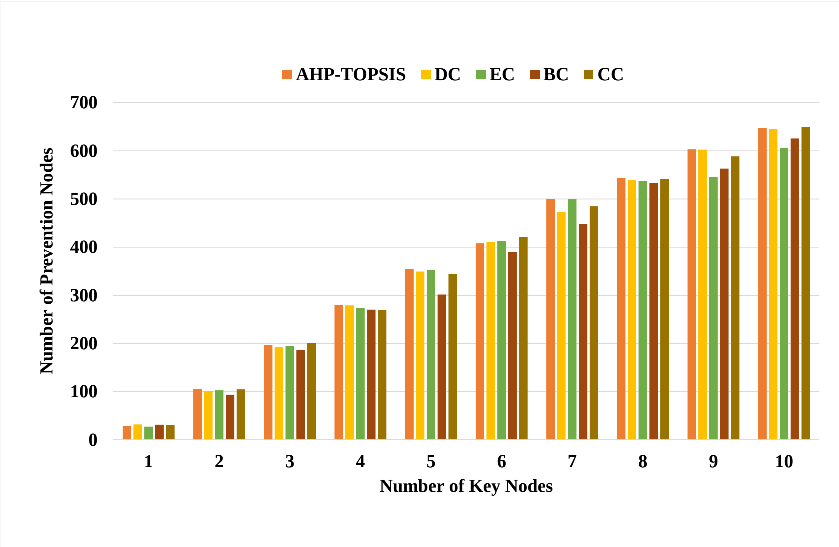


FIGURE 5.9: AHP-TOPSIS vs other centrality measures for ER model

TABLE 5.4: Comparison of percentage of agents required from AHP-TOPSIS and other individual centrality measure

Dataset	AHP-TOPSIS	DC	EC	BC	CC
EN	0.5192	0.5473	0.5894	0.4912	0.5333
ES	0.8820	0.8820	0.9036	1.0327	1.0542
PT	0.7845	0.7322	0.8368	1.0460	0.9937
RU	0.9578	1.0034	1.0034	1.0262	0.9806
Average	**0.7859**	**0.7912**	**0.8333**	**0.8989**	**0.8905**

5.3.4 Effect of Number of Initial Rumor Infectors

This experiment discusses the effect of the number of rumor-initiators on the number of agents using figure 5.10. The figure shows that for a number of initial infectors, we have a fixed number of agents that increases gradually after a number of rumor-initiators in a linear way. Upto initial infectors = 7, we need 4 agents for the BA network. However, after 7 rumor-initiators, the number of agents also tends to increase to put the system into preventive mode. This is self-explanatory from figure 5.10 that we need fewer agents than initiators when the number of initiators is greater. However, according to our simulation results, this finding is limited to the BA network and not to the ER network. For an ER network, no such linear relation is observed. Since BA networks simulate real social networks and ER networks simulate random networks, we find this finding useful to be discussed here; however, it needs further investigation.

5.3.5 Comparison of Proposed SIRPA model with SIR model

The proposed counter-rumor diffusion model SIRPA is a modification to the popular epidemic model SIR by adding two new compartments of preventive nodes P and agents A to existing susceptible S, infected I and recovered R nodes. So, the SIR model serves as the baseline model for our work. Figure 5.11 shows a comparative analysis of the performance of the SIRPA model with SIR. When $\beta = 0.25$ and $\gamma = 0.05$, both models have the same result as the system is in a controlled state for SIRPA and $\beta > \gamma$. In this scenario, the performance of both models is similar as

