MESSAGE DISSEMINATION ON SOCIAL MEDIA IN DISASTERS AND EXTREME EVENTS

A Dissertation

by

XIN MA

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ABSTRACT

In recent years, there has been an increasing use of social media in disseminating emergency messages to the public by various governmental and non-governmental emergency management organizations and agencies. These messages, including alerts, warnings and updates, carry important event-related information that helps improve individuals' situational awareness and decision making before, during and after an event. Therefore, wide and timely dissemination of these messages among the public especially the population at risk will be a key for successful emergency preparedness, response, and recovery. However, there is too little knowledge about the impact of social media message propagation on individual message reception as well as the identification of strategies to facilitate message dissemination under the complex environments in disasters and extreme events.

This research was motivated by these facts and takes a first step to conduct quantitative analysis on social media messaging strategies for emergency management organizations and agencies. Specifically, it examines the message propagation process on social media networks and explores message targeting strategies under the constraints of the length of planning horizon, source messaging capability as well as network structure and conditions. Three message dissemination scenarios are studied, including a single-network single-message scenario, a single-network multi-message scenario, and a multi-network multi-message scenario. The impacts of various factors on message dissemination outcomes and targeting decision making are examined through computational experiments on smaller-scale random and Twitter networks. Results and implications for real-world applications are discussed.

This research contributes to the theory and application of social media use in emergency communication mainly in three aspects. First, it summarizes the mainstream literature on this topic and points out the research need for social media messaging strategies for emergency management organizations and agencies in disasters and extreme events. Second, it conceptualizes the problem, develops three message dissemination application scenarios, and provides discrete optimization models for each of them. Third, it conducts extensive computational experiments on small-scale random and Twitter networks to verify the models and study their performance. The implications derived from the results provide valuable insights for emergency management organizations and agencies in developing social media messaging strategies in the real-world applications.

To my parents and my wife

ACKNOWLEDGEMENTS

I would like to express my deepest appreciation to my committee chair, Dr. Justin Yates, who has continuously supported, guided, and inspired me during my Ph.D. study. I am so honored to have had the pleasure of working with him throughout the course of this research.

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Finally, I would like to thank my parents for their encouragement and my wife for her patience and love.

NOMENCLATURE

CDC	Centers for Disease Control and Prevention
DHS	Department of Homeland Security
FEMA	Federal Emergency Management Agency
NOAA	National Oceanic and Atmospheric Administration
NWS	National Weather Service

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CHAPTER I

INTRODUCTION

Social media is defined as any online or digital medium that is provided or collected through a channel that enables the two-way sharing of information, involving multiple parties. This includes social networking sites, texting, and blogs (DHS, 2014). In recent years, social media has been receiving significant attentions from various governmental and non-governmental emergency management organizations and agencies as a viable and accessible emergency communication platform in disasters and extreme events. In particular, there has been an increasing use of social media in disseminating emergency messages to the public. These messages carry important event-related information that contributes to improve individuals' situational awareness and decision making in an event. Hundreds of emergency management organizations and agencies, including FEMA, NWS, and NOAA, have their own accounts or pages on social media sites like Twitter and Facebook (Sutton et al., 2012). They broadcast disaster knowledge, safety instructions for different emergency events and other disaster-related educational information to the public during normal (day-to-day) conditions (Figure 1.1), and disseminate alert and warning messages, event updates as well as evacuation information before, during and after an extreme event (Figure 1.2). More importantly, social media empowers these organizations and agencies to conduct two-way and many-to-many communications during an event, greatly improving the scale and efficiency of communication.

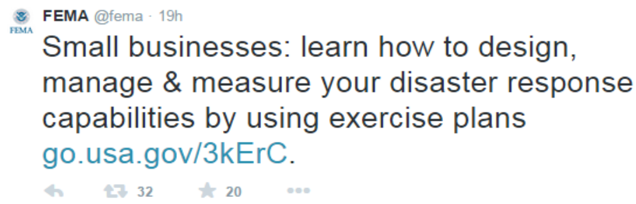

Figure 1.1 An example of FEMA educational message on Twitter (FEMA, 2015)

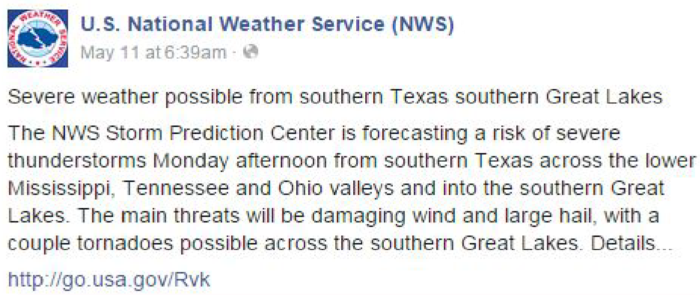

Figure 1.2 An example of NWS warning message on Facebook (NWS, 2015)

To obtain timely and accurate event-related information, the public may follow (Twitter), like (Facebook), or in some other way, connect to official social media accounts of governmental organizations and agencies at the national and local levels, such as FEMA or NWS, as well as non-governmental organizations (e.g., The Red Cross). FEMA has 396,773 followers on Twitter and NWS has 387,589 page likes on Facebook as of May 13, 2015 (obtained directly from twitter.com and facebook.com). This ease of accessibility, coupled with real-time (or near real-time) communication capabilities, enables social media users to actively engage in disaster preparation, response and recovery by either re-releasing/re-phrasing organization information or relaying their own observations, experiences, thoughts and actions. In disasters and extreme events, individuals use social media to express emotional feelings (fear, concern, etc.), ask for help, check the wellbeing of their family and friends, and/or seek disaster-related information, among other uses. Responders or any member of the general public on the scene or near the scene of an extreme event incident are able to post on-the-ground information, including observations, images, and videos, to social media using any number of commercially available mobile devices (e.g., smartphone, iPad, etc.). In certain circumstances, members of the general public are actually serving in a pseudo-first responder role to help relay important information back to official emergency responders (Wukich & Mergel, 2014).

Under current situations, the message dissemination process typically starts from an official source posting a message to its page on one or several social media sites, as illustrated in Figure 1.3. This message will be automatically shown on the wall of each user it is connected to (i.e., follower or page liker). The users who received and read the message may choose to redistribute it by sharing (retweeting) to their friends (followers) on the same network. They can even “transfer” this message to another social media site they use. This could happen when there is a link in the original message, which typically directs them to an article and they will have multiple redistribution options there. This is illustrated in Figure 1.4. When they do the transfer, they are actually redistributing this message on another social media site. As message redistribution continues on these sites, more and more people are potentially exposed to the message (we use the term potentially exposed as receipt of any social media message requires action on the part of the receiver to read the message. While a message may have been delivered to a social

Figure 1.3 A FEMA message on Facebook (left) and Twitter (right) (FEMA, 2015)

Figure 1.4 An illustration of message transfer between sites (FEMA, 2015)

media user, there is no guarantee when that message will be read).

As one of the major stakeholders in an event, the official source would likely hope for the best dissemination outcome from any message distribution, which one might interpret as delivering the message to as many people as possible within a short period of time (i.e., within the planning horizon for a specific event). However, the simple one-to-all, post-and-wait message dissemination strategy typical of most social media sites and tools may not satisfy such expectation and in practice quite often tends to fail in delivering key messages to specific audiences in need (CDC, 2012). An important reason for this failure is the lack of engagement in this process. Only a small portion of an active social media population (those who ‘follow’ or ‘like’ the official source) can receive directly from the source, leaving the majority of the population to receive the message from their friends or some other third-party in the network with whom they share a connection. While such a “word of mouth” message propagation mechanism is beneficial in emergency communication contexts due to the fact that people tend to react more actively when information is provided by family members and close friends than government officials (Crowe, 2010), the ultimate dissemination outcome will largely depend on the message’s starting points on the network (followers, page likers, and/or intended message receivers) and the degree of willingness and responsiveness of every recipient of the message to pass on the message so that it will be visible to other friends/users on the social media site (Kempe et al., 2003) . At the same time, the message dissemination outcome is also affected significantly by the length of planning horizon for the event or extreme event being discussed as well as the structure and condition of the underlying social media network during the event (within which we include consideration to the physical and cyber infrastructure necessary to reliably run and allow access to the social media site). A social media messaging strategy without considering these factors and limitations could barely be effective in the complex and dynamic environments in disasters and extreme events.

Given the aforementioned observations and challenges in distributing time-sensitive messages through social media, it is necessary to identify ways in which emergency management organizations and agencies could play a more engaged role in the message dissemination process, exploiting those well-known and exhibited social media behaviors to increase message penetration and message retention to influence or induce derivative action of a population. As an alternative to the current practice of message ‘blasting’ through social media during extreme events, a social media messaging strategy that integrates decision environments with an emphasis on node targeting could be a viable solution for emergency management organizations and agencies to achieve wide and timely message dissemination in disasters and extreme events. Specifically, agencies and managers could take into account the major factors impacting message dissemination outcomes, including length of planning horizon, source messaging capacity, social media network structure and conditions, and user behaviors, to target specific groups of users. This selective targeting, as it is reasoned, would achieve faster message propagation and wider message reception on the social media sites. This phenomenon is similar traditional message dissemination observed in evacuation warning: message source and content are two very key indicators of message reception, retention and subsequent action. By targeting messages towards known users during an extreme, emergency managers/agencies increase their capability to exploit these two indicators in extreme event message dissemination. An illustration of such a strategy is given in Figure 1.5, in which FEMA, NWS and a local agency could target users in the given way to achieve a better message dissemination outcome.

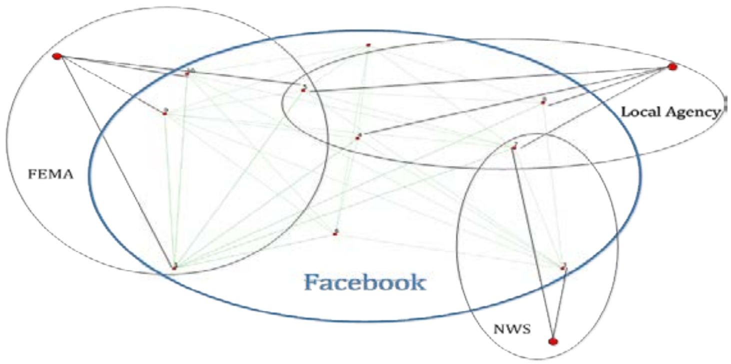

Figure 1.5 An illustration of social media messaging strategy with node targeting

In this research, we examine the message propagation process on social media networks and explore effective message targeting strategies under the constraints of the length of planning horizon, source messaging capability, user behaviors as well as network structure and conditions. Three message dissemination application scenarios are studied, including a single-network single-message scenario, a single-network multi-message scenario, and a multi-network multi-message scenario. The impacts of various factors on message dissemination outcomes and targeting decision making are examined through computational experiments on smaller-scale random and Twitter networks. Results and implications for real-world applications are discussed.

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The remainder of this dissertation is organized as follows. Chapter II provides a thorough literature review, which summarizes recent research on social media use in emergency communication and compares the proposed problem with the existing ones from other fields. Chapter III through Chapter V detail three research problems, the Single-network Single-message Social Media Message Dissemination Problem (SS-SMMDP), the Single-network Multi-message Social Media Message Dissemination Problem (SM-SMMDP), and the Multi-network Multi-message Social Media Message Dissemination Problem (SM-SMMDP), which correspond to three message dissemination application scenarios. Chapter VI concludes the dissertation and discusses some directions for future research.

CHAPTER II

LITERATURE REVIEW

2.1. Social Media in Emergency Communication

There has been a wealth of literature put forth in the past few years on social media use in emergency communication, which is also referred to as disaster communication or crisis communication in different application contexts. Based on the method used, we can categorize them as either qualitative or quantitative. Table 2.1 and Table 2.2 summarize the notable literature in recent years for these two categories, respectively. We can also put the qualitative literature into two categories based on the publication type, including: (1) agency reports, which were released by governmental and non-governmental emergency management organizations and agencies, and (2) research papers, which were typically published on academic journals and conference proceedings. We elaborate on each of these categories in the following.

2.1.1. A review on agency reports

A large portion of the agency reports is detailing examples, practices as well as recommendations for social media use in emergency communication. Queensland Police Service (2011) details a successful use of social media in 2010 Australian Tropical Cyclone Tasha. They attribute a big part of their success to the capability empowered by social media that allowed them to push out large volumes of specific information straight to communities before the mainstream media coverage was available to them, and

Table 2.1 A summary of the recent qualitative literature on social media use in emergency communications

Authors and Year	Method	Domain	Relevance to Emergency Communication	Doc Type
Sorensen (2000)	Literature Review	Disaster Warning System	Advances in warning-related predictions, forecasts, disseminations, and responses over the past 20 years	Research Paper
Jaeger et al. (2007)	Analysis/Examples	Emergency Management/Policy Making	The concept of and need for CRGs that allows residents and responders to share information, communicate, and coordinate activities in response to a major disaster, and policy issue related to such a system	Research Paper
Lindell et al. (2007)	Literature Review	Emergency Communication	Emergency information flow path and evacuation decision making. Warning reception time distribution	Research Paper
Hughes et al. (2008)	Case Study/Questionnaire	Emergency Communication	Online behavior corresponding to socially convergent activity in disaster events	Research Paper
Shklovski et al. (2008)	Case Study/Questionnaire/Interview	Emergency Communication	Social media as a means for communicating community-relevant information especially when members become geographically dispersed	Research Paper
Sutton et al. (2008)	Case Study/Questionnaire/Interview	Emergency Communication	Social media as backchannel in emergency communications, allowing for wide-scale interaction	Research Paper
White et al. (2009)	Survey and Population Sampling	Emergency Management	Social media paradigm can be used to enable collaboration in all stages of emergency management	Research Paper
Crowe (2010)	Analysis/Examples	Emergency Management	Current and future use as well as challenges of using social media in emergency communication	Research Paper
Sutton (2010)	Case Study/Content Analysis	Emergency Communication/Policy making	Use of Twitter following a technological disaster, showing how geographically dispersed individuals broadcast information about the impact of the disaster and its long-term effects	Research Paper
Artman et al. (2011)	Analysis/Examples	Emergency Communication	Concepts of dialogical emergency management that stresses the inherent dual relation between emergency management organizations and the public, and strategic awareness that stresses one's knowledge of what others know in order to establish reciprocal communication	Research Paper
Latonero and Shklovski (2011)	Case Study	Emergency Management	Organizational innovation, risk communication, and technology adoption by emergency management and practices and challenges of new media implementation for emergency management	Research Paper
Lindsay (2011)	Analysis/Examples	Policy Making	Current use, lessons learned, best practices, and policy implications	Agency Report
Queensland Police Service (2011)	Case Study	Emergency Communication	Social media strategy centered on public communications and community engagement issues	Agency Report
Sutton et al. (2011)	Case Study/Interview	Emergency Communication	The role of social media in information-sharing in a disaster compared to traditional news media	Research Paper
Veil et al. (2011)	Literature Review	Emergency Communication	Integration of the best practices in emergency communication into social media use	Research Paper
Wardell III and Su (2011)	Analysis/Examples	Emergency Management	Current and future use of social media in emergency communication, by taking the domestic response community as an enterprise and applying enterprise transformation theory	Agency Report
Yates and Paquette (2011)	Case Study	Emergency Knowledge Management	Social media as a knowledge management system in dynamic emergency environment	Research Paper
CDC (2012)	Literature Review/Case Study	Emergency Communication	Work with social media before and during a crisis, keep up with and respond to social media during a crisis	Agency Report
Holmes (2012)	Literature Review	Emergency Communication	Positive and negative impact of social media on developing best practices of emergency communication	Research Paper
Magro (2012)	Literature Review	E-Government	Social media use in emergency management as part of the E-Government	Research Paper
Mergel (2012a)	Case Study/Examples	Government Management	An overview of current strategies for using Twitter to interact with citizens. In addition, hands-on best practices are presented for both public managers and social media administrators	Agency Report
Mergel (2012a)	Case Study/Examples	Government Management	A review of the most common measurements to evaluate government social media interactions	Agency Report
Tyshchuk and Wallace (2013)	Case Study	Emergency Communication	Community emergency management successfully utilized Facebook during disaster event by closing a feedback loop between first responders and the public, by monitoring information flow and by providing regular updates to the public	Research Paper
DHS (2014)	Analysis/Examples	Emergency Situational Awareness	Examples of how agencies currently leverage social media to enhance situational awareness and support operational decision-making, as well as challenges and potential applications	Agency Report
Funk (2014)	Literature Review/Interview	Emergency Management	Summary of current use of social media during various stages of disasters by government organizations and communities	Research Paper

Table 2.2 A summary of the recent quantitative literature on social media use in emergency communications

Authors and Year	Method	Domain	Relevance to Emergency Communication	Doc Type
Sakaki et al. (2010)	Machine Learning/Statistical Analysis	Emergency Management	An algorithm to monitor tweets and to detect a target event by taking social media users as social sensors	Research Paper
Starbird and Palen (2010)	Case Study/Statistical Analysis/Content Analysis	Emergency Communication	Examine retweet behaviors in emergency in terms of the source and content of tweets	Research Paper
Vieweg et al. (2010)	Case Study/Statistical Analysis/Content Analysis	Emergency Situational Awareness	Use disaster communication data to identify and measure features that may contribute to enhancing situational awareness	Research Paper
Spiro et al. (2012a)	Statistical Modeling/Time Series/Case Study	Emergency Communication	Test some of the proposed rumor determinants in a disaster event and identify influential factors of rumor dissemination	Research Paper
Spiro et al. (2012b)	Statistical Analysis/Content Analysis	Emergency Communication	A preliminary model for the time between information dissemination and redistribution on Twitter, i.e. the waiting time of a retweet	Research Paper
Sutton et al. (2012)	Social Network Analysis/Content Analysis/Case Study	Emergency Communication	Networks, roles, and conversation dynamics of official accounts during a significant disaster event	Research Paper
Tyshchuk et al. (2012)	Social Network Analysis/Content Analysis	Emergency Communication	Understanding of how social media complements official warnings as well as facilitates warning response process, particularly in terms of sharing information, directing people to information, and clarifying information	Research Paper
Vieweg (2012)	Content Analysis/Natural Language Processing	Emergency Situational Awareness	Analysis of tweet content relevant to situational awareness and Twitter information that contributes to situational awareness	Research Pape
Widener et al. (2012)	Agent-based Simulation	Emergency Evacuation	Influence of various types of social networks and communication strategies on participation in evacuation	Research Paper
Yin et al. (2012)	Data Mining/Natural Language Processing	Emergency Situational Awareness	A system that uses social media to enhance emergency situation awareness by extracting and analyzing Twitter text stream	Research Paper
Lachlan et al. (2014a)	Case Study/Content Analysis/Statistical Analysis	Emergency Management	Examine the volume, content, and dissemination of tweets in an emergency event	Research Pape
Lachlan et al. (2014b)	Case Study/Content Analysis/Statistical Analysis	Emergency Management	Examine the content and impact of using localized and nonlocalized hashtags during a weather event	Research Paper
Litou et al. (2014)	Graph Theory/Algorithm Design	Emergency Communication	An approach that investigates the interactions and relationships established between the members of the social group, and develops a scalable dissemination mechanism that selects the most efficient routes to maximize the information reach	Research Paper
Sutton et al. (2014)	Statistical Analysis/Content Analysis/Case Study	Emergency Communication	Key elements that affect public retransmission of messages during the emergency phase of an unfolding disaster	Research Paper
Vieweg et al. (2014)	Machine Learning/Topic Modeling/Case Study/Interview	Emergency Communication	Provide valuable and timely information for rapid disaster assessment to formal response agencies and the public by automatic analysis of social media communication data at a community level during disasters	Research Pape
Wukich and Mergel (2014)	Case Study/Statistical Analysis/Content Analysis	Emergency Communication	Empirically demonstrate how and to what extent state-level emergency management agencies employ social media to increase public participation and induce behavioral changes intended to reduce household and community risk in all stages of emergency management	Research Paper

suggest social media should be used immediately instead of waiting till a disaster strikes and be used for both disseminating information and receiving feedback.

Wardell III and Su (2011) discuss social media adoption in the emergency management community, and conclude that social media technologies have been predominantly used by public information officers (PIOs) to disseminate information to the public and monitor streams of publicly available information. Lindsay (2011) point out that the public may increasingly expect emergency management agencies to use social media to meet their informational needs due to the fact that a significant number of people will likely choose social media as their main source of information as its popularity grows. They also suggest a systematic use of social media in disasters and extreme events including issuing alerts and warnings, receiving requests for assistance, monitoring user activities to establish situational awareness, and using uploaded images to create damage estimates.

Mergel (2012a) provide a manager's guide for using Twitter in government by detailing relevant Twitter features, such as retweeting, mentioning, hashtagging, direct messaging and so on, while Mergel (2012b) focus on the metrics to measure government social media interactions and discuss five potential approaches, including breadth (who they are reaching and if they are reaching the right audience), depth (how the audience percept and respond to their information), loyalty (how often citizens return to their social media sites), sentiments (how is engagement rate of citizens with their social media content), as well as data (what online and offline data indicate).

Meanwhile, challenges, considerations and gaps associated with the use of social media in emergency communication are discussed in detail in these reports as well. Wardell III and Su (2011) point out the gap between the current state and the desired state of social media usage in emergency communication and recommend one major focus for the emergency management community is examining social influences on citizen preparedness and response behavior with inclusion of the effect of social networks when coupled with various messaging strategies. Mergel (2012a) particularly mention the need for an effective tool to get an assessment of how many individuals were reached by the message send from a governmental account on Twitter, instead of simply looking at the number of followers and retweets. CDC (2012) think social media and their use on mobile devices is a rapidly changing landscape that requires constant analysis and proactive planning, and provide a social media communications strategy worksheet which considers target audience, objectives, resources and capacity, and so on. DHS (2014) discuss the challenges associated with the integration of social media data within the information sharing and operational environment as well as the considerations for better leveraging social media to enhance situational awareness and decision support. One of these challenges is how to use of social media data to predict and model potential outcomes and cascading effects.

2.1.2. A review on research papers

Magro (2012) examine the progress of social media policies in emergency management over time and point out the research need in long-range plans for citizen participation and involvement as well as strategies associated with that for using social media in e-government. Jaeger et al. (2007) and Tyshchuk and Wallace (2013) discuss a similar topic at the community level. Specifically, Jaeger et al. (2007) explore the concept of and need for developing community response grid (CRG) for community emergency response and examine the issues of public policy and technology related to such a system. Using the case of Del Norte County, CA during 2011 Japan tsunami, Tyshchuk and Wallace (2013) demonstrate that governmental organizations may successfully utilize social media during disaster events by closing a feedback loop between first responders and the public, by monitoring information flow, and by providing regular updates to the public.

Shklovski et al. (2008), Hughes et al. (2008), and Sutton (2010) study the phenomenon that geographically dispersed users broadcast local and community-relevant information in social media during an emergency event. They believe such interactions via information and communications technology (ICT) not only have immediate benefits, but also establish emergent practices that prepare for the future. Sutton et al. (2011) examine the role of social media in information-sharing in disasters compared to traditional news media, showing that pre-existing networks and community partnerships are the foundation for information sharing in an emergency event, while Yates and Paquette (2011) propose to use social media as a knowledge management system in the dynamic emergency environment by studying the US response to 2010 Haiti Earthquake. Artman et al. (2011) introduce the concepts of dialogical emergency management and strategic awareness to enhance communication between emergency management organizations and the public in social media.

White (2012) and Crowe (2012) conduct systematic and comprehensive studies on social media, Web 2.0 technology, and leveraging them in emergency management and emergency communication.

Quantitative research papers include applied or adapted methods that include data mining, machine learning, statistical analysis and modeling, content analysis, natural language processing as well as simulation. In these cases, Twitter is often the main social media venue used due to its popularity as a social networking site as well as its free accessibility to real-time and archived tweets (through the Firehose or other streaming/querying methods). A summary of these selected papers which emphasize a more mathematical or statistical research approach is provided in Table 2.2 previously.

Taking social media users as social sensors, Sakaki et al. (2010) propose an algorithm to monitor tweets in real-time and detect earthquake event. They show that 96% of the earthquakes with intensity scale 3 or more in Japan can be detected by the algorithm. By examining a population's participation in evacuation with the presence of social network communications using agent-based simulation, Widener et al. (2012) find social networks with greater geographic dispersion result in more residents evacuating and suggest that the impact of social network on individuals' evacuation decisions should be considered by emergency managers when they develop strategies to encourage evacuation in extreme events.

Vieweg et al. (2010), Yin et al. (2012), Vieweg (2012), and Vieweg et al. (2014) examine social media as a critical tool to enhance emergency situational awareness. Yin et al. (2012) detail the architecture of a system developed for the Crisis Coordination

Center in Australia, which gathers tweets in real-time and integrates components for burst detection, text classification, online clustering, geotagging as well as visualization, while Vieweg et al. (2010), Vieweg (2012), and Vieweg et al. (2014) focus on applying behavioral and linguistic analysis to the extracted Twitter text stream and communication data during specific events to help emergency managers understand the "big picture" in time- and safety-critical situations.

Tweeting/retweeting behaviors and the impact on message propagation in emergency events are studied in Starbird and Palen (2010), Spiro et al. (2012a), Spiro et al. (2012b), Lachlan et al. (2014a), Lachlan et al. (2014b), and Sutton et al. (2014). Specifically, Starbird and Palen (2010) summarize the characteristics of the tweets that are more likely to be retweeted during an emergency, in terms of the source and content of the tweets. Spiro et al. (2012a) identify perceived importance and potential to impact decision-making behavior as influential determinants in informal message dissemination by examining the case of 2010 Deepwater Horizon oil spill, while Spiro et al. (2012b) define the time between information dissemination and redistribution on Twitter as the waiting time of a tweet, and propose a preliminary model for the relationship between this time and features about the users involved, the external context, and the message itself.

Lachlan et al. (2014a) examine the volume and content of tweets and dissemination of tweets in Hurricane Sandy and find tweet rate increased during the storm but governmental and organizational responses were largely absent, while Lachlan et al. (2014b) focus on the impact of hashtag use (i.e., localized hashtags vs nonlocalized hashtags) on message dissemination during Snowstorm Nemo, showing that tweets with localized hashtag tend to provide more useable information and using appropriate hashtags may contribute to a greater visibility of the tweets in the affected population. Sutton et al. (2014) examine the retransmission of tweets during 2012 Waldo Canyon Fire in Colorado and find the tweets containing hazard impact, safety instructions, and/or links (URL) to protective action guidance (e.g., evacuation) were more likely to be retweeted than others. They also conclude that in this event officials utilized Twitter to relay information that is broadly applicable to the entire local public rather than using Twitter to post timely, focused, warning guidance for populations under imminent threat.

2.1.3. Alert and warning messages

Alert and warning messages carry critical and time-sensitive information about the event (e.g., real-time updates, safety instructions, evacuation guidance, etc.) that emergency management organizations and agencies want to convey to the public. These messages, helps improve individuals' situational awareness and decision making before, during and after an event, so wide and timely dissemination among the public especially the population at risk will be a key for successful emergency preparedness, response, and recovery. The content and style of these messages would affect the information dissemination and communication effectiveness to a large extent. Sorensen (2000) specify the aspects that warning messages should include in terms of content (nature, location, guidance, time, and source of the hazard or risk) and style (specificity, consistency, accuracy, certainty, and clarity) respectively. Lindell et al. (2007), Veil et al. (2011), Vieweg (2012), and CDC (2012) emphasize that emergency managers must be aware of and take into account the differences among population segments, including culture diversity, ethnic background, community history, and socioeconomic status, while developing and distributing emergency warning messages. By Lindell et al. (2007), Tyshchuk et al. (2012), and Sutton et al. (2014) warnings are most effective when a credible source provides a message that is clear, consistent, easily understood and contain information about the potential impacts and risks of the threat, and include what action should be taken. Several key message components are also identified to increase the chance of retweet and improve effectiveness of communication. Such components include localized information and emergency-related terms (Starbird & Palen, 2010; Spiro et al., 2012a; Lachlan et al., 2014b), pictures/videos from the scene of event and maps showing the exact locations of evacuation zones and emergency shelters (Sutton et al., 2011), as well as hashtags, URLs (shortened or truncated URLs), and mentions of other users (Mergel, 2012; Spiro et al., 2012b; Lachlan et al., 2014a; Lachlan et al., 2014b).

2.2. Related Problems from Other Fields

2.2.1. Network flow problems (NFPs)

There are several network flow problems that share some features with the social media dissemination problems we propose in this dissertation. These problems include the Minimum Cost Network Flow Problem (MCNFP) and the Shortest Path Problem (SPP), which can be viewed as a special case of MCNFP. The objective of MCNFP is to ship the available supply through the network to satisfy demand at minimum cost by determining the amount of flow traveling on each available arc in the given transportation network (Bazaraa et al., 2009). If no arc capacity constraint is enforced, then MCNFP will become SPP. Another notable variant of MCNFP is called Minimum Cost Flow Over Time Problem (MCFOTP), which can be viewed as a dynamic version of the original MCNFP with additional restrictions on arc transit times and a time horizon (Skutella, 2009).

2.2.2. Gossiping and broadcasting problems (GBPs)

In communications and wireless networks, gossiping and broadcasting (Hedetniem et al., 1988; Fraigniaud & Vial, 1997; Ravi, 1994) are two well-known problems that have some overlap with the social media dissemination problems. In the gossiping problem, every person in the network knows a unique item of information and needs to communicate it to everyone else, while in the broadcasting problem one individual has an item of information which needs to be communicated to everyone else. A node is allowed to communicate to one or several of its neighbors at a time, and the time delay for message transmission is typically assumed to be one unit of time. The objective is minimizing node communications or time spent such that every node receives the message(s), by determining a sequence of pairs each one representing a communication process to be performed between two nodes (information exchange either one-way or two-way). Lower bound and/or upper bound of the objective are typically proved as the main pursuit of the problems.

2.2.3. Influence maximization problems (IMPs)

The Influence Maximization Problem (IMP) was motivated by the "word of mouth" effects and the design of viral marketing strategies. IMP aims to find a small subset of nodes in a social network to maximize the spread of influence over the entire network (Kempe et al., 2003). Linear Threshold and Independent Cascade Models are two of the most basic and wildly-studied diffusion models. In Linear Threshold model, a node becomes active once the total influence from its active neighbors reaches a predefined threshold, while in Independent Cascade model any active node has a single chance to activate each of its inactive neighbors with a predefined probability in each step. Variants of the IMP and algorithmic development can be found in Kimura and Saito (2006), Leskovec et al. (2007), Chen et al. (2009) and Guo et al. (2013).

2.3. Summary

It has been the practice and dominating trend for governmental and non-governmental emergency management organizations and agencies to adopt social media as a main platform for emergency management especially for emergency communication in disasters and extreme events. Guidelines and considerations for an effective use of social media to disseminate information, including alerts, warnings and updates are provided and successful use cases and examples at different levels and under different backgrounds are studied. However, there is still a gap between the current state and the desired state of social media usage for effective and reliable emergency message dissemination. In particular, there is a lack of tools for message dissemination planning and outcome assessment as well as strategies integrating all decision parameters to facilitate message propagation on social media in disasters and extreme events.

Quantitative analysis that combines social media and emergency management generally focuses on data acquisition, event detection, text processing, geotagging, visualization, and specifics in the information sharing process (e.g., message content, format and style) so that fails to provide emergency managers with effective and actionable social media strategies in the complex decision environments in disasters and extreme events. Compared to these results, some works from other fields are more relevant in terms of developing social media messaging strategies to facilitate message dissemination, but they cannot accurately capture the situations or satisfy the requirements of emergency communication either. This mainly lies in the following aspects.

- In a social media message dissemination (SMMD) scenario, the only decision a source node (e.g., FEMA, NWS, etc.) can make is when and to whom it should send its direct message. The message propagation after that purely depends on individual's decision to pass on or not. However, in NFPs and GBPs the (amount of) flow on each arc is to be dictated to achieve the best outcome. For example, in the optimal solution node i should send a message to node j, which is not realistic in real-world SMMD scenario.
- Typically, alert and warning messages are useful when they are received within a certain period of time, (i.e., planning horizon), and the length of this time is specific to disaster (event) type. All the message dissemination outcomes should

be evaluated based on this planning horizon. At the same time, a message source may have limited messaging capacity in an emergency situation and may enforce messaging intervals to avoid message overload. However, such considerations are generally missing in NFPs, GBPs, and IMPs.

- When a user shares a message in social media, there is typically a delay between the time she receives the message and when she shares it. This delay generally varies by users and is related to the content and source of the message as well. And once she shares, the message goes to all the friends (followers) of her on the network. Neither the communication mechanism in GBPs (node-to-node, unit delay) nor the diffusion models in IMPs (accumulated or probabilistic) can sufficiently capture such behaviors.
- Each user may receive messages from different sources (e.g., FEMA, NWS, etc.) on multiple social media sites (e.g., Facebook, Twitter, etc.), and it'd be necessary for individuals to gather as much information as possible before they make any decisions (Lindsay, 2011). Such a scenario with multiple networks and multiple messages and considering message aggregation effect at the user end cannot be addressed using any variants of NFPs, GBPs or IMPs.

This research was motivated by the above facts and observations, and is intended to provide insights in assessment and decision support on social media messaging for emergency management organizations and agencies. Specifically, it examines the message propagation process on social media networks and explore message targeting strategies under the constraints of the length of planning horizon, source messaging capability, user behaviors as well as network structure and conditions. Three message dissemination application scenarios are studied, including a single-network single-message scenario, a single-network multi-message scenario, and a multi-network multi-message scenario. The impacts of various factors on message dissemination outcomes and targeting decision making are examined through computational experiments on smaller-scale random and Twitter networks. Results and implications for real-world applications are discussed. Details are presented in the following chapters.

CHAPTER III

SINGLE-NETWORK SINGLE-MESSAGE SOCIAL MEDIA MESSAGE DISSEMINATION PROBLEM *

3.1. Problem Description and Definition

The Single-network Single-message Social Media Message Dissemination Problem (SS-SMMDP) considers the scenario in which one message needs to be disseminated on one social media network within a predefined planning horizon. The network is represented by $G = (I, A)$, where each node $i \in I$ represents a user in the social media and each arc $\langle i, j \rangle \in A$ represents the relationship on the network (i.e., friend or follower) between users $i, j \in I$, through which messages can flow from i to j. The message source is represented by O (not included in network G). The planning horizon is given by set T, where each $t \in T$ represents a time period in the planning horizon. The last time period as well as the length of the planning horizon are both represented by $|T|$.

Message propagation on the network is initiated by the source O through node targeting (i.e., send direct messages to some nodes in a predefined candidate set $M \subseteq I$) and continues as individual nodes redistribute the received messages to their friends or followers, as illustrated in Figure 3.1. The source O can send the message multiple waves if time allows, with a minimum reset time l between two consecutive waves and a

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capacity p in each wave. Accordingly, a subset of p nodes (i.e., nodes to be targeted) needs to be determined corresponding to each wave of messages send from O. This process is illustrated in Figure 3.2. Message propagation on the network is modeled using a time delay d_{ij}, which is defined on each $\langle i, j \rangle \in A$. Under normal conditions, this delay time may represent the time a message is spent unviewed in the user's inbox (maybe the user did not hear the message receipt notification or did not have direct access to their mobile device or computer immediately). Under conditions experienced in extreme events, this delay time could also represent the user's inability to access the message and/or some elongated transmission delay time due to damage of the underlying communications system (e.g., cell phone tower damage) or excessive load (i.e., too many users simultaneously sending messages has jammed the system and prevented messages from being sent). A user node i is considered active after receiving the message, and the message dissemination outcome is expressed as a net gain (i.e., the total gain from activating nodes within the planning horizon minus the total cost of sending messages from the source), which essentially encourages wider message reception on the network with minimum targeted nodes.

Now the SS-SMMDP can be formally stated as follows: Given social media network $G = (I, A)$, candidate set M, planning horizon T, source messaging capacity p, source reset time l, and delay matrix $D(I, I)$, SS-SMMDP optimizes the message dissemination outcome by determining a sequence of subsets, each containing at most p nodes from the candidate set M, to be targeted by the source. Problem formulation is presented in section 3.2.

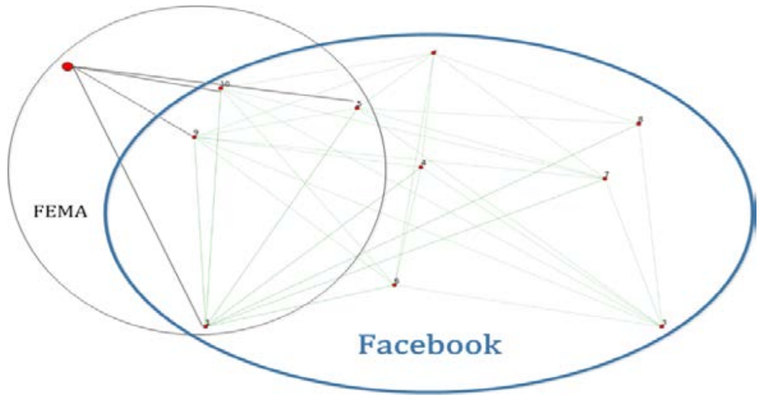


Figure 3.1 Conceptualization of SS-SMMDP

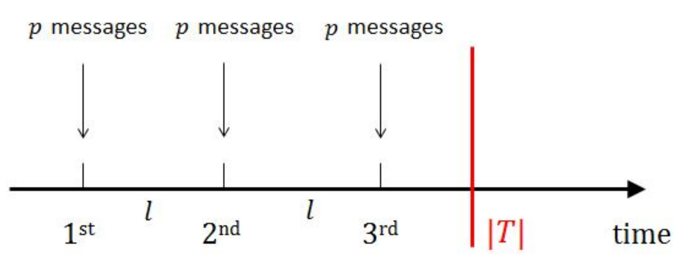


Figure 3.2 An illustration of source messaging behavior

3.2. Problem Formulation

3.2.1. Sets and parameters

I = the set of user nodes

O = the message source

M = the set of candidate nodes for targeting, $M \subseteq I$

T = the set of time periods

$a_{ij} = 1$ if arc $\langle i, j \rangle \in A$, 0 otherwise

d_{ij} = the time delay of a message flowing from node i to node j

w_i = the reward for node i being active within the planning horizon

c_i = the cost of sending a direct message to node i from the source

p = the source messaging capacity

l = the source reset time

3.2.2. Decision variables

$z_{it} = 1$ if node i is active at time t, 0 otherwise

$x_{ijt} = 1$ if a message flows on arc $\langle i, j \rangle$ at time t, 0 otherwise

3.2.3. Formulation

$$max \sum_{i \in I} w_i z_{i|T|} - \sum_{j \in M} \sum_{t \in T} c_j x_{ojt} \qquad (3.1)$$

$s.t.$

$$\sum_{j \in M} \sum_{s=t}^{t+l} x_{ojs} \leq p \qquad \forall\ t \in T \qquad (3.2)$$

$$z_{it} - z_{i,t+1} \leq 0 \qquad \forall\ i \in I, t \in T \qquad (3.3)$$

$$\sum_{i \in I \cup O} \sum_{t \in T} x_{ijt} \leq 1 \qquad \forall\ j \in I \qquad (3.4)$$

$$z_{jt} - \sum_{i \in I \cup O} \sum_{s \in \{T : s \leq t - d_{ij}\}} x_{ijs} \leq 0 \qquad \forall\ j \in I, t \in T \qquad (3.5)$$

$$x_{ijt} - z_{it} \leq 0 \qquad \forall\ i, j\ \in I, t \in T \qquad (3.6)$$

$$x_{ijt}\left(1 - a_{ij}\right) = 0 \qquad \forall\ i, j \in I, t\ \in T \qquad (3.7)$$

The use of weight and cost parameters makes the objective flexible and adaptive to different preferences of emergency managers. When $w_i = c_j = 1$, the objective is altered to emphasize sending as few messages as possible. When $w_i = 1$ and $c_j = 0$, the objective is altered to emphasize activating the largest set of nodes possible. In this way, (3.1) can be slightly altered but always focuses on maximizing some prioritized combination of activated users minus a calculated messaging cost.