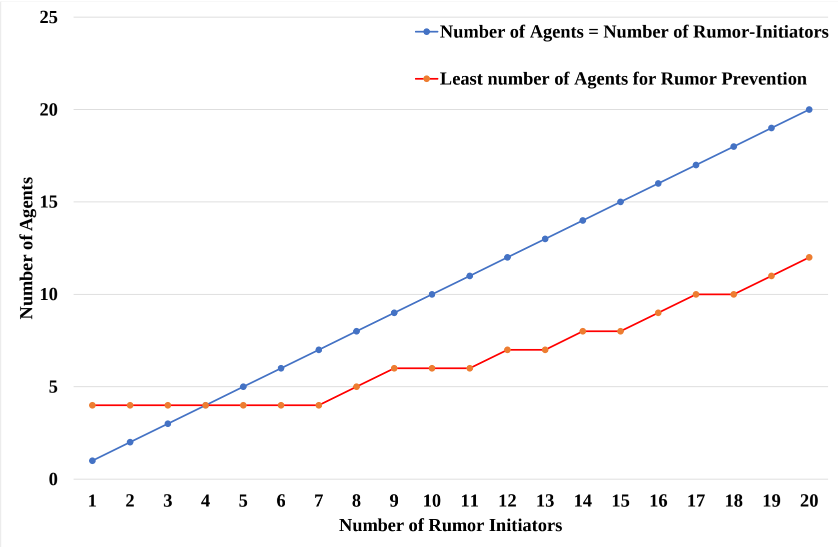
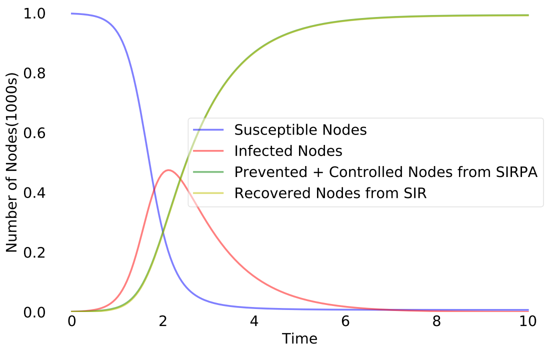


FIGURE 5.10: Effect of number of Rumor-Initiators on Number of Agents on BA network

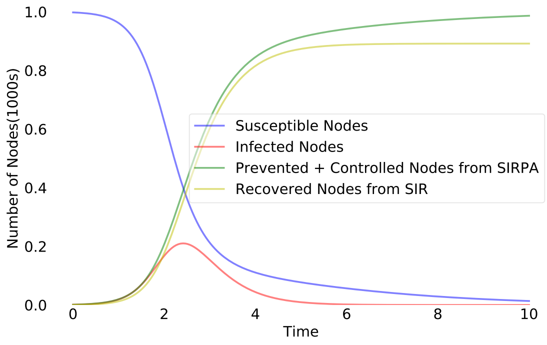
recovered nodes from SIR are equal to the sum of recovered and prevented nodes. As the value of γ increases, the SIRPA model outperforms the SIR model and prevents more rumors from occurring than the SIR model. Thus, we can say that the proposed SIRPA model is better than the SIR model for countering rumors on a social network.

5.3.6 Comparison of AHP-TOPSIS with TOPSIS for keynode selection

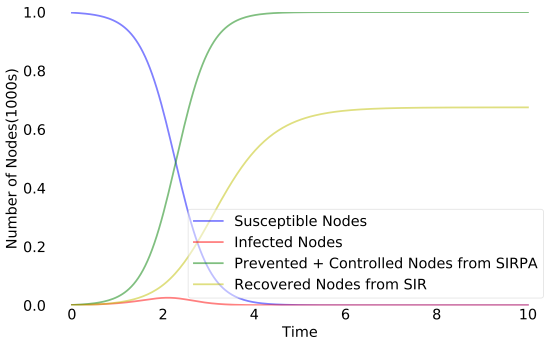
Among various MCDM-based strategies [60, 61, 64, 128, 133], TOPSIS emerged as the most popular. It takes criteria values along with their criteria weights and generates a TOPSIS score to rank the nodes according to their importance. We can assign criteria weights randomly, uniformly, or using some approach. Figure 5.12 shows the effect of uniformly assigning criteria weights (TOPSIS) and using the AHP method to assign criteria weights (AHP-TOPSIS) in the SIRPA model for six datasets. From the figure, it is evident that AHP-TOPSIS performs better than the TOPSIS method for rumor prevention.