Constraint (3.2) limits the source node messaging capability to a maximum value p and constraint (3.4) ensures no nodes receive redundant messages. We employ constraint (3.3) to ensure that chronology in user activity is preserved. Constraints (3.5) and (3.6) control message dissemination through the social network such that messages are delayed appropriately and that no inactive nodes send a message. Constraint (3.7) guarantees messages are passed only through existing arcs.

The use of a candidate set for each message is helps managers/agencies yield the highest versatility from the model. If the model is used in the operational stage of an extreme event, the candidate set should be established according to the real situation (i.e., the connections that each government user has at that moment). If the model is used in the planning stage, then the candidate set can be set equal to the whole user set I. The implication of such a setting is, assuming all the users in set I could be candidates for receiving messages directly, which of them should the governmental node target given the constraint on the number of allowable connections. These users are obviously more important for the message dissemination purpose, so the government could take measures to build connections to them in advance.

3.3. Computational Experiments

We develop two cases upon which to test SS-SMMDP performance. The first is a computational experimental design testing five key model parameters and resulting in 660 unique problem scenarios. Per scenario, we generate 20 replications and make observations on the mean, standard deviation, minimum and maximum performance measures (e.g., objective value, CPU time, etc.). All generated graphs are assumed to be undirected for this case. The second test case, which will be presented in section 3.3.2, uses a social network generated by crawling the Twitter user space with 20 replicates under a smaller number of selected scenario combinations. Some networks areexamined in both directed and undirected scenarios. Note that the time requirement for message dissemination varies over different types of events and different levels of emergency. For example, NWS issues a hurricane watch 24-36 hours in advance of a potential event and a hurricane warning when the event is expected in 24 hours or less. While for tornados, the warning time may be only a few minutes or even less. Without loss of generality, the basic time unit being assumed here is hours. Each test case is now presented and discussed.

3.3.1. Experiments on random networks

The experimental design tests the following five factors: arc delay (D), source messaging capacity (p), source messaging interval (l), length of time horizon ($|T|$) and network size ($|I|$). Factor levels $D = \{0,1\}$, $p = \{1,2,\dots,7,8\}$, $L = \{2,3,4,5,6\}$, $|T| = \{2,3,4,5,6\}$ and $|I| = \{50,100,150\}$ resulted in 660 unique scenario combinations tested with 20 replications. Arc delay (d_{ij}) randomly assigned delay times to arcs using a uniform distribution between 1 and 10 time units (integer) for $D = 0$ and set all arc delay times to 1 when $D = 1$. A randomly generated social network is created at each replication with a 30% probability of connection between any pair of users. All networks generated for a specific scenario are tested to ensure completeness and uniqueness within the replication set. Parameters are set as $w_i = 1$ and $c_i = 0.5$ for all $i \in I$, which is to emphasize activating the largest set of users possible. The candidate set M is set equal to set I in all instances.

Generating our networks randomly and with a uniform connectivity probability between user pairs has been shown to yield networks that do not share certain characteristics with online social networks (Butts, 2008). In general, randomly generated networks are significantly more uniform in their structure and do not possess the low-frequency of highly connected (i.e., high degree) nodes and high-frequency of sparsely connected (i.e., low degree) nodes witnessed in online social networks. This shortcoming leads to lower betweenness and geodesic network measures that can shorten message dissemination. At the same time, our network generation approach comes with less computational overhead than is typically observed in generating more representative online social network structures. Knowing this, we choose to institute the randomly generated network design for our experimental design in an effort to identify SS-SMMDP computational trends. Results and observations from this experimentation will drive parameter selection in the second test case where real-world Twitter user sub-graphs are used. All the instances are computed using ILOG Concert Technology with

C++/CPLEX 12.4 on a Dell OptiPlex 755 computer (Inter Core 2 Duo E8500 3.17GHz, 4GB RAM and Windows 7 System), and the solution time are capped at 7,200 seconds.

Table 3.1 introduces results for a selection of scenarios at the $D = 0$ and $|I| = 50$ level. The most striking observation from the table is the increase in CPU time from $|T| = 4$ to $|T| = 6$ (increased by around 100%). As the time horizon $|T|$ increases, CPU time becomes more unpredictable. This is not unexpected (a $|T| = 4$ scenario will have 10,812 variables and 21,164 constraints while $|T| = 6$ the size increases to 16,218 variables and 31,772 constraints) and is aligned with expected computational performance in other network-based models. Statistically, the time horizon $|T|$ and the source messaging capacity p significantly affect CPU time (p-value < 0.05 using single-factor ANOVA). Aside from CPU time, the other three metrics observed are objective function value ($OBJECTIVE$), number of active nodes at time $|T|$ ($ACTIVE$), and the number of messages sent by the source ($MESSAGES$). Of the three active parameters p, l and $|T|$ in Table 3.1, only the time horizon $|T|$ significantly affects mean value and standard deviation in all three metrics statistically, which indicates that the amount of time allowed for message dissemination is a crucial factor that affects the overall performance.

The litmus test for SS-SMMDP is that it exhibits behavior that we would intuitively expect from such a message dissemination model. To this extent, the model performs quite well, showing better objective performance as $|T|$ increases, a decrease in messages sent as l increases, and an increase in the number of active users as p and $|T|$ increase. Similar trends are indicated in Table 3.2 and Table 3.3, which introduce

Table 3.1 Selected SS-SMMDP results at $D = 0$ and $|I| = 50$

p	l	|T|	|I|	***OBJECTIVE***				***ACTIVE***				***MESSAGES***				***CPU TIME***			
				AVG	StDev	MIN	MAX	AVG	StDev	MIN	MAX	AVG	StDev	MIN	MAX	AVG	StDev	MIN	MAX
2	2	2	50	8.850	1.236	7.0	12.0	9.850	1.236	8	13	2.000	0.000	2	2	0.438	0.063	0.33	0.58
2	2	4	50	37.250	3.315	30.0	43.0	39.250	3.315	32	45	4.000	0.000	4	4	3.519	1.312	1.62	6.58
2	2	6	50	48.875	0.311	48.0	49.5	50.000	0.000	50	50	2.250	0.622	1	4	5.379	1.657	2.93	8.80
2	4	4	50	34.950	4.663	27.0	43.0	35.950	4.663	28	44	2.000	0.000	2	2	4.489	0.636	3.53	6.12
2	4	6	50	48.925	0.286	48.0	49.5	50.000	0.000	50	50	2.150	0.572	1	4	5.199	1.190	3.70	8.60
2	6	6	50	48.700	0.534	48.0	49.5	49.650	0.477	49	50	1.900	0.300	1	2	5.422	1.717	3.24	9.69
4	2	2	50	16.250	1.972	13.0	21.0	18.250	1.972	15	23	4.000	0.000	4	4	0.532	0.131	0.41	1.05
4	2	4	50	45.200	1.435	43.0	47.5	48.950	1.161	47	50	7.500	0.866	5	8	3.671	0.953	1.59	5.46
4	2	6	50	48.900	0.339	48.5	49.5	50.000	0.000	50	50	2.200	0.678	1	3	5.580	1.879	3.20	11.12
4	4	4	50	42.800	2.135	38.0	46.0	44.800	2.135	40	48	4.000	0.000	4	4	3.868	1.121	2.45	6.12
4	4	6	50	48.925	0.363	48.0	49.5	50.000	0.000	50	50	2.150	0.726	1	4	5.135	1.585	3.03	8.92
4	6	6	50	48.925	0.286	48.5	49.5	50.000	0.000	50	50	2.150	0.572	1	3	5.061	1.465	2.93	7.83
6	2	2	50	21.750	2.142	19.0	26.0	24.750	2.142	22	29	6.000	0.000	6	6	0.595	0.096	0.44	0.80
6	2	4	50	46.650	0.502	45.5	47.5	50.000	0.000	50	50	6.700	1.005	5	9	2.403	0.685	1.48	4.12
6	2	6	50	48.975	0.192	48.5	49.5	50.000	0.000	50	50	2.050	0.384	1	3	5.324	1.532	3.04	8.77
6	4	4	50	45.850	1.226	43.0	47.5	48.800	1.166	46	50	5.900	0.300	5	6	2.984	0.867	1.61	4.62
6	4	6	50	49.075	0.286	48.5	49.5	50.000	0.000	50	50	1.850	0.572	1	3	5.451	1.082	4.29	8.17
6	6	6	50	48.925	0.286	48.0	49.5	50.000	0.000	50	50	2.150	0.572	1	4	5.369	1.696	2.92	9.22
8	2	2	50	25.250	2.467	20.0	29.0	29.250	2.467	24	33	8.000	0.000	8	8	0.463	0.106	0.33	0.84
8	2	4	50	46.575	0.618	45.5	47.5	50.000	0.000	50	50	6.850	1.236	5	9	2.409	0.767	1.45	4.31
8	2	6	50	49.050	0.269	48.5	49.5	50.000	0.000	50	50	1.900	0.539	1	3	5.071	1.277	3.20	8.72
8	4	4	50	46.400	0.970	44.0	47.5	49.750	0.536	48	50	6.700	1.145	5	8	2.349	0.849	1.25	4.66
8	4	6	50	48.975	0.295	48.5	49.5	50.000	0.000	50	50	2.050	0.589	1	3	5.110	2.247	2.87	9.84
8	6	6	50	48.950	0.150	48.5	49.0	50.000	0.000	50	50	2.100	0.300	2	3	5.003	1.514	3.37	8.33

Table 3.2 Selected SS-SMMDP results at $D = 0$ and $|I| = 100$

p	l	|T|	|I|	***OBJECTIVE***				***ACTIVE***				***MESSAGES***				***CPU TIME***			
				AVG	StDev	MIN	MAX	AVG	StDev	MIN	MAX	AVG	StDev	MIN	MAX	AVG	StDev	MIN	MAX
2	2	2	100	15.550	1.244	14.0	18.0	16.550	1.244	15	19	2.000	0.000	2	2	1.418	0.325	0.98	2.26
2	2	4	100	92.300	2.027	88.0	95.0	94.300	2.027	90	97	4.000	0.000	4	4	17.819	3.391	12.84	25.49
2	2	6	100	99.500	0.000	99.5	99.5	100.000	0.000	100	100	1.000	0.000	1	1	32.512	6.383	16.91	50.01
2	4	4	100	91.250	2.826	85.0	96.0	92.250	2.826	86	97	2.000	0.000	2	2	18.061	6.559	9.63	37.58
2	4	6	100	99.475	0.109	99.0	99.5	100.000	0.000	100	100	1.050	0.218	1	2	33.568	6.182	24.32	43.91
2	6	6	100	99.500	0.000	99.5	99.5	100.000	0.000	100	100	1.000	0.000	1	1	30.418	7.487	23.31	55.32
4	2	2	100	28.150	2.151	24.0	33.0	30.150	2.151	26	35	4.000	0.000	4	4	1.000	0.122	0.87	1.28
4	2	4	100	97.950	0.415	97.0	98.5	100.000	0.000	100	100	4.100	0.831	3	6	11.745	1.969	8.89	15.96
4	2	6	100	99.500	0.000	99.5	99.5	100.000	0.000	100	100	1.000	0.000	1	1	32.551	6.933	20.45	47.74
4	4	4	100	97.775	1.030	94.0	98.5	99.650	0.963	96	100	3.750	0.433	3	4	13.979	5.717	8.64	36.15
4	4	6	100	99.500	0.000	99.5	99.5	100.000	0.000	100	100	1.000	0.000	1	1	32.694	8.608	22.12	50.09
4	6	6	100	99.500	0.000	99.5	99.5	100.000	0.000	100	100	1.000	0.000	1	1	32.640	6.565	22.48	46.43
6	2	2	100	37.650	1.621	35.0	40.0	40.650	1.621	38	43	6.000	0.000	6	6	1.376	0.305	0.97	2.26
6	2	4	100	98.025	0.334	97.0	98.5	100.000	0.000	100	100	3.950	0.669	3	6	11.749	2.416	7.02	17.44
6	2	6	100	99.500	0.000	99.5	99.5	100.000	0.000	100	100	1.000	0.000	1	1	29.512	5.044	18.80	35.82
6	4	4	100	97.900	0.255	97.5	98.5	100.000	0.000	100	100	4.200	0.510	3	5	11.894	3.476	8.19	22.96
6	4	6	100	99.500	0.000	99.5	99.5	100.000	0.000	100	100	1.000	0.000	1	1	31.771	9.926	22.50	64.21
6	6	6	100	99.500	0.000	99.5	99.5	100.000	0.000	100	100	1.000	0.000	1	1	30.465	7.060	22.00	46.88
8	2	2	100	46.450	2.037	44.0	50.0	50.450	2.037	48	54	8.000	0.000	8	8	1.564	0.396	1.00	2.62
8	2	4	100	97.975	0.334	97.0	98.5	100.000	0.000	100	100	4.050	0.669	3	6	12.344	3.541	8.17	21.14
8	2	6	100	99.500	0.000	99.5	99.5	100.000	0.000	100	100	1.000	0.000	1	1	28.795	7.365	19.86	57.25
8	4	4	100	97.950	0.269	97.5	98.5	100.000	0.000	100	100	4.100	0.539	3	5	12.819	3.932	7.16	26.43
8	4	6	100	99.500	0.000	99.5	99.5	100.000	0.000	100	100	1.000	0.000	1	1	28.097	3.246	21.51	32.59
8	6	6	100	99.500	0.000	99.5	99.5	100.000	0.000	100	100	1.000	0.000	1	1	27.420	6.121	17.50	43.52

Table 3.3 Selected SS-SMMDP results at $D = 0$ and $|I| = 150$

p	l	|T|	|I|	*OBJECTIVE*				*ACTIVE*				*MESSAGES*				*CPU TIME*			
				AVG	StDev	MIN	MAX	AVG	StDev	MIN	MAX	AVG	StDev	MIN	MAX	AVG	StDev	MIN	MAX
2	2	2	150	21.250	1.639	18.0	24.0	22.250	1.639	19	25	2.000	0.000	2	2	2.560	0.569	1.68	4.45
2	2	4	150	147.350	1.566	145.0	149.0	149.000	1.265	147	150	3.300	0.781	2	4	209.969	267.931	20.67	954.27
2	2	6	150	149.500	0.000	149.5	149.5	150.000	0.000	150	150	1.000	0.000	1	1	125.494	23.537	83.49	175.92
2	4	4	150	146.850	1.982	143.0	149.0	147.850	1.982	144	150	2.000	0.000	2	2	339.245	422.334	19.80	1285.00
2	4	6	150	149.500	0.000	149.5	149.5	150.000	0.000	150	150	1.000	0.000	1	1	131.272	43.082	46.07	204.45
2	6	6	150	149.500	0.000	149.5	149.5	150.000	0.000	150	150	1.000	0.000	1	1	115.522	29.550	43.03	154.69
4	2	2	150	39.200	2.293	35.0	44.0	41.200	2.293	37	46	4.000	0.000	4	4	2.162	0.300	1.81	2.93
4	2	4	150	148.575	0.238	148.0	149.0	150.000	0.000	150	150	2.850	0.477	2	4	42.474	16.068	18.39	89.12
4	2	6	150	149.500	0.000	149.5	149.5	150.000	0.000	150	150	1.000	0.000	1	1	116.654	25.703	76.78	182.72
4	4	4	150	148.600	0.255	148.0	149.0	150.000	0.000	150	150	2.800	0.510	2	4	44.442	29.456	24.84	123.18
4	4	6	150	149.500	0.000	149.5	149.5	150.000	0.000	150	150	1.000	0.000	1	1	124.295	28.509	45.27	185.27
4	6	6	150	149.500	0.000	149.5	149.5	150.000	0.000	150	150	1.000	0.000	1	1	116.837	32.968	38.58	164.38

selected experimental results for $|I| = 100$ and $|I| = 150$. From Table 3.1 through 3.3 , another notable trend is that the mean value and standard deviation of CPU time increase significantly from $|I| = 50$ to $|I| = 150$ (the maximum CPU time reaches 1,285 seconds for some instance of $|I| = 150$), which suggests that fast solving procedures (e.g., heuristics) may be needed to solve large-scale problems efficiently. In light of this, we designed a standard Tabu Search procedure for SS-SMMDP as an initial study on heuristic performance, detailed discussions of which will be given in section 3.4.

3.3.2. Experiments on Twitter sub-networks

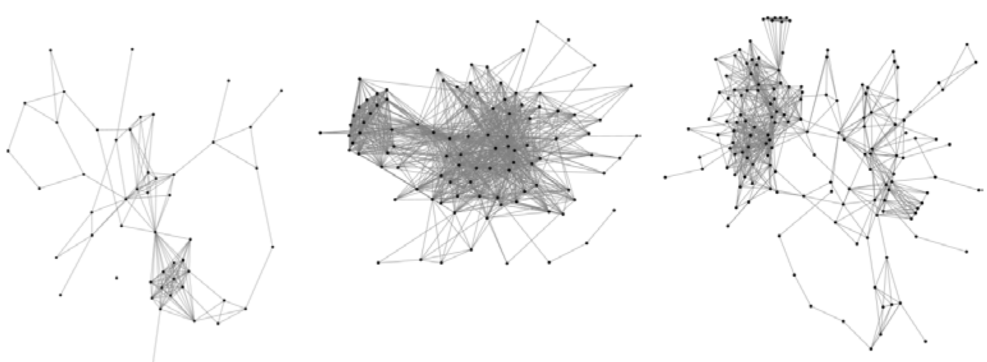
The results presented in section 3.3.1 are derived from SS-SMMDP applications on randomly generated networks with a pre-specified connectivity rate (e.g., 30% connected) and where focus was on computational experimentation. Using random networks enabled us to create a large body of diverse networks upon which to test SS-SMMDP performance without significant computational burden. Realistically, however, randomly generated networks do not closely approximate the structure and properties of on-line social networks (Butts, 2008). Random networks tend to be significantly more uniform in structure and do not exhibit the small-world properties greatly present in social media (Butts, 2008; Gjoka et al., 2010).

Having demonstrated the computational properties of SS-SMMDP in section 3.3.1, we now apply it to a series of collected, real-world social media networks. Our test networks are pulled from Twitter using a Python script that implemented a Metropolis-Hastings Random Walk (MHRW) in the friend and follower directions and initiating at a randomly generated Twitter user node. We choose MHRW as it has been shown to generate social sub-networks with properties that are strongly consistent to the large-scale (Gjoka et al., 2010). Appropriate network approximation is critical in cases of social network analysis as (1) it is impossible to capture and apply methods to the entire social network itself, and (2) sampling and approximation techniques introduce inherent bias to network applications.

For this analysis, we create two separate types of networks from the MHRW and will refer to them as the RED and GREEN networks. To generate both networks, we start from an initial randomly generated node in the Twitter network. We apply the MHRW to trace through the actual Twitter network of users and log both the selected nodes and the friends/followers of each selected node. The RED network represents a strong MHRW where only those nodes selected through the random walk are included in the graph. In the GREEN network, we include all nodes of the RED user nodes and augment the graph with all common friends/followers. In this way, the GREEN network can be substantially larger than the RED network. Three separate MHRW were conducted to the Twitter network in July 2013 with $|I| = \{50, 100, 150\}$. The resulting six networks are presented in Figure 3.3 and Figure 3.4 with RED and GREEN network statistics provided in Table 3.4.

(a) (b) (c)

Figure 3.3 RED networks for (a) $|I| = 50$, (b) $|I| = 100$, and (c) $|I| = 150$



(a) (b) (c)

Figure 3.4 GREEN networks for (a) $|I| = 50$, (b) $|I| = 100$, and (c) $|I| = 150$

Table 3.4 Network statistics for the RED and GREEN Twitter cases

	Nodes	Arcs	Density	*Node Degree Statistics* AVG	StDev	MIN	MAX
Red	50	62	0.051	2.480	1.024	1	6
	100	259	0.052	5.180	4.801	1	18
	150	235	0.021	3.133	1.711	1	10
Green	50	162	0.132	6.480	4.842	0	20
	100	1088	0.220	21.760	14.247	1	72
	150	720	0.064	9.600	7.096	1	36

In testing SS-SMMDP performance on the RED networks, we examine both the directed and undirected cases noting that Twitter is a directed network of those who receive your tweets (follower) and those whose tweets you receive (following). We apply the same experimental design used in section 3.3.1 with 20 replications per factor combination which randomly generate the arc delay values. Parameters are set as $w_i = 1$ and $c_i = 0.5$ for all $i \in I$, which is to emphasize activating the largest set of users possible. The candidate set M is set equal to set I in all instances. All the computations are done with AMPL/CPLEX 12.1 on a Dell OptiPlex 755 computer (Inter Core 2 Duo E6750 2.67GHz, 2GB RAM and Windows 7 System). Tables 3.5 and Table 3.6 provide summarized results for the undirected and directed networks, respectively.

Table 3.7 gives experimental results for the GREEN network. In this network, we set the arc delay values between any two nodes *i* and *j* to be a function of the common connections (followers/following) between them. With *n* representing the number of common connections, we establish three levels of delay $D = \{0, 1, 2\}$ where $D = 0$

represents a reciprocal delay function ($d_{ij} = 10/n$), $D = 1$ constant delay ($d_{ij} = 1$), and $D = 2$ exponential delay ($d_{ij} = 10e^{-n/10}$). Given our definition of arc delay, only one problem instance is run for each factor combination (i.e., no replications are made for the GREEN network).

Table 3.5 Selected SS-SMMDP results for $D = 0$ and undirected RED networks

p	l	|T|	|I|	*OBJECTIVE*				*ACTIVE*				*MESSAGES*				*CPU TIME*			
				AVG	StDev	MIN	MAX	AVG	StDev	MIN	MAX	AVG	StDev	MIN	MAX	AVG	StDev	MIN	MAX
2	2	4	50	6.350	0.654	5.0	8.0	8.350	0.654	7	10	4.000	0.000	4	4	0.128	0.027	0.11	0.23
2	2	6	50	11.850	1.682	9.0	15.0	13.850	1.682	11	17	4.000	0.000	4	4	0.243	0.072	0.17	0.45
2	4	4	50	5.250	0.698	4.0	7.0	6.250	0.698	5	8	2.000	0.000	2	2	0.137	0.021	0.12	0.17
2	4	6	50	9.100	1.480	6.0	11.0	11.100	1.480	8	13	4.000	0.000	4	4	0.186	0.048	0.14	0.36
2	6	6	50	8.650	1.621	7.0	13.0	9.650	1.621	8	14	2.000	0.000	2	2	0.215	0.039	0.16	0.28
8	2	4	50	18.750	1.512	15.0	22.0	26.750	1.512	23	30	16.000	0.000	16	16	0.069	0.011	0.06	0.09
8	2	6	50	28.950	2.801	24.0	35.0	36.950	2.801	32	43	16.000	0.000	16	16	0.117	0.063	0.08	0.36
8	4	4	50	14.900	1.972	9.0	18.0	18.900	1.972	13	22	8.000	0.000	8	8	0.063	0.014	0.05	0.12
8	4	6	50	25.900	2.119	21.0	29.0	33.900	2.119	29	37	16.000	0.000	16	16	0.197	0.227	0.08	1.17
8	6	6	50	22.000	1.897	16.0	25.0	26.000	1.897	20	29	8.000	0.000	8	8	0.142	0.039	0.08	0.2
2	2	4	100	11.900	1.044	10.0	14.0	13.900	1.044	12	16	4.000	0.000	4	4	0.267	0.141	0.12	0.83
2	2	6	100	25.950	2.247	23.0	30.0	27.950	2.247	25	32	4.000	0.000	4	4	5.644	4.031	1.08	15.96
2	4	4	100	11.200	1.030	9.0	13.0	12.200	1.030	10	14	2.000	0.000	2	2	2.422	2.198	0.16	7.14
2	4	6	100	22.750	2.567	19.0	28.0	24.750	2.567	21	30	4.000	0.000	4	4	5.271	2.316	0.76	9.2
2	6	6	100	21.550	1.627	19.0	24.0	22.550	1.627	20	25	2.000	0.000	2	2	5.558	3.987	1.09	15.37
8	2	4	100	31.300	1.977	27.0	36.0	39.300	1.977	35	44	16.000	0.000	16	16	1.005	1.147	0.11	3.42
8	2	6	100	54.050	3.471	47.0	61.0	62.050	3.471	55	69	16.000	0.000	16	16	23.968	35.351	1.76	128.2
8	4	4	100	28.400	1.881	24.0	31.0	32.400	1.881	28	35	8.000	0.000	8	8	1.013	1.279	0.11	3.42
8	4	6	100	50.000	2.214	46.0	54.0	58.000	2.214	54	62	16.000	0.000	16	16	58.694	167.400	0.7	763.19
8	6	6	100	44.600	2.973	39.0	52.0	48.600	2.973	43	56	8.000	0.000	8	8	40.107	83.632	0.75	308.83
2	2	4	150	8.650	0.910	7.0	10.0	10.650	0.910	9	12	4.000	0.000	4	4	4.096	2.639	0.17	8.27
2	2	6	150	19.000	2.345	14.0	24.0	21.000	2.345	16	26	4.000	0.000	4	4	9.988	3.830	2.06	16.49
2	4	4	150	7.800	1.122	6.0	11.0	8.800	1.122	7	12	2.000	0.000	2	2	6.328	3.213	1.93	11.43
2	4	6	150	14.650	1.682	10.0	17.0	16.650	1.682	12	19	4.000	0.000	4	4	7.672	3.428	0.92	14.01
2	6	6	150	14.450	1.431	12.0	17.0	15.450	1.431	13	18	2.000	0.000	2	2	6.395	3.710	0.7	13.87
8	2	4	150	28.200	1.568	25.0	31.0	36.200	1.568	33	39	16.000	0.000	16	16	1.698	2.683	0.19	10.33
8	2	6	150	50.350	2.886	45.0	57.0	58.350	2.886	53	65	16.000	0.000	16	16	426.876	581.582	2.7	1805.39
8	4	4	150	23.700	1.819	21.0	27.0	27.700	1.819	25	31	8.000	0.000	8	8	2.333	2.283	0.14	8.81
8	4	6	150	43.200	2.502	38.0	47.0	51.200	2.502	46	55	16.000	0.000	16	16	122.591	383.643	1.17	1763.72
8	6	6	150	39.950	2.479	35.0	44.0	43.950	2.479	39	48	8.000	0.000	8	8	30.302	48.073	0.66	228.43

Table 3.6 Selected SS-SMMDP results for $D = 0$ and directed RED networks

p	l	|T|	|I|	*OBJECTIVE*				*ACTIVE*				*MESSAGES*				*CPU TIME*			
				AVG	StDev	MIN	MAX	AVG	StDev	MIN	MAX	AVG	StDev	MIN	MAX	AVG	StDev	MIN	MAX
2	2	4	50	5.450	0.865	4.0	7.0	7.450	0.865	6	9	4.000	0.000	4	4	0.128	0.028	0.11	0.23
2	2	6	50	9.550	0.973	8.0	11.0	11.550	0.973	10	13	4.000	0.000	4	4	0.182	0.064	0.12	0.41
2	4	4	50	4.150	0.726	3.0	5.0	5.150	0.726	4	6	2.000	0.000	2	2	0.123	0.028	0.09	0.23
2	4	6	50	7.650	0.963	6.0	10.0	9.650	0.963	8	12	4.000	0.000	4	4	0.160	0.023	0.12	0.19
2	6	6	50	6.000	0.775	5.0	7.0	7.000	0.775	6	8	2.000	0.000	2	2	0.168	0.019	0.14	0.2
8	2	4	50	17.850	1.276	16.0	21.0	25.850	1.276	24	29	16.000	0.000	16	16	0.128	0.022	0.11	0.2
8	2	6	50	26.900	2.663	22.0	32.0	34.900	2.663	30	40	16.000	0.000	16	16	0.140	0.020	0.12	0.19
8	4	4	50	14.350	1.424	11.0	18.0	18.350	1.424	15	22	8.000	0.000	8	8	0.125	0.014	0.11	0.16
8	4	6	50	24.200	1.749	21.0	28.0	32.200	1.749	29	36	16.000	0.000	16	16	0.135	0.020	0.11	0.19
8	6	6	50	20.100	2.468	16.0	26.0	24.100	2.468	20	30	8.000	0.000	8	8	0.133	0.015	0.11	0.17
2	2	4	100	11.650	1.195	9.0	13.0	13.650	1.195	11	15	4.000	0.000	4	4	2.664	1.976	0.11	6.54
2	2	6	100	23.500	1.775	20.0	26.0	25.500	1.775	22	28	4.000	0.000	4	4	3.425	2.163	0.59	7.11
2	4	4	100	11.200	1.249	10.0	14.0	12.200	1.249	11	15	2.000	0.000	2	2	1.772	1.630	0.12	5.52
2	4	6	100	20.750	1.337	17.0	23.0	22.750	1.337	19	25	4.000	0.000	4	4	4.182	1.439	0.84	6.54
2	6	6	100	19.500	0.975	18.0	21.0	20.500	0.975	19	22	2.000	0.000	2	2	4.912	0.530	4.12	6.36
8	2	4	100	30.450	1.774	27.0	34.0	38.450	1.774	35	42	16.000	0.000	16	16	1.524	1.389	0.11	3.2
8	2	6	100	50.550	2.673	45.0	56.0	58.550	2.673	53	64	16.000	0.000	16	16	4.388	3.672	0.33	14.74
8	4	4	100	26.400	1.715	22.0	31.0	30.400	1.715	26	35	8.000	0.000	8	8	1.149	1.203	0.09	3.34
8	4	6	100	42.400	2.498	38.0	50.0	50.400	2.498	46	58	16.000	0.000	16	16	3.942	1.648	0.27	7.3
8	6	6	100	38.350	2.080	34.0	42.0	42.350	2.080	38	46	8.000	0.000	8	8	3.237	1.618	0.37	6.05
2	2	4	150	8.150	1.195	6.0	10.0	10.150	1.195	8	12	4.000	0.000	4	4	3.878	2.481	0.2	9.84
2	2	6	150	15.700	1.584	13.0	19.0	17.700	1.584	15	21	4.000	0.000	4	4	6.056	3.297	0.83	11.79
2	4	4	150	6.650	1.014	5.0	8.0	7.650	1.014	6	9	2.000	0.000	2	2	5.390	4.097	0.19	16.16
2	4	6	150	12.450	1.322	10.0	15.0	14.450	1.322	12	17	4.000	0.000	4	4	5.050	2.408	0.76	10.22
2	6	6	150	10.950	1.465	7.0	14.0	11.950	1.465	8	15	2.000	0.000	2	2	6.223	3.447	2.09	16.08
8	2	4	150	25.450	1.857	22.0	30.0	33.450	1.857	30	38	16.000	0.000	16	16	3.517	3.643	0.31	10.31
8	2	6	150	45.300	2.283	40.0	50.0	53.300	2.283	48	58	16.000	0.000	16	16	16.327	14.164	0.58	58.87
8	4	4	150	21.550	1.431	19.0	25.0	25.550	1.431	23	29	8.000	0.000	8	8	3.284	3.084	0.12	14.04
8	4	6	150	36.100	2.047	31.0	39.0	44.100	2.047	39	47	16.000	0.000	16	16	5.135	4.176	0.51	18.95
8	6	6	150	33.350	1.851	30.0	38.0	37.350	1.851	34	42	8.000	0.000	8	8	6.495	4.464	1.28	16.16

Table 3.7 Selected SS-SMMDP results for the GREEN networks

D	p	l	|T|	|I| = 50				|I| = 100				|I| = 150				|I| = 200			
				OBJ	*ACT*	*MSG*	*CPU*	*OBJ*	*ACT*	*MSG*	*CPU*	*OBJ*	*ACT*	*MSG*	*CPU*	*OBJ*	*ACT*	*MSG*	*CPU*
0	2	2	4	22.0	24	4	0.12	78.0	80	4	13.91	43.0	45	4	25.23	127.0	129	4	22.99
0	2	2	6	25.0	27	4	1.23	91.0	93	4	7.94	91.0	93	4	874.88	161.0	163	4	244.38
0	2	4	4	21.0	22	2	0.19	77.0	78	2	14.98	42.0	43	2	59.75	126.0	127	2	21.89
0	2	4	6	25.0	27	4	0.38	91.0	93	4	29.22	79.0	81	4	909.65	153.0	155	4	171.66
0	2	6	6	24.0	25	2	0.34	90.0	91	2	15.12	78.0	79	2	1460.78	152.0	153	2	187.78
0	8	2	4	29.0	37	16	0.09	91.0	99	16	2.82	91.0	99	16	1806.87	155.0	163	16	13.93
0	8	2	6	35.0	43	16	0.23	94.5	100	11	13.63	114.0	122	16	7.89	179.0	187	16	50.43
0	8	4	4	25.0	29	8	0.09	87.0	91	8	6.11	87.0	91	8	1813.98	151.0	155	8	36.54
0	8	4	6	35.0	43	16	0.27	94.5	100	11	2.51	113.0	121	16	139.48	179.0	187	16	1055.96
0	8	6	6	31.0	35	8	0.23	93.0	97	8	31.59	109.0	113	8	676.12	175.0	179	8	14.18
1	2	2	4	48.5	50	3	2.50	99.5	100	1	16.65	144.0	146	4	1762.18	198.5	200	3	187.67
1	2	2	6	49.0	50	2	0.72	99.5	100	1	29.73	149.5	150	1	38.05	198.5	200	3	1207.92
1	2	4	4	48.0	49	2	2.54	99.5	100	1	24.21	143.0	144	2	241.30	198.0	199	2	456.26
1	2	4	6	49.0	50	2	0.56	99.5	100	1	27.52	149.5	150	1	46.86	194.5	196	3	1833.87
1	2	6	6	49.0	50	2	1.12	99.5	100	1	63.76	149.5	150	1	78.83	198.0	199	2	1551.20
1	8	2	4	48.5	50	3	0.77	99.5	100	1	16.74	148.5	150	3	9.74	198.5	200	3	263.17
1	8	2	6	49.0	50	2	0.69	99.5	100	1	33.43	149.5	150	1	60.20	198.5	200	3	1673.54
1	8	4	4	48.5	50	3	0.23	99.5	100	1	30.98	148.5	150	3	6.15	198.5	200	3	254.03
1	8	4	6	49.0	50	2	0.58	99.5	100	1	57.64	149.5	150	1	62.48	198.5	200	3	1263.91
1	8	6	6	49.0	50	2	0.70	99.5	100	1	80.84	149.5	150	1	127.95	198.5	200	3	1350.73
2	2	2	4	16.0	18	4	0.20	55.0	57	4	4.13	21.0	23	4	11.75	68.0	70	4	33.35
2	2	2	6	21.0	23	4	0.25	70.0	72	4	10.55	41.0	43	4	310.18	100.0	102	4	198.40
2	2	4	4	15.0	16	2	0.08	54.0	55	2	7.88	20.0	21	2	13.35	67.0	68	2	15.60
2	2	4	6	21.0	23	4	0.20	66.0	68	4	15.10	27.0	29	4	210.82	92.0	94	4	71.84
2	2	6	6	20.0	21	2	0.16	65.0	66	2	10.17	26.0	27	2	336.38	91.0	92	2	87.19
2	8	2	4	22.0	30	16	0.12	69.0	77	16	2.08	49.0	57	16	227.10	93.0	101	16	17.21
2	8	2	6	27.0	35	16	0.14	83.0	91	16	4.16	74.0	82	16	293.58	125.0	133	16	21.82
2	8	4	4	18.0	22	8	0.09	65.0	69	8	6.97	45.0	49	8	170.04	89.0	93	8	20.12
2	8	4	6	27.0	35	16	0.16	83.0	91	16	43.57	70.0	78	16	1358.71	123.0	131	16	36.91
2	8	6	6	23.0	27	8	0.16	79.0	83	8	6.05	66.0	70	8	1802.55	119.0	123	8	21.14

3.3.3. Observations and discussions

The SS-SMMDP model discussed in this paper is meant to be used as tools to inform communicators in emergency events and to help illuminate some of the intricacies in social media communications that may enhance or inhibit message dissemination through social networks. To this extent, the experimentation has led us to identify a few key observations that may be of use to practitioners and planners. First, there is a clear difference in the distribution of messages between the randomly generated networks of section 3.3.1 and the Twitter sub-networks of section3.3.2. Specifically, randomly generated networks can be shown through our experimentation to overestimate the number of active nodes and the cost-modified reach of the message (i.e., the objective function). This is consistent with our knowledge of social media networks and illustrates the importance of network connectivity/structure. Social media networks elicit ‘small world’ structures that are not well replicated through random network generation (Butts, 2008).

We also observe differences in the behavior of the sources in the RED and GREEN Twitter sub-networks. For the RED network, the source always sends as many messages as possible. Given a maximum messages possible per scenario $MAX = \lceil |T|/(l+1) \rceil \times p$, the mean number of messages sent by the RED sources always reaches MAX (further indicated by the $StDev = 0$) as seen in Table 3.5 and Table 3.6 (note that this behavior is also observed in certain cases for the randomly generated networks for SS-SMMDP in Table 3.1). This behavior is not observed in the GREEN network is largely due to the structure of the RED networks, which have a more stem-and-petal. This structure, often observed in online social networks, makes message distribution difficult as the single-friend connections through the stem act as a bottleneck for message movement. To combat this strategy, the source must initiate more message transmissions in an effort to force a wider distribution.