$\beta = 0.25, \gamma = 0.05$



$\beta = 0.25, \gamma = 0.10$



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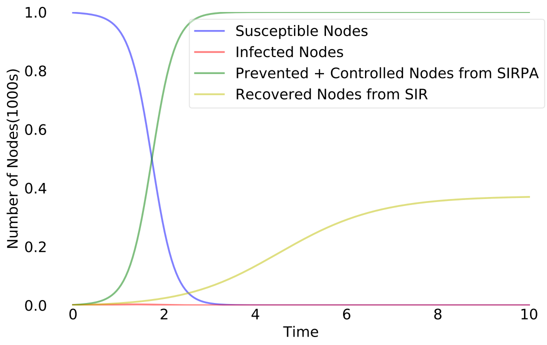

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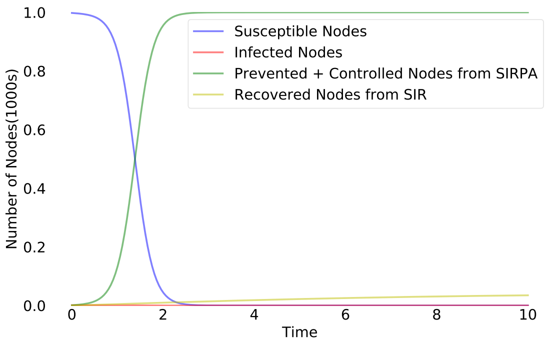
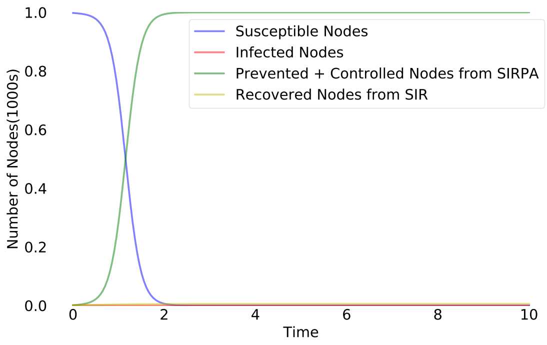
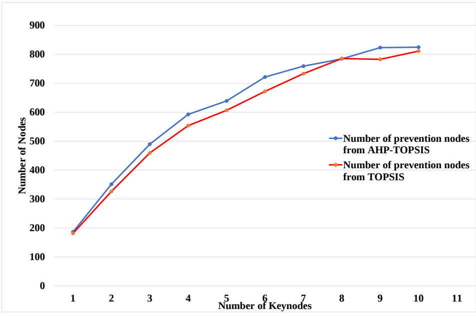


$\beta = 0.25, \gamma = 0.25$

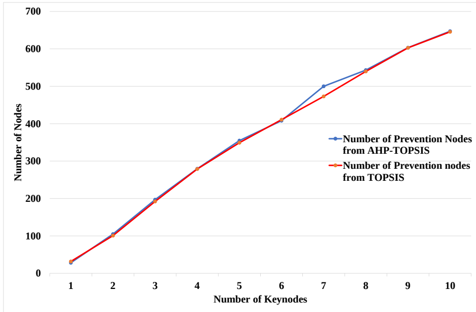


$\beta = 0.25, \gamma = 0.30$

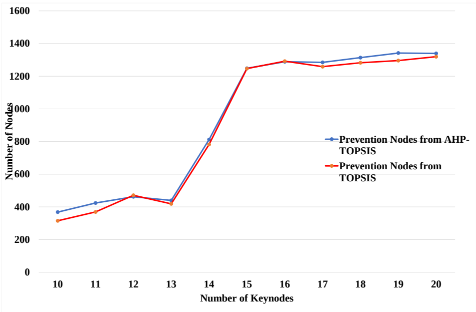
FIGURE 5.11: Comparative Analysis of performance of SIRPA and SIR models