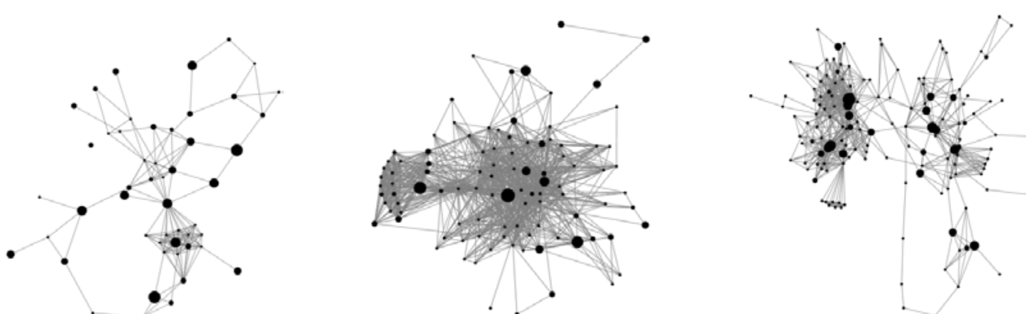
Table 3.8 looks at the observed correlation of our experimental runs to the timing of message reception. Here, we focus on the first two waves of messages sent from the source, call them $Wave$ 1 and $Wave$ 2 which reflect the extent of observed correlation between node degree and message reception (either first or second wave). $Degree$ and $AVG\ Delay$ refer to individual nodes, with observed correlation provided against message reception ($Wave$ 1 vs. $Wave$ 2). Figure 3.5 and Figure 3.6 illustrate message reception for each node by frequency (nodes receiving more messages have a larger radius than nodes receiving fewer messages). From figures and the table, we can see strong correlations between degree and $Wave$ 1 for both RED networks (undirected and directed) and note that very strong correlation is present in all but the $|I| = 100$ case. This implies that nodes with higher degrees are more likely to receive messages from the source in $Wave$ 1. The lack of correlation and consistency through the GREEN network is likely the result of either our arc delay calculations (which were not random but dependent on common friendships/connections) or on network structure (Table 3.4 showed the increased connectivity/density of GREEN networks compared to RED). The combination of GREEN and RED $|I| = 100$ results seems to indicate that network structure itself plays an important role in message targeting, though further investigation is necessary to uncover this relationship. In terms of degree and average delay, the

Table 3.8 Correlation by network

Networks	Wave 1	Wave 2	Degree	AVG Delay
RED (50) - Undirected	**0.864**	-0.357	-0.263	0.593
GREEN (50)	-0.162	-0.490	-0.273	0.380
RED (50) - Directed	**0.912**	0.225	-0.204	0.458
RED (100) - Undirected	0.590	-0.607	-0.465	0.354
GREEN (100)	0.096	-0.433	-0.458	0.581
RED (100) - Directed	0.559	-0.497	-0.443	0.246
RED (150) - Undirected	**0.902**	-0.047	-0.497	0.283
GREEN (150)	0.459	-0.202	-0.496	0.458
RED (150) - Directed	**0.876**	-0.026	-0.523	0.305
RED (200) - Undirected	**0.891**	0.011	-0.469	0.142
GREEN (200)	0.078	-0.371	-0.340	0.551
RED (200) - Directed	**0.883**	0.206	-0.439	0.329

(a) (b) (c)

Figure 3.5 $Wave$ 1 for RED (a) $|I| = 50$, (b) $|I| = 100$, and (c) $|I| = 150$



(a) (b) (c)

Figure 3.6 $Wave$ 1 for GREEN (a) $|I| = 50$, (b) $|I| = 100$, and (c) $|I| = 150$

results are as expected. Nodes with higher degree will receive messages earlier (i.e., lower batch number) and are thus negatively correlated with wave number while nodes with high delay characteristics are less likely to be targeted. Note that this last relationship is consistent in that average node delay is always positively correlated with wave number but that it is not a strong or significant correlation (ranging in [0.142 - 0.593] in our samples).

Computationally, the SS-SMMDP model shares similar properties with other network models. As the network's size increases (in this case, from $|I| = 50$ to $|I| = 150$), computation time increases. We note that this increase is exponential and is magnified in the GREEN network case, which inherently more dense than either the RED or random networks. We also see an expected trend in the effect of the time horizon $|T|$ on objective performance and message distribution. In all cases, larger $|T|$ implies a larger mean objective function value and better reach of the message. While this is not true for comparison of specific replications due to the random arc delay, it is in general always beneficial, when possible, to increase the time horizon $|T|$.

3.4. Implementation of Tabu Search

Looking into the experimental results, we observe that CPU times increased significantly with the increase of network size $|I|$, length of time horizon $|T|$ as well as source messaging capacity p, which motivates us to examine how known heuristics or meta-heuristics might help improve the computational efficiency. Therefore, we implement a Tabu Search procedure for SS-SMMDP as an initial test on heuristic performance versus the CPLEX strategy implemented to this point. Detailed information of the proposed Tabu Search procedure is given in the following.

3.4.1. Technical details

3.4.1.1. Encoding of a solution

Given time horizon $|T|$ and source messaging interval l, we fix the time points when the source node is eligible to send messages in the first place. Literally the set of eligible time points is $E = \{1, l+2, 2l+3, 3l+4, \dots, TL\}$, where TL is the last time point for sending message within the planning horizon. Let m be the cardinality of set E. For each time point, at most p users can receive the message from the source, so we designate p variables (each one represents a certain user, i.e., node index) for each time point and in total we have $m \times p$ variables. All these variables are then combined in a chronological order to form a solution X, which can be viewed as a message recipient list as illustrated in Figure 3.7. It assumes $p = 4$ and users are indexed from 1 to $|I|$. Note that 0 in the third box means empty (i.e., only 3 nodes are receiving the message at that time point).

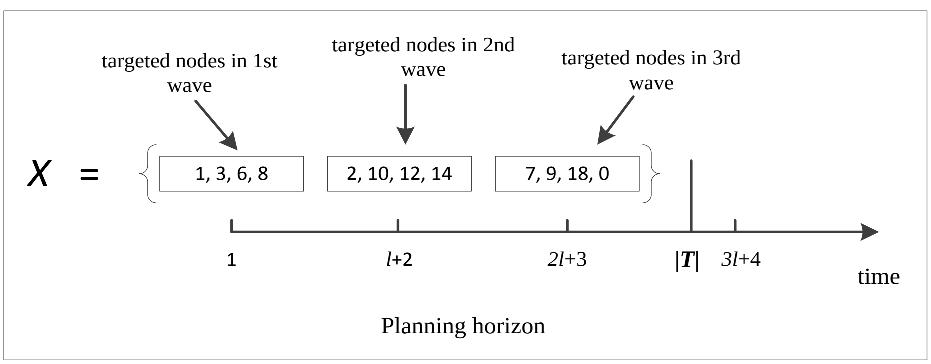


Figure 3.7 An illustration of the structure of an encoded solution X

3.4.1.2. Neighborhood definition

Given two solutions X and Y, they are defined as neighbors if they are different by only one variable value. Using the example in Figure 3.8, $X = \{1,3,6,8,2,10,12,14,7,9,18,0\}$ and let $Y = \{1,3,6,5,2,10,12,14,7,9,18,0\}$. Then Y is a neighbor of X because it's are different from X only at the 4th position. Given a solution X, a certain number of neighbors of X are generated by exchanging a node i in X with any node j ($j \neq i$) to form a set of candidate solutions for evaluation. The first exchange that improves the current objective value will be adopted to form a new solution for next iteration.

3.4.1.3. Evaluation function

Given a solution or message recipient list X, the activation time of each node can be determined by implementing a shortest path algorithm. That is, the activation time of node i is the minimum of the accumulated delay from any node j in the recipient list to node i plus the activation time of node j. In this way, the objective value for X can be calculated and evaluated. According to the encoding of solutions and the neighborhood definition, any solution constructed is feasible. Therefore, no punishment is needed and the objective function can be used as evaluation function directly.

3.4.1.4. Tabu criterion

In each iteration, the node selected to enter the current solution will be recorded in Tabu list (denoted by $TabuList$) and forced to stay in the solution for a certain number of iterations, which is referred to as the Tabu length Lt. The node will be released from $TabuList$ after Lt iterations.

3.4.1.5. Aspiration criterion

In any iteration, if the best exchange is Tabu (i.e., the node selected to enter the current solution is in the $TabuList$), then this exchange is not allowed. In this case, aspiration criterion applies only if the objective value associated with this exchange is better than the best objective value found so far.

3.4.2. Tabu Search procedure

3.4.2.1. Notations

$iter$: iteration counter

$iterMax$: total number of iterations to be performed

Lt: Tabu length

X: the current solution

Y: neighbor of the current solution X

$XInit$: the initial solution

$XBest$: the best known solution

$YBest$: the best neighbor of X

$objX$: the objective value corresponding to X

$objY$: the objective value corresponding to Y

$objXBest$: the objective value corresponding to $XBest$

$objYBest$: the objective value corresponding to $YBest$

$TabuList$: the Tabu list. When an exchange is adopted (e.g., node i enters the current solution), the i^{th} value of $TabuList$ will be increased by Lt

3.4.2.2. Steps

- **Step 0: Initialization**

  Initialize p, l, $|T|$, $TabuList$, $XInit$, $XBest$, $objBest$, and let $iter := 1$ and $X := XInit$.

- **Step 1: Neighborhood construction**

  Construct a neighbor of X, denoted by Y, by exchanging a node i in X with any node j ($j \neq i$) and calculate the objective value $objY$.

- **Step 2: Solution evaluation**

  If $objY$ is better (greater) than $objX$, then go to Step 3. Otherwise, go back to Step 1. If all the neighbors have been examined, then let $YBest := Y$ and $objYBest := objY$ and go to step 4.

- **Step 3: Tabu check**

  If node i is in $TabuList$, then check aspiration criterion. If aspiration criterion is met, let $YBest := Y$ and $objYBest := objY$, and then go to Step 4. Otherwise, go back to Step 1. If node i is not in $TabuList$, let $YBest := Y$ and $objYBest := objY$, and then go to Step 4.

- **Step 4: Update**

  Let $X := YBest$ and $objX := objYBest$. Update $TabuList$. If $objX > objBest$, then set $objBest := objX$ and $XBest := X$. Otherwise go to Step 5.

- **Step 5: Termination check**

  Let $iter := iter + 1$. If $iter > iterMax$, then stop and output $XBest$ and $objBest$. Otherwise go to Step 1.

3.4.3. Implementation and discussions

We test the performance of the proposed Tabu Search procedure using instances of the RED Twitter undirected sub-network, in which $|I| = 200$, $|T| = 6$ and 10 replications for each problem scenario. CPLEX results are obtained using AMPL/CPLEX 12.1 and the Tabu Search procedure is performed using MATLAB R2012B. All computations are performed on a Dell OptiPlex 755 computer (Inter Core 2 Duo E6750 2.67GHz, 2GB RAM and Windows 7 System).

Table 3.9 gives the computational results for CPLEX and compares them with the Tabu Search strategy implemented, in which OBJ and ACT refer to the average of the best objective values found and the average number of active nodes, respectively. CPU refers to the average of the time elapsed to get the best objective value. From the table, we can see that the objective values given by the Tabu Search are very close to the optimal objective values (i.e., small gaps), which are given by CPLEX, especially for the instances where $l = 4$ and $l = 6$. Similar trend can also be observed for the number of active users. Note that the absolute gap of the ACT is exactly the same as that of the OBJ. The reason is that maximum number of messages are sent from the source in all instances, so the difference of the OBJ is essentially the difference of the ACT between CPLEX and Tabu Search (recall that $w_i = 1$ for all $i \in I$). More importantly, these near-optimal objective values are obtained in a very short time, compared to the time required by CPLEX. In addition, the CPU time of the Tabu Search procedure appears to be stable as p increases. All these observations justify our initial idea in designing such an

Table 3.9 Computational results given by CPLEX and Tabu Search

p	l	|T|	|I|	*CPLEX*			*TABU SEARCH*			*GAP of OBJ*		*GAP of ACT*	
				OBJ	*ACT*	*CPU*	*OBJ*	*ACT*	*CPU*	*Absolute*	*Percentage*	*Absolute*	*Percentage*
4	2	6	200	53.1	57.1	356.31	52.3	56.3	0.88	0.8	1.507%	0.8	1.401%
4	4	6	200	44.3	48.3	21.78	44.2	48.2	0.93	0.1	0.226%	0.1	0.207%
4	6	6	200	39.5	41.5	48.99	39.5	41.5	0.67	0.0	0.000%	0.0	0.000%
6	2	6	200	65.8	71.8	1212.11	64.4	70.4	1.19	1.4	2.128%	1.4	1.950%
6	4	6	200	55.7	61.7	302.99	55.5	61.5	1.19	0.2	0.359%	0.2	0.324%
6	6	6	200	49.9	52.9	471.83	49.9	52.9	0.77	0.0	0.000%	0.0	0.000%
8	2	6	200	76.3	84.3	1623.43	75.1	83.1	1.44	1.2	1.573%	1.2	1.423%
8	4	6	200	65.1	73.1	757.86	65.0	73.0	1.62	0.1	0.154%	0.1	0.137%
8	6	6	200	61.3	65.3	642.87	61.3	65.3	0.96	0.0	0.000%	0.0	0.000%

algorithm and also imply that the proposed Tabu Search procedure is potentially valuable for solving large-scale SS-SMMDP in the future study.

3.5. Closing Remarks for SS-SMMDP

In this chapter, we examine the single-network single-message application scenario in which one message needs to be disseminated on one social media network within a predefined planning horizon. While we anticipate this model being useful in extreme event scenarios as a planning tool for emergency managers to determine communication strategies that will promote message dissemination and great situational awareness among the population at risk, the model and its parameters are flexible enough to be used in other mass convergence events (e.g., civil violence/rioting, sporting events such as the Super Bowl, etc.) or in modeling social media communication in general.

Through computational experiments, we show that the length of time horizon $|T|$ is the most important problem factor in determining the number of active users at the end of the planning horizon and CPU time of a test instance. Surprisingly, source messaging interval l and source messaging capacity p are not significant, indicating that social media message dissemination can be effective with very few starting messages given enough time to work the message through the network.

We observe some significant differences between randomly generated and real-world sub-networks. As expected, real-world social networks are less densely connected, leading to an over-estimation of message dissemination in randomly generated networks. We also see that the arc structure (directed or undirected) did not dramatically alter objective or computational performance. Lastly, we notice a distinct correlation between the time a message is received and the degree of the receiving node with higher-degree nodes consistently targeted earlier in our RED Twitter sub-networks.

It is prudent to note that the SS-SMMDP model derived here is not devoid of limitation. As mentioned previously, there is a negative computational relationship between increased parameter values, increased network size and solution time. Although the proposed Tabu Search procedure works well for the test instances, it still needs to be examined and improved before larger and more realistic problems can be evaluated. Additionally, today's social media networks are not independent but very integrated. Twitter users can post messages from photo and video social media such as Instagram and Vine while also sending their Twitter post to their Facebook accounts. To create more realistic application environments, it would be interesting to examine message dissemination scenarios which consider multiple message types and/or multiple social media sites in the future research.

CHAPTER IV

SINGLE-NETWORK MULTI-MESSAGE SOCIAL MEDIA MESSAGE DISSEMINATION PROBLEM

4.1. Problem Description and Definition

The Single-network Multi-message Social Media Message Dissemination Problem (SM-SMMDP) considers the scenario in which multiple messages need to be disseminated on one social media network within a predefined planning horizon. The network is represented by $G = (I, A)$, where each node $i \in I$ represents a user in the social media and each arc $\langle i, j \rangle \in A$ represents the relationship on the network (i.e., friend or follower) between users $i, j \in I$, through which messages can flow from i to j. The messages to be disseminated are given by set M. Each message $m \in M$ is assumed to be independent from others and corresponds to a unique source (i.e., it can only send its own message to the user nodes), and the number of unique messages is $|M|$. The planning horizon is given by set T. Each $t \in T$ represents a time period in the planning horizon and the length of the planning horizon is $|T|$.

Message propagation on the network is initiated by the sources through node targeting (i.e., send direct messages to the selected nodes) and continues as individual nodes redistribute the received messages to their friends or followers, as illustrated in Figure 4.1. The source for any message m can send its message multiple waves if time

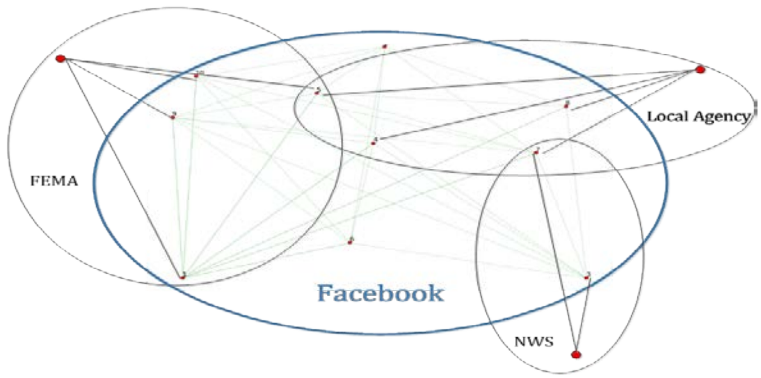


Figure 4.1 Conceptualization of SM-SMMDP

allows, with a minimum reset time l_m between two consecutive waves and a capacity p_m in each wave. Accordingly, a subset of p_m nodes (i.e., nodes to be targeted) needs to be determined corresponding to each wave of message m from its source. This process is illustrated in Figure 4.2. Individuals' redistribution behaviors are modeled using a time delay called user share delay, which represents the time between message arrival at a user's device (e.g., PC, cell phone, iPad, etc.) and when the user shares the message. It is assumed to be specific to individual node, message and the social media network through which the message is being distributed, and denoted by matrix DS, with $ds_{im} \in DS$ representing the share delay of node i for message m (We don't need a subscript for network since the nodes are on the same network). There is another type of delay, message transmission delay dm, which reflects the physical transmission time between devices and is assumed to be specific to the network. This delay could be non-negligible in emergency events due to cell phone tower damages and/or excessive load within a short period. The illustration of delays is given in Figure 4.3. A user node i is considered active after receiving all messages, and the message dissemination outcome is defined as the weighted sum of the activation status of all individual nodes over the planning horizon, which essentially encourages wider and sooner message reception on the network.

Now the SM-SMMDP can be formally stated as follows: Given social media network $G = (I, A)$, message set M, planning horizon T, source messaging capacity matrix $P(M)$, source reset time matrix $L(M)$, user share delay matrix $DS(I, M)$, and message transmission delay dm, SM-SMMDP optimizes the message dissemination outcome by determining a sequence of subsets, each containing at most p_m nodes, to be targeted for each message m. Problem formulation is presented in section 4.2.

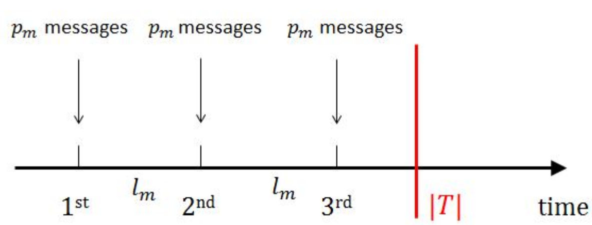


Figure 4.2 An illustration of source messaging behavior (e.g., message m)

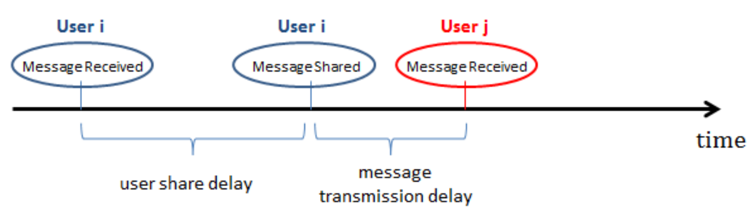


Figure 4.3 An illustration of the delays in SM-SMMDP

4.2. Problem Formulation

4.2.1. Sets and parameters

I = the set of user nodes

M = the set of messages

T = the set of time periods

T'_m= the set of time periods eligible for the source of m to send messages

N_i = the set of nodes j such that $\langle j, i \rangle \in A$

w_{it} = the reward for node i being active at time t

p_m = the source messaging capacity for message m

ds_{im} = the share delay of node i for message m

dm = the message transmission delay

4.2.2. Decision variables

$z_{it} = 1$ if node i is active at time t, 0 otherwise

$x_{imt} = 1$ if node i is targeted for message m at time t, 0 otherwise

$y_{imt} = 1$ if node i is active for message m at time t, 0 otherwise

4.2.3. Formulation

$$max \quad \sum_{i \in I} \sum_{t \in T} w_{it} z_{it}. \tag{4.1}$$

s.t.

$$\sum_{i \in I} x_{imt} \leq p_m, \quad \forall\, m \in M, t \in T'_m. \tag{4.2}$$

$$y_{imt} \leq \sum_{l \leq t} x_{iml} + \sum_{j \in N_i} y_{jm(t-dm-ds_{jm})}, \quad \forall\, i \in I, m \in M, t \in T. \tag{4.3}$$

$$z_{it} \leq y_{imt}, \quad \forall\, i \in I, m \in M, t \in T. \tag{4.4}$$

$$y_{imt} \leq y_{im,t+1}, \forall\, i \in I, m \in M, t \in T. \tag{4.5}$$

$$z_{it} \leq z_{i,t+1}, \forall\, i \in I,\ t \in T. \tag{4.6}$$

$$x_{imt}, y_{imt}, z_{it} \in \{0,1\}, \forall\, i \in I, m \in M, t \in T. \tag{4.7}$$

The objective function (4.1) optimizes the message dissemination outcome (i.e., maximizing the total reward for message reception over all user nodes within the planning horizon). For each node i, the weight w_{it} is a decreasing function of time t, which serves to encouraging early reception. In this way, the ultimate goal of the objective is to encourage wider and sooner message reception on the network. Constraint (4.2) enforces the messaging capacity of the sources. Note that for any message m, set T'_m is developed based on T and l_m. Constraint (4.3) states that, node i is active for message m at time t, if it received the message either from the source node prior to t or from a friend node j who shared the message previously. The lead time is node $j's$ share delay for message m, ds_{jm}, plus the transmission delay dm on the network. Constraint (4.4) ensures the message aggregation effect at the user end (i.e., a node has to receive all the messages to become active). Constraints (4.5) and (4.6) mean that node status preserves over time, and Constraint (4.7) imposes that all decision variables are binary.

4.3. Computational Experiments

In this section, we present the results of computational experimentation on SM-SMMDP. In particular, this analysis illustrates how decision factors/parameters affect computational performance as well as message dissemination outcomes. The factors being tested include length of planning horizon ($|T|$), source messaging capacity (P), source messaging interval (L), network type (N), network structure (density), and network condition (dm). We use 100-node networks in these computational experiments and consider three unique messages are to be disseminated through the network (i.e., $|I|$ = 100, $|M|$ = 3). Three different network types are examined: complete connectivity, random connectivity and a Twitter sub-network. The Twitter sub-networks are generated through a Metropolis-Hastings Random Walk (MHRW) on Twitter, with four such networks generated (each using a different, randomly selected Twitter user as Node 0 in the random walk). All networks are treated as undirected where two nodes are connected with an edge if they have a friend/follower relationship originally or they have at least one common friend/follower. We use the network density of the MHRW Twitter networks as the expected density to generate the random networks (in this process, two nodes are connected with an edge with probability = expected density). Table 4.1 provides a summary of the Twitter sub-networks and Figures 4.4 gives the illustrations of them.

Table 4.1 Statistics of the Twitter sub-networks

				Node Degree Statistics			
Notation	Nodes	Arcs	Density	AVG	StDev	MIN	MAX
T1	100	454	0.09	9.08	6.90	2	32
T2	100	545	0.11	10.90	9.47	2	37
T3	100	716	0.14	14.32	12.05	2	51
T4	100	1102	0.22	22.04	14.12	2	72

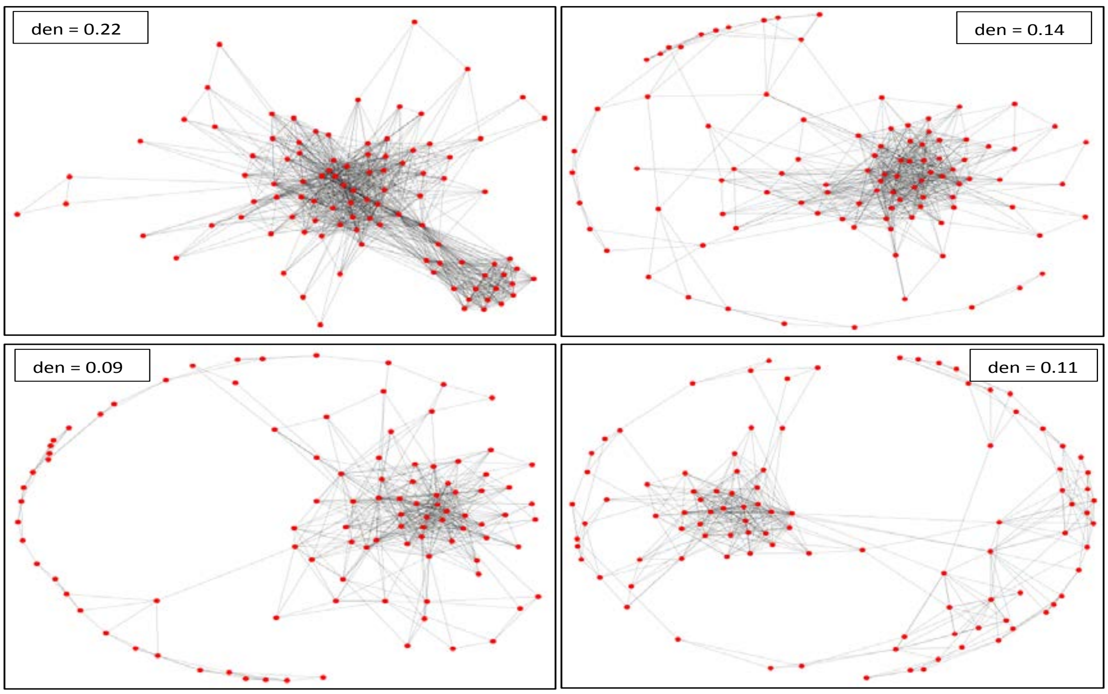


Figure 4.4 Twitter sub-networks with 100 nodes generated from MHRW results

4.3.1. Experimental design

Table 4.2 provides the factors and levels for the implemented experimental design. It is known that the planning horizon for message dissemination varies by extreme event. For example, NWS issues a hurricane watch 24-36 hours in advance of a potential event and a hurricane warning when the event is expected in 24 hours or less, while the warning time may be only a few minutes or less for a tornado. For the purposes of our experimentation, we assume the basic time unit to be hours (we note that such an assumption may easily be changed to adapt the SM-SMMDP for different extreme event circumstances/scenarios).

Complete network is denoted by C and random networks denoted by $R1$, $R2$, $R3$ and $R4$ corresponding to the density values of $T1$, $T2$, $T3$ and $T4$, respectively. Source messaging capacity and messaging interval are assumed to be identical for all message sources on each network, i.e., $p_1 = p_2 = p_3 = p$ and $l_1 = l_2 = l_3 = l$. Message transmission delay dm is assumed to be constant, as discussed in section 4.1. Individual's share delay is assumed to be independent over messages, and each element $ds_{im} \in DS$ is an integer sampled from $Uniform(1,7)$ or $Poisson(4)$ distribution. The parameters of the distributions are chosen such that the sampled values are expected to have same mean and variance. The reward coefficient w_{it} in the objective function is assumed to be $w_{it} = 1/t$ for any node $i \in I$.

Table 4.2 A summary of experimental factors and levels

Factors	Levels
Network (N)	C, $R1$, $R2$, $R3$, $R4$, $T1$, $T2$, $T3$, $T4$
Messaging capacity (p)	1, 2, 3, 4, 5
Planning horizon ($\|T\|$)	1, 2, 3, 4, 5, 6 ,7 ,8
Messaging interval (l)	1, 2
Transmission delay (dm)	1, 2, 3
User share delay (DS)	1-$Uniform$, 2-$Poisson$

We define a problem scenario as a combination of decision parameters $(p, l, |T|, N, dm)$, in which $(p, l, |T|)$ can represent an emergency manager's considerations and (N, dm) reflects network structure. Based on all the factors and levels given in Table 4.2, there are 2,160 unique problem scenarios. Due to the random nature of user sharing behavior, we use two common distributions ($Uniform$ and $Poisson$) and generate 10 replications for each scenario and each distribution in terms of the delay matrix DS to capture the variations, which results in 43,200 test instances in total (From the angle of network type, 4,800 instances for complete network, 19,200 for random network and Twitter network each). All the test instances are computed using ILOG Concert Technology with C++/CPLEX 12.4 on a Dell OptiPlex 755 computer (Inter Core 2 Duo E8500 3.17GHz, 4GB RAM and Windows 7 System), and the solution time are capped at 1,800 seconds for each test instance. Computational results and analysis are presented in the following

4.3.2. Results and analysis on CPU time

Table 4.3 provides an overall summary of objective gap and CPU time by network type. We note that nearly all the instances can be solved to optimality within the 1,800-second solution time cap (exceptions being for the random network). This suggests that the SM-SMMDP model is tractable for 100-node networks, though disparity exists depending upon network structure. Complete and Twitter network instances (denoted as $C\ Instances$ and $T\ Instances$ in the following analysis) solve on average within 4-7 CPU seconds with a maximum of 100 CPU seconds observed in our experiments.

Random network instances (denoted as $R\ Instances$ in the following analysis), alternatively, account for all non-optimal solutions (where 1,800 CPU seconds is not enough to generate an optimal solution) and exhibit significantly larger averages (30 CPU seconds) and more variation (i.e., high standard deviation). These incomplete instances are typically associated with longer planning horizon (i.e., $|T| = 8$) and larger messaging capacity (i.e., $p = 4$ or $p = 5$).

Figure 4.5 shows the impact of length of planning horizon $|T|$ on CPU time (i.e., AVG and $StDev$ of CPU times) and compares this impact over network type and source messaging capacity p. In each individual chart, p is fixed and instances are aggregated and averaged for each planning horizon length (i.e., $|T| = 1, \ldots, 8$) and each network type (i.e., complete, random, and Twitter). We denote the lines as $C\ Lines$, $R\ Lines$ and $T\ Lines$ for complete, random, and Twitter networks, respectively. It is clear that CPU time increases as the increase of |T|. This is expected since problem size grows as the planning horizon gets longer. For a specific planning horizon length, $R\ Lines$ and $C\ Lines$ provide the highest and lowest values respectively while $T\ Lines$ stay in the middle (this is particularly obvious when $|T| >= 4$), which is true for both AVG and $StDev$. This actually extends the trend observed in Table 4.3, which considers network type only.

Table 4.3 A summary of objective gap and CPU time

Network Type	Num of Instances	% of Optimal	Objective Gap				CPU Time			
			AVG	*StDev*	*MIN*	*MAX*	*AVG*	*StDev*	*MIN*	*MAX*
Complete	4,800	100.00%	0.000	0.000	0.000	0.000	4.533	3.795	0.000	52.026
Random	19,200	99.97%	0.000	0.000	0.000	0.033	29.339	106.553	0.000	1800.000
Twitter	19,200	100.00%	0.000	0.000	0.000	0.000	6.131	7.606	0.000	99.544

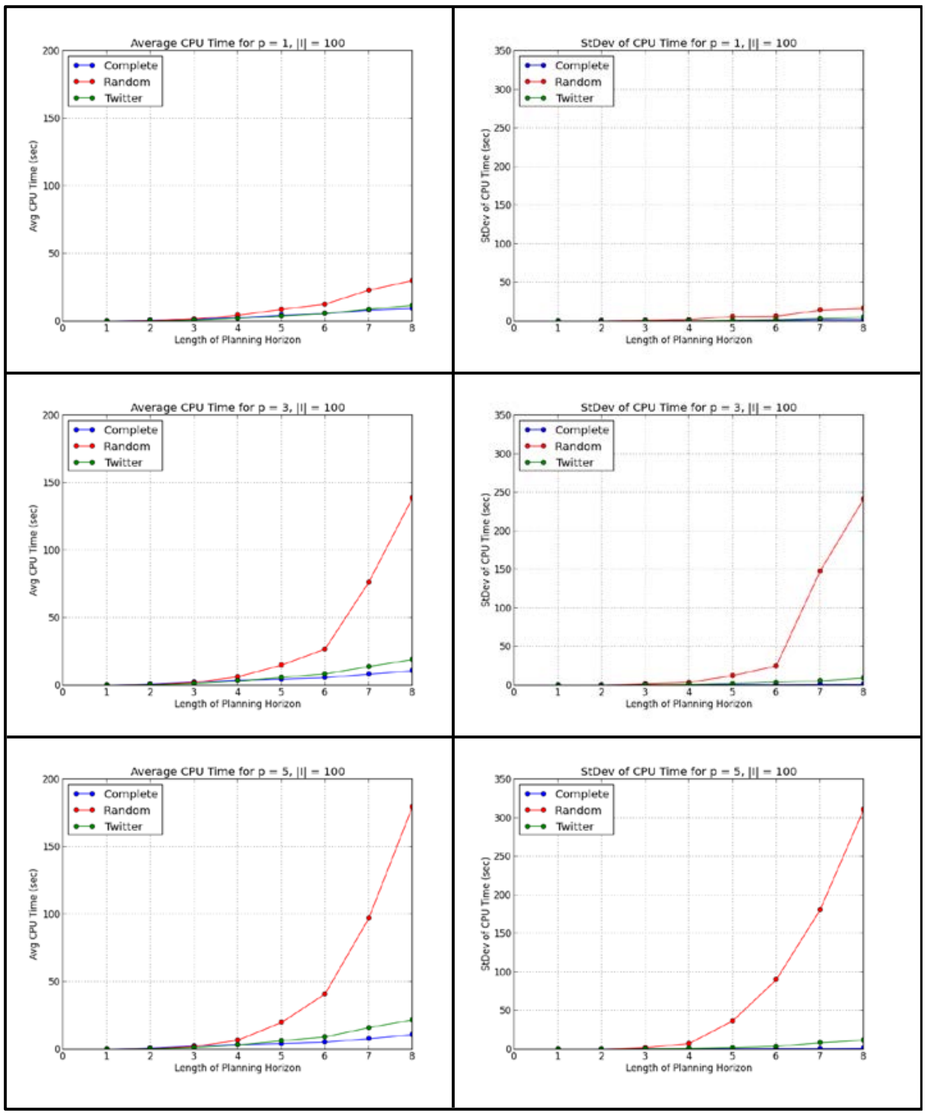


Figure 4.5 CPU time vs. $|T|$ by p and network type

Given a source messaging capacity p, all lines appear to grow exponentially with $|T|$, but the $R\ Line$ grows much faster than the $T\ Line$ and the $C\ Line$, which is true for both AVG and $StDev$. And as p increases, the $R\ Lines$ are affected more significantly than the other two, which is interesting considering that p is not a factor that determines the problem size. In a word, the characteristics of CPU times for $T\ Instances$ are very similar to that for $C\ Instances$, as being relatively insensitive to the change of length of planning horizon $|T|$ and source messaging capacity p. As a general implication, such a property would potentially enable emergency managers to evaluate more node targeting alternatives (e.g., develop and compare strategies under different planning horizon length and messaging capacity) before they make final decisions in real-world applications.

Figure 4.6 shows the impact of length of planning horizon $|T|$ on CPU time (i.e., AVG and $StDev$ of CPU times) and compares this impact over network type, density and source messaging capacity p. $C\ Lines$ are added to each chart for comparison, denoted as $den = 1$. We may still see AVG increase as the increase of $|T|$ for a given network type and density, but it is not always the case for $StDev$ (e.g., $den = 0.09$, $p = 5$, $R\ Lines$). It is noticeable that for a specific messaging capacity p, the network density doesn't show a consistent impact on AVG or CPU time. For example, the line corresponding to a higher density is not always higher than that to a lower density along the horizontal axis, or vice versa. However, distinction can still be identified between $R\ Instances$ and $T\ Instances$. Specifically, higher density tends to imply smaller AVG and $StDev$ for $T\ Instances$, while the opposite trend might be observed for

$R\ Instances$. Lastly, some $T\ Instances$ appear to be easier to solve than $C\ Instances$, such as when $|T| <= 5$ for $p = 1$ and $|T| <= 4$ for $p = 2$ or $p = 3$. The reason for this is not clear at this point and this could be an interesting observation to examine in future studies.

4.3.3. Results and analysis on objective values

The objective function for SM-SMMDP is defined as the weighted sum of the activation status of all individual nodes over the planning horizon, which essentially encourages wider and sooner message reception on the networks. Given a specific $|T|$, a larger objective value implies a better overall message dissemination outcome. Table 4.4 introduces selected SM-SMMDP computational results, in which the average and standard deviation of objective values over 10 replications (denoted as AVG and $StDev$) are given for each problem scenario (a total of 5,760 test instances are selected to populate these tables). The networks are listed according to the density, from the smallest to largest.