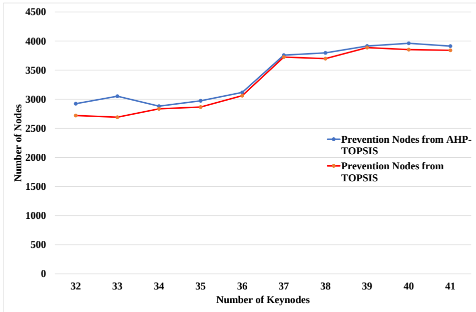
BA Network



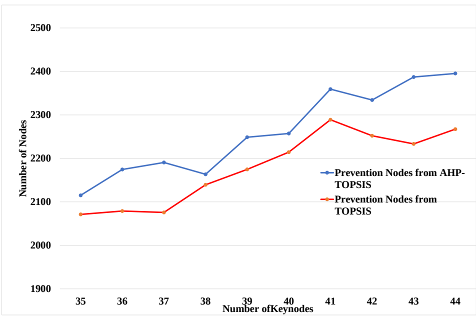
ER Network



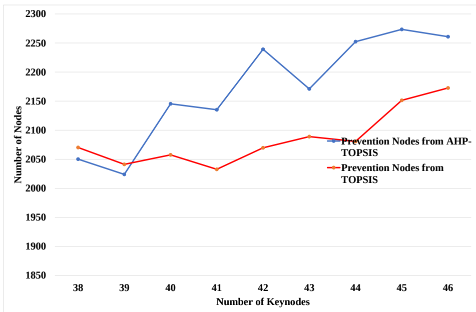
PT Network



EN Network



ES Network



RU Network

FIGURE 5.12: Effect of selecting key nodes from AHP-TOPSIS and TOPSIS methods on rumor prevention using SIRPA model

5.4 Conclusion

In this chapter, we proposed a counter-rumor diffusion mechanism-based rumor prevention model. Numerous experiments have been performed for the analysis of our proposed model by changing various parameters, which established the efficacy of our model for rumor prevention in social networks. The experimental results show that introducing a small number of influential nodes as agents, less than 1% of the total population of nodes in the network, helps effectively prevent rumors using our proposed SIRPA model. However, we need to find the minimum number of agents required for the prevention of rumors. Any further reduction in agents from the minimum number of agents obtained will result in a rumor controlled state rather than rumor prevention state using the SIRPA model. This is an important step in our proposed method because the number of agents determines the trade-off between rumor prevention and rumor control as choosing too few agents will be insufficient for rumor prevention and choosing too many will not have a significant effect on the prevention process. We selected the agents using AHP-TOPSIS which is a consolidated way of considering multiple features like popularity, accessibility, and closeness in a network and demonstrated that AHP-TOPSIS method performs better than individual centrality criteria. AHP-TOPSIS is slightly better than DC; however, DC contains information about the local structure of the graph and does not consider the global structure. So, it is not a good choice to use DC alone. EC, BC and CC do contain the information about global structure of the graph but are limited in providing single features, i.e. popularity, accessibility, and closeness, respectively. So, AHP-TOPSIS provides a better choice for selecting agents. One of the main aspects of our proposed method is that it distinguishes between rumor control and rumor prevention. The SIRPA model ensures that more nodes are immune to rumors. So, even if some nodes do get infected by rumor, we have to recover a smaller number of nodes than that of the SIR model. So, this method is more effective than the SIR model in rumor prevention.

The proposed work has some limitations. Firstly, the pairwise comparison matrix used in the AHP method to determine the weights of the criteria for AHP-TOPSIS depends on the subjective knowledge and judgment of experts. This may result in a not so optimal solution. So, there is also a need to explore other weight-assignment methods. Secondly, the effect of the number of agents required to put the system in preventive state is analyzed for AHP-TOPSIS and other centrality measures. However, further investigation is needed for other structural characteristics of the network, such as density, clustering etc. Thirdly, we provided a method for selection of the agents, however, this chapter lacks discussion on the orchestration and placement of the agents in the social network to make rumor prevention more effective.

In the next chapter 6, we provide an overall conclusion of this thesis along with some future work possibilities.