Generally speaking, all model parameters impact the objective value, but the degree of impact varies from case to case. When the planning horizon is very short (i.e., $|T| = 1$), the objective values are totally determined by the source messaging capacity p. In other words, no one can receive messages from his/her friends in this scenario. The objective values tend to increase as the increase of planning horizon length $|T|$ and messaging capacity p. However, they affect the variation of objective values differently. Specifically, larger $|T|$ tends to lead to larger variations (i.e., higher $StDev$ values),

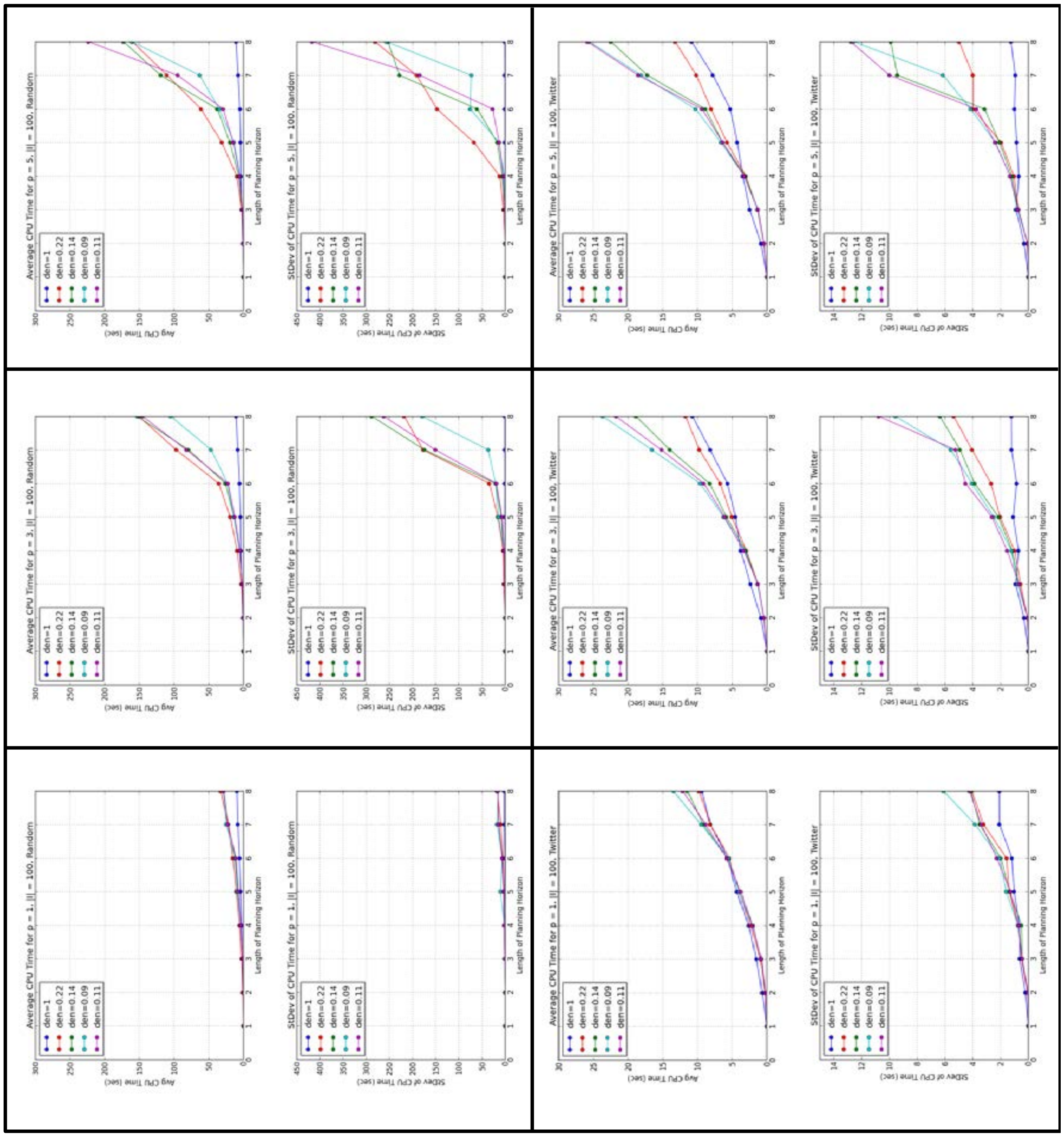


Figure 4.6 CPU time vs. $|T|$ by p, network type and density

Table 4.4 Selected objective values for SM-SMMDP

					Random Neworks								Twitter Networks							
p	|T|	l	dm	DS	R1 (exp. den = 0.09)		R2 (exp. den = 0.11)		R3 (exp. den = 0.14)		R4 (exp. den = 0.22)		T1 (den = 0.09)		T2 (den = 0.11)		T3 (den = 0.14)		T4 (den = 0.22)	
					AVG	*StDev*	*AVG*	*StDev*	*AVG*	*StDev*	*AVG*	*StDev*	*AVG*	*StDev*	*AVG*	*StDev*	*AVG*	*StDev*	*AVG*	*StDev*
1	1	1	1	1	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
1	1	1	1	2	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
1	1	1	3	1	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
1	1	1	3	2	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
1	1	2	1	1	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
1	1	2	1	2	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
1	1	2	3	1	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
1	1	2	3	2	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
1	4	1	1	1	6.325	2.517	7.367	2.326	9.251	3.153	9.517	1.992	11.058	2.238	13.916	3.134	16.801	3.380	21.827	5.051
1	4	1	1	2	4.867	0.950	5.167	1.025	6.309	1.483	8.775	2.546	9.734	2.732	11.116	3.769	15.092	3.494	18.983	5.290
1	4	1	3	1	2.667	0.000	2.667	0.000	2.667	0.000	2.667	0.000	2.667	0.000	2.667	0.000	2.667	0.000	2.667	0.000
1	4	1	3	2	2.667	0.000	2.667	0.000	2.667	0.000	2.667	0.000	2.667	0.000	2.684	0.050	3.242	1.111	3.284	1.234
1	4	2	1	1	5.325	2.097	6.142	2.795	6.392	2.010	9.041	2.419	9.516	2.516	12.717	3.683	18.575	3.046	22.919	3.641
1	4	2	1	2	3.908	0.981	5.425	3.246	5.216	1.438	9.267	2.351	8.133	3.068	9.833	2.752	13.708	3.511	18.726	5.121
1	4	2	3	1	2.333	0.000	2.333	0.000	2.333	0.000	2.333	0.000	2.333	0.000	2.333	0.000	2.333	0.000	2.333	0.000
1	4	2	3	2	2.333	0.000	2.333	0.000	2.333	0.000	2.425	0.275	2.333	0.000	2.333	0.000	2.333	0.000	3.342	1.255
1	8	1	1	1	27.538	4.612	34.659	6.169	49.441	8.095	60.604	3.484	34.626	5.620	43.573	5.265	55.565	5.728	77.744	7.453
1	8	1	1	2	26.064	3.890	31.665	4.562	46.033	5.800	60.350	8.696	33.472	6.084	40.159	4.767	47.795	4.827	66.882	8.062
1	8	1	3	1	11.755	1.460	12.223	2.095	13.782	1.857	18.282	3.060	15.601	2.333	19.593	2.472	24.255	4.799	30.772	3.214
1	8	1	3	2	9.280	0.913	10.921	1.035	12.380	3.000	16.627	2.491	15.117	2.170	17.493	3.474	19.316	2.215	28.906	4.657
1	8	2	1	1	23.501	3.808	28.811	4.009	39.375	4.211	56.282	7.006	34.433	6.610	40.945	7.674	50.338	5.076	69.366	8.265
1	8	2	1	2	25.078	5.668	26.650	6.792	38.038	6.511	56.764	7.440	30.055	6.034	38.914	8.143	47.139	10.241	66.042	8.512
1	8	2	3	1	9.761	2.072	10.013	1.764	11.841	2.620	15.510	2.515	13.960	2.864	17.936	2.421	20.552	3.510	26.711	6.184
1	8	2	3	2	7.747	1.296	9.056	0.987	10.581	1.257	15.151	2.899	11.650	1.844	15.121	2.786	20.735	3.381	26.300	3.079
3	1	1	1	1	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000
3	1	1	1	2	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000
3	1	1	3	1	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000
3	1	1	3	2	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000
3	1	2	1	1	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000
3	1	2	1	2	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000
3	1	2	3	1	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000
3	1	2	3	2	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000	3.000	0.000
3	4	1	1	1	15.810	1.914	17.400	2.426	21.160	2.252	28.416	2.023	22.509	3.647	26.008	2.344	28.299	2.461	43.284	3.528
3	4	1	1	2	14.507	1.032	15.526	1.467	18.842	2.137	28.743	3.931	21.066	3.340	23.399	3.951	26.175	4.225	44.183	6.798
3	4	1	3	1	8.000	0.000	8.000	0.000	8.000	0.000	8.000	0.000	8.000	0.000	8.000	0.000	8.000	0.000	8.000	0.000
3	4	1	3	2	8.042	0.085	8.108	0.183	8.233	0.266	8.408	0.556	8.000	0.000	8.067	0.139	8.125	0.230	9.275	1.451
3	4	2	1	1	12.233	0.747	14.443	2.462	17.950	2.450	27.041	1.805	20.525	2.226	21.567	2.578	28.833	2.490	43.141	2.867
3	4	2	1	2	12.200	2.119	13.974	1.854	17.108	2.597	28.700	4.735	18.310	2.404	19.809	3.306	26.467	3.472	37.893	8.879
3	4	2	3	1	7.000	0.000	7.000	0.000	7.000	0.000	7.000	0.000	7.000	0.000	7.000	0.000	7.000	0.000	7.000	0.000
3	4	2	3	2	7.300	0.384	7.725	0.607	7.700	0.660	8.500	0.822	7.975	1.371	7.775	0.786	7.500	0.512	8.825	1.388
3	8	1	1	1	59.082	3.206	65.083	4.447	75.916	3.087	90.618	3.101	63.734	4.387	64.749	4.974	80.005	6.311	101.415	4.126
3	8	1	1	2	56.589	3.753	61.856	4.137	72.410	5.174	90.465	4.587	60.187	6.731	60.249	6.510	73.222	8.216	98.996	9.431
3	8	1	3	1	26.398	2.123	30.189	3.350	34.049	1.266	44.074	3.549	31.838	3.036	35.410	2.407	40.140	2.908	54.713	2.378
3	8	1	3	2	26.604	1.730	28.484	2.386	32.626	2.078	42.054	3.333	32.515	2.054	35.193	3.124	38.227	3.215	53.193	3.942
3	8	2	1	1	53.005	3.894	57.561	4.858	66.475	3.823	84.800	3.520	57.891	5.110	59.128	5.265	71.263	3.442	99.078	5.450
3	8	2	1	2	49.015	3.815	54.436	2.985	67.821	4.908	86.262	5.880	52.563	6.171	57.761	6.530	72.739	8.493	94.551	6.296
3	8	2	3	1	23.448	3.207	25.875	3.036	28.008	2.763	35.780	3.454	28.594	1.700	32.130	1.814	37.554	2.372	50.751	2.674
3	8	2	3	2	21.419	1.382	23.639	2.302	26.776	2.084	33.042	2.252	26.730	2.677	29.781	3.172	33.629	4.806	46.954	4.791
5	1	1	1	1	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000
5	1	1	1	2	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000
5	1	1	3	1	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000
5	1	1	3	2	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000
5	1	2	1	1	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000
5	1	2	1	2	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000
5	1	2	3	1	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000
5	1	2	3	2	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000	5.000	0.000
5	4	1	1	1	25.717	1.470	27.734	1.874	33.526	3.360	46.425	3.262	31.600	2.003	33.684	1.898	38.234	2.968	52.334	2.744
5	4	1	1	2	23.468	1.975	26.491	2.512	30.559	4.048	45.859	3.821	29.759	3.749	29.250	4.397	36.799	4.130	50.224	6.775
5	4	1	3	1	13.330	0.000	13.330	0.000	13.330	0.000	13.330	0.000	13.330	0.000	13.330	0.000	13.330	0.000	13.330	0.000
5	4	1	3	2	13.473	0.212	13.724	0.298	13.923	0.518	14.340	1.203	13.814	1.452	13.372	0.126	13.914	0.668	14.822	1.861
5	4	2	1	1	23.383	2.468	24.210	2.502	27.901	2.873	42.751	1.960	29.475	2.238	31.725	1.551	37.367	3.357	48.292	3.987
5	4	2	1	2	19.451	1.159	22.643	2.409	28.291	3.062	41.617	7.833	25.568	2.025	26.733	3.198	33.101	5.017	41.775	6.541
5	4	2	3	1	11.670	0.000	11.670	0.000	11.670	0.000	11.670	0.000	11.670	0.000	11.670	0.000	11.670	0.000	11.670	0.000
5	4	2	3	2	12.470	0.630	12.945	1.126	12.770	1.174	14.145	1.839	12.495	0.448	12.745	0.936	12.695	1.748	13.220	1.503
5	8	1	1	1	78.513	4.377	86.250	1.711	95.571	2.948	111.300	2.959	81.235	2.961	83.605	4.087	90.663	2.910	114.170	2.628
5	8	1	1	2	72.698	4.422	82.168	4.841	89.115	5.599	110.180	4.140	78.185	2.399	79.409	5.594	87.412	8.237	108.887	8.177
5	8	1	3	1	44.516	2.432	45.997	2.948	53.174	2.271	63.629	1.315	49.147	1.732	48.308	3.101	54.324	2.191	67.815	2.979
5	8	1	3	2	41.948	1.513	44.218	1.635	49.247	1.752	60.325	2.142	45.013	2.278	45.238	2.673	52.411	4.053	64.973	6.088
5	8	2	1	1	70.397	2.824	75.053	3.037	86.845	3.531	104.399	3.565	76.076	4.297	73.983	4.319	85.548	5.883	110.210	3.749
5	8	2	1	2	68.932	5.883	75.342	4.316	83.863	5.300	104.149	5.465	68.142	4.989	72.425	4.933	82.241	6.100	102.682	5.493
5	8	2	3	1	36.444	2.574	38.518	2.727	42.536	2.174	54.617	1.996	40.596	1.915	41.514	2.444	47.048	3.636	60.264	2.917
5	8	2	3	2	35.664	2.652	36.416	1.729	40.271	2.594	53.166	3.185	37.743	3.554	42.624	4.562	46.252	3.672	57.374	1.717

while larger p tends to do the opposite. From this perspective, emergency organizations and agencies could take measures to improve their node targeting capability in order to reduce the variations in message dissemination outcome due to the changes of user sharing behaviors in disasters and extreme events.

Compared to $|T|$ and p, source massaging interval l and message transmission delay dm have the opposite effect on the objective values. When l or dm gets larger, the object values are likely to get smaller. The distribution of share delay DS appears to have the least impact on the objective values. It seems that the objective values are slightly larger for $DS = 1$ than $DS = 2$, where the delay values are sampled from $Uniform(1,7)$ and $Poisson(4)$ respectively, but it is not always the case. Such examples can be found in different problem scenarios from both $R\ Instances$ and $T\ Instances$. Although the exact characteristics of user information sharing behaviors on social media are not clear yet, this property is desirable for emergency managers in that otherwise a messaging strategy could potentially perform poorly due to user behavior changes (i.e., different from the predicted behaviors at the planning stage) in disasters and extreme events.

Looking at each table horizontally, we may find some interesting trends. For each problem scenario, the objective values tend to increase as network density increases, which is true for both $R\ Instances$ and $T\ Instances$. This implies that denser networks are potentially beneficial for message dissemination. In particular, this increase tends to be more drastic when source messaging capacity is low (i.e., $p = 1$). However, similar trend cannot be identified for $StDev$, which means that network density itself may not influence the variation of message dissemination outcomes significantly.

Another interesting trend to observe is how network type impacts the objective values. By comparing the $R\ Instances$ and $T\ Instances$ with same density, it is obvious that Twitter networks tend to result in larger objective values and this trend can be identified in almost all problem scenarios. This means that more nodes may become active and/or nodes may become active sooner within the planning horizon on a Twitter network than random network, which motivates us to examine node activation over time and compare the results between different types of networks. This analysis is presented in section 4.3.4.

4.3.4. Results and analysis on node activation

Here we examine node activation within the planning horizon. In particular, we're interested in how the number of active nodes increases over time within the planning horizon, and how network and model parameters impact this increase. To answer these questions, we create a chart for each pair of $R\ Instance$ and $T\ Instance$. Results of the corresponding $C\ Instance$ are also added for comparison. Each line in the chart corresponds to a network type for the whole planning horizon and each dot on the line represents the average number of active nodes (over 10 replications) for a specific time period. By examining these charts, we are able to identify some key trends across problem scenarios (we focus specifically on $|T| = 4$ or $|T| = 8$ scenarios).

Figure 4.7 and Figure 4.8 introduce some of the scenarios for $|T| = 4$. Figure 4.7 shows the impact of p and network density on node activation for different networks. Specifically, charts on the left-hand-side are for $p = 1$ and charts on the right-hand-side for $p = 5$. Top and bottom charts are based on the networks with density 0.09 and 0.22 respectively. Figure 4.8 illustrates the impact of l and DS by horizontal and vertical comparisons in a similar way and all the charts are based on the networks with density 0.22. Figure 4.9 and Figure 4.10 show the same thing as in previous two but for $|T| = 8$. We still denote the lines as $C\ Lines$, $R\ Lines$, and $T\ Lines$ in the following analysis.

It is obvious that $C\ Lines$ are highly distinct from the other two. They are characterized by a sharp increase in a short period of time (e.g., period 2 to 3 in Figure 4.7 and Figure 4.9) and all nodes can become active quickly regardless of the change of other parameters. Compared to that, $R\ Lines$ and $T\ Lines$ appear more stable. They don't grow as drastically as the $C\ Lines$ in general and are more sensitive to the change of parameters. Specifically, there are more active nodes in each time period for a larger p or higher density on random and Twitter networks. Also, there tends to be more active nodes for a smaller l or DS, especially in the early periods of the planning horizon.

Having seen the similarities between the $R\ Lines$ and $T\ Lines$, we are more interested in observing how they behave differently. A first trend to notice is that $T\ Lines$ grow much faster than $R\ Lines$ in the initial phase of message dissemination, which is true for both $|T| = 4$ and $|T| = 8$ scenarios. It appears to be more significant for some of the scenarios, such as when messaging capacity is relatively small, (i.e., $p = 1$ or $p = 3$) and share delay are sampled from $Uniform$ distribution (i.e., $DS = 1$). Another trend to notice is that, for $|T| = 4$ the $T\ Lines$ tend to be higher than the $R\ Lines$ (i.e., more nodes are active) in each time period of the planning horizon, while for $|T| = 8$ the $R\ Lines$ run below the $T\ Lines$ during the first few periods but surpass

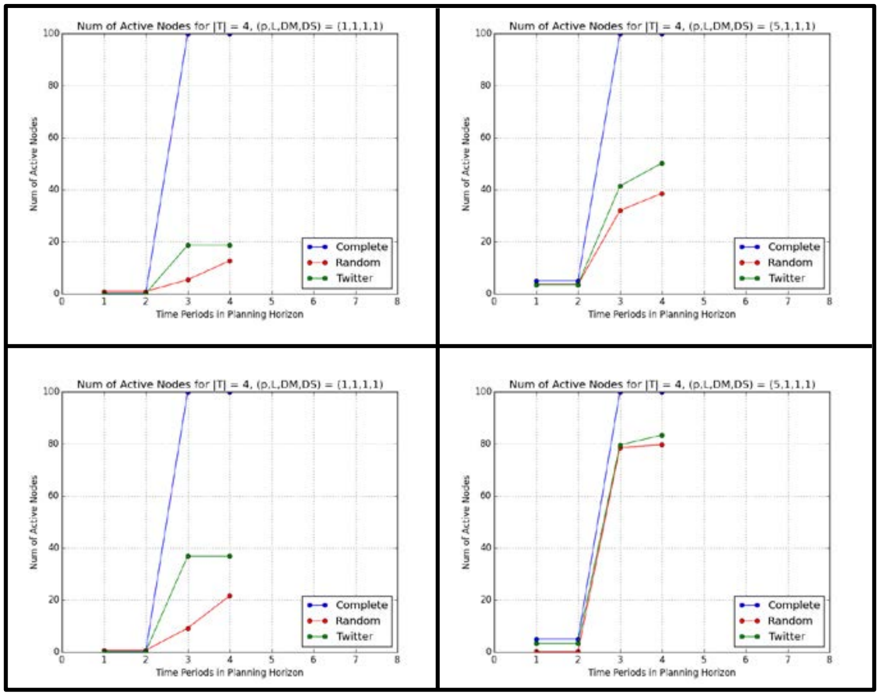


Figure 4.7 Active nodes for $|T| = 4$ comparing p and density

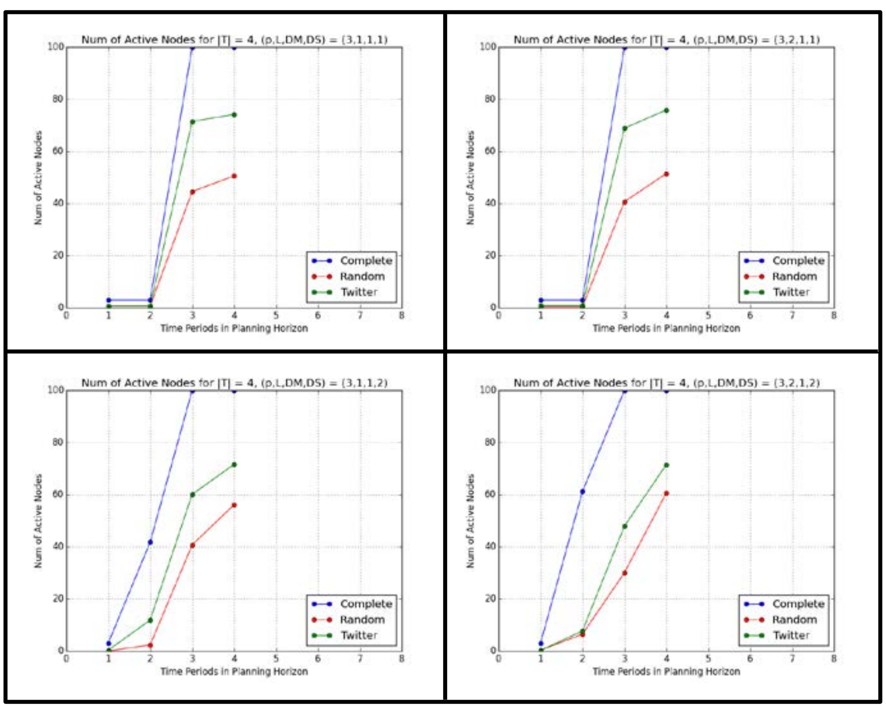


Figure 4.8 Active nodes for $|T| = 4$ comparing l and DS

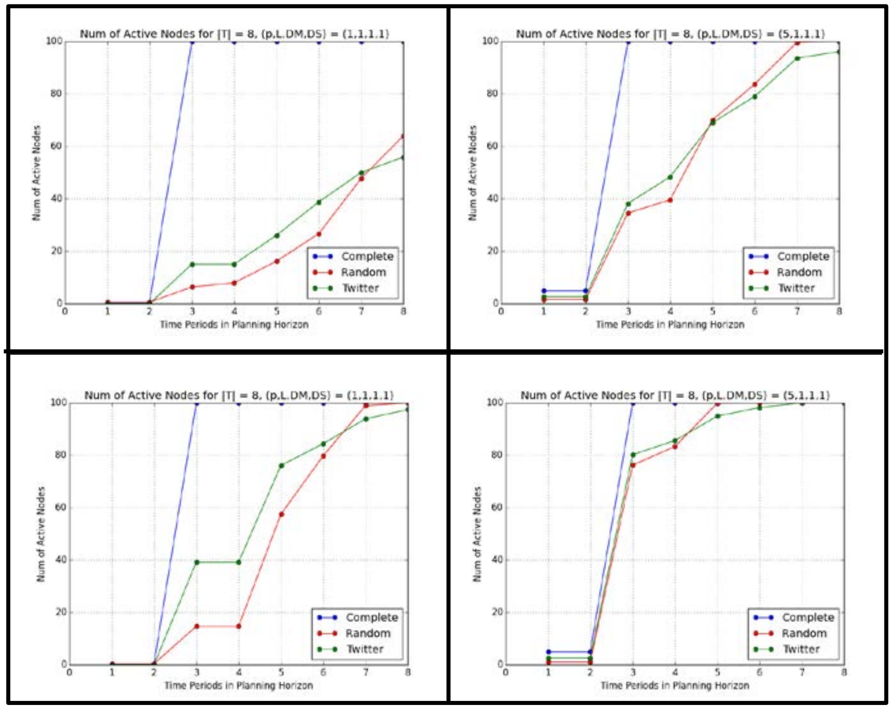


Figure 4.9 Active nodes for $|T| = 8$ comparing p and density

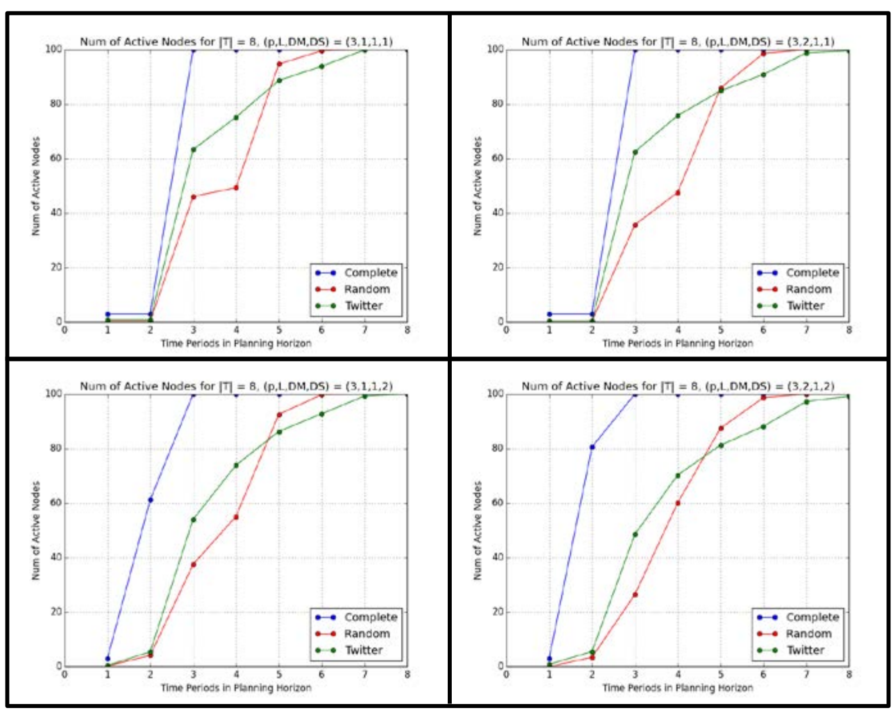


Figure 4.10 Active nodes for $|T| = 8$ comparing l and DS

them at a later point of the planning horizon, as illustrated in Figure 4.9 and Figure 4.10. This surpassing point varies over different scenarios, but it tends to come sooner when the situation is more suitable for message dissemination (e.g., larger p, smaller l, higher network density, etc.). Given that each of the comparisons is made on networks with the same density, we are inclined to attribute these trends to the structural difference between random and Twitter networks. That is, the clustered structure of a Twitter sub-network may contribute to wide message dissemination within a short period of time. However, some low-degree nodes (i.e., petal nodes) far from the center of the network are hard to reach. We further examine this in section 4.3.5.

4.3.5. Further analysis on node activation

Here we are interested in two questions: (1) Which nodes are more likely to become active within the planning horizon, and (2) Which nodes should be targeted by the sources to facilitate message dissemination, especially in the initial phase of the planning horizon. The answers to these questions may help the emergency managers better understand the nature of the message dissemination process in extreme events, and could be used as general guidelines when they develop social media message dissemination strategies in reality.

Social networks are highly distinct from other networks (e.g., random networks) in that their node degree follows power law distribution. Therefore, we'd like to see how node degree may impact the activation of individual nodes and whether this impact varies by network type. To that end, we first examine degree centrality of active and inactive nodes for random and Twitter networks respectively. The degree centrality of a node i is defined as the degree of i divided by the maximum possible degree in the network. We apply hypothesis test to see whether the active and inactive nodes are significantly different in terms of degree centrality. Specifically, for each test instance, we divide the nodes into 2 subsets, active (ACT) and inactive ($INACT$). If both of them have a size greater than or equal to 30 (in this case, we call this instance is valid for testing), we performed a z-test to compare the mean of degree centrality and observed the p-value. Table 4.5 provides a summary of the z-test results. Overall, we can find that 100% of the valid instances are showing a significant difference (p-value < 0.05) in degree centrality between active and inactive nodes for Twitter networks, while this percentage is 61.49% for random networks. It appears that node degree has significantly stronger impact on message reception in Twitter networks than random networks. More importantly, such impact exists regardless of network density. Compared to that, the percentage is showing a decreasing trend as network density increases for random networks.

Table 4.5 A summary of the z-test results on degree centrality

Network Type	Network Density	% of Instances with p-value < 0.05	Valid Instances	Total Instances
Random	0.09	71.78%	1,205	4,800
	0.11	66.94%	1,204	4,800
	0.14	57.12%	1,152	4,800
	0.22	48.13%	1,043	4,800
	Overall	61.49%	4,604	19,200
Twitter	0.09	100.00%	1,846	4,800
	0.11	100.00%	2,090	4,800
	0.14	100.00%	1,977	4,800
	0.22	100.00%	885	4,800
	Overall	100.00%	6,798	19,200

To further examine the extent to which node degree may affect message reception in both types of networks, we create a box plot for each comparing the distributions of degree centrality between active and inactive nodes as well as the change from $|T| = 4$ to $|T| = 8$, as shown in Figure 4.11. Note that ACT and $INACT$ aggregate degree centrality of the nodes from all test instances for a specific $|T|$. For each test instance, if a node turns out to be active, then we put its node centrality value into ACT, otherwise into $INACT$, and we do this for all the test instances. The information given for each subset of nodes includes min value, max value, first quartile, median and third quartile of degree centrality.

Not surprisingly, we can observe a larger gap between two subsets of nodes for both $|T| = 4$ and $|T| = 8$ as well as a more obvious change from $|T| = 4$ to $|T| = 8$ for Twitter networks than random networks. Now we focus the attention on Twitter networks, the results of which can provide more insights for real-world applications.

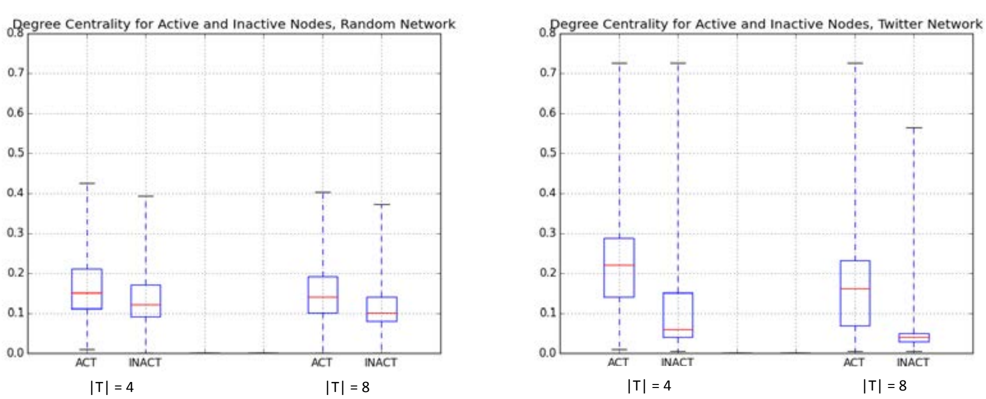


Figure 4.11 Distributions of degree centrality for active and inactive nodes

When $|T| = 4$, 75% of the active nodes have at least 14 friends (i.e., degree centrality is about 0.14) while 75% of the inactive nodes have at most 14 friends. Such distinction appears to be more obvious when $|T| = 8$. Specifically, 75% of the active nodes have at least 8 friends and 50% of them have at least 16 friends, while 75% of the inactive nodes have 5 friends or less. It is also noticeable that when a node has more than 57 friends, it is active in any problem scenario (the largest value in $INACT$ is about 0.57). Some nodes are hard to become active, such as those with 2 - 3 friends, even if the planning horizon gets longer. When $|T| = 8$, 50% the inactive nodes have only 2 - 5 friends (between first and third quartiles). Given all these figures, we can conclude with more confidence that node degree can significantly impact individuals' message reception on Twitter sub-networks. More importantly, node degree has shown its potential to be a strong indicator of message reception. In other word, the chance a node can receive messages within the planning horizon might be predicted solely based on its degree on the social network. If this is true, then it would be really helpful for emergency managers to assess message reception and manage message dissemination on social media in reality.

Here we move the attention to the nodes targeted by the sources in the planning horizon and examine their degree centrality and closeness centrality for short and long planning horizon respectively. The closeness centrality of a node i is defined as the reciprocal of the sum of the shortest path distances from i to all the other nodes in the network, and it can be normalized by multiplying it by the sum of minimum possible distances. In SM-SMMDP, the share delay of a node is specific to message type, so each node in the network has $|M|$ closeness values, corresponding to $|M|$ message types. Also note that the distance (in terms of delay) from node u to node v for message m is given by $(ds_{um} + dm)$, while this distance is $(ds_{vm} + dm)$ for the opposite direction. Therefore, to calculate the shortest path distances, we have to construct $|M|$ directed multigraphs based on the original undirected social graph. This process is illustrated in Figure 4.12. In this way, we can get one degree value (DG) and three closeness values ($CL1$, $CL2$ and $CL3$) for each node in our experiments. To better characterize the closeness centrality of each node, we include average closeness ($AvgCL$) and standard deviation of closeness ($StdCL$) in the analysis.

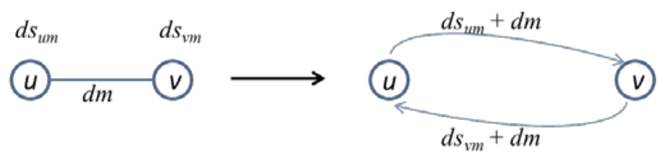


Figure 4.12 Constructing directed multigraphs

Figure 4.13 introduces the comparisons between targeted nodes in different time periods of the planning horizon for Twitter networks. Specifically, the targeted nodes are divided into three categories, including 1st Wave, Later Waves, and Overall. 1st Wave represents the nodes targeted by the sources in the first time period of the planning horizon, while Later Waves represents those targeted in later times. Overall includes all the targeted nodes, which is the union of nodes in the first two categories. We aggregated the instances for $|T| = 4$ and $|T| = 8$ respectively and each value shown in the figure is the average of DG, $AvgCL$ or $StdCL$ over all nodes in a specific category.

It is noticeable but not surprising that, the 1st-wave nodes are exhibiting some properties that make them highly distinct from others. They have significantly larger DG, $AvgCL$ and $StdCL$ (comparing the blue bar and red bar in each block). Large DG means they typically have more friends on the network, which can help create more message outlets in the early periods of the planning horizon. Large $AvgCL$ indicates their messages can reach other nodes faster in general, while large $StdCL$ implies they may be particularly helpful in disseminating a certain type of message. Further, when we compare the blue bars in each chart, we may find the 1st-wave nodes appear to have more potential for $|T| = 8$ than $|T| = 4$ (i.e., larger DG and $AvgCL$ can be observed for $|T| = 8$). These observations prove that degree and closeness centrality can reflect the potential of individual nodes in facilitating message dissemination to some extent. As a result, emergency managers could take them into account when making message targeting decisions, especially for the initial phase of the planning horizon.

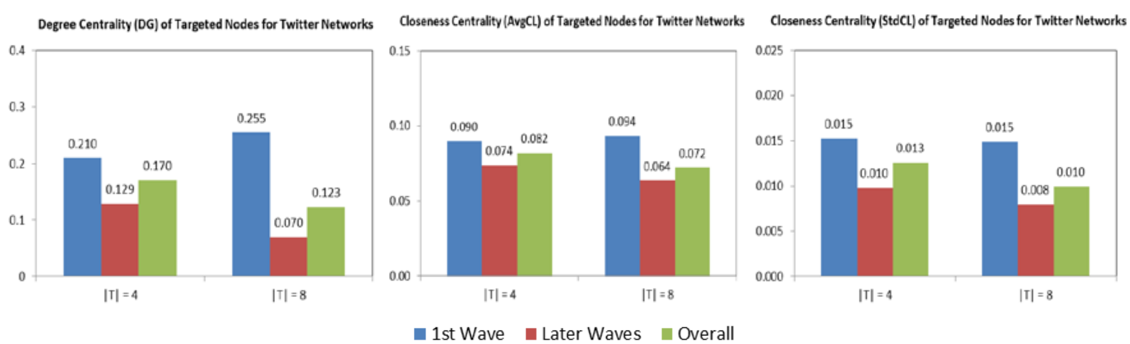


Figure 4.13 Comparisons of DG, $AvgCL$ and $StdCL$ for targeted nodes

4.4. Closing Remarks for SM-SMMDP

In this chapter, we examine the single-network multi-message application scenario in which multiple messages need to be disseminated on one social media network within a predefined planning horizon. A discrete optimization model for SM-SMMDP is provided and discussed. Through the computational experiments on small-scale test networks, we show that all model parameters, including network type, network density, source messaging capacity, length of planning horizon and so on, can impact the computational performance as well as message dissemination outcomes, but the degree of their impact varies. We also find that the Twitter networks are more like the complete network in terms of impacting CPU time, while they show similar trends to random networks in the way they affect objective values and active nodes.

In addition to observing the trends of CPU time, objective values and number of active nodes, we further investigate some underlying factors that impact message reception of individual nodes and that may help emergency managers with message targeting decisions. We find a clear distinction in degree centrality between active nodes and inactive nodes in Twitter networks and such distinction appears more significant for a longer planning horizon. We also find that the nodes targeted in the initial period of the planning horizon are typically associated with larger degree and closeness centrality. The method applied in the analysis as well as the findings could potentially be valuable to emergency management organizations and agencies in developing social media communication strategies, especially in predicting message reception and generating message targeting alternatives.

Some future research directions can be pursued to get a better understanding of the SM-SMMDP. An first direction is gaining more understanding about message sharing behaviors in social media, including how users respond to messages received from difference sources (family members, friends, organizations at different levels, etc.) and how they behave in different social media (Twitter, Facebook, etc.). This is extremely helpful in characterizing and modeling delays in the message propagation process. Another direction is extending the scope of this paper, by studying message dissemination on large-scale networks and on other popular social networks. The trends observed here can be examined in these new scenarios and more implications could be derived potentially from the comparisons for real-world application.

CHAPTER V

MULTIPLE-NETWORK MULTI-MESSAGE SOCIAL MEDIA MESSAGE DISSEMINATION PROBLEM

5.1. Problem Description and Definition

The Multi-network Multi-message Social Media Message Dissemination Problem (MM-SMMDP) considers the scenario in which multiple messages need to be disseminated to a population within a predefined planning horizon in the presence of multiple social media networks. The MM-SMMDP extends the previously discussed single-network message dissemination problems and is meant to illustrate and identify the impacts of integrated social media use (e.g., Twitter plus Instagram plus Facebook). This model is motivated by the observation that social messages can easily transfer between social media sites through users who either replicate or reiterate message content from one social media site onto another. These networks are represented by $G_n = (I, A_n),\ n \in N$, where a set of nodes, I is considered. Each node $i \in I$ represents a user and each arc $\langle i, j \rangle \in A_n$ represents the relationship on network n (i.e., friend or follower) between users $i, j \in I$, through which messages can flow from i to j on the network. The messages to be disseminated are given by set M. Each message $m \in M$ is assumed to be independent from others and corresponds to a unique source (i.e., it can only send its own message to the user nodes on each network), and the number of unique messages is

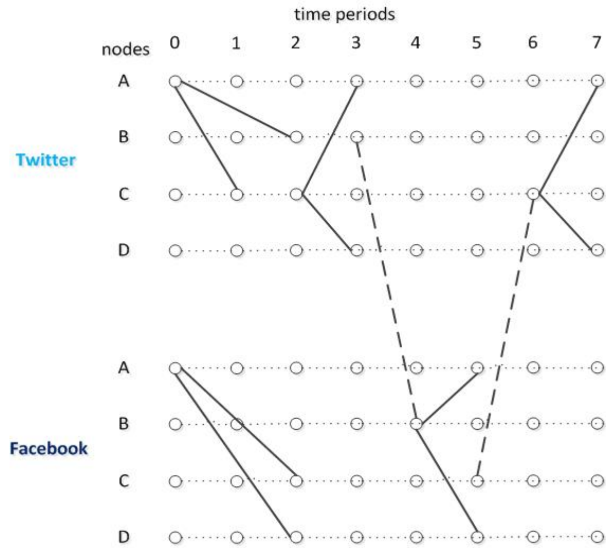


Figure 5.1 Conceptualization of MM-SMMDP

$|M|$. The planning horizon is given by set T. Each $t \in T$ represents a time period in the planning horizon and the length of the planning horizon is $|T|$.

Message propagation on each network is initiated by the sources through node targeting (i.e., send direct messages to the selected nodes) and continues as individual nodes redistribute the received messages to their friends or followers, as illustrated in Figure 5.1. Note that the redistribution can be either message sharing on the current network or message transferring from the current network to other networks. The source for any message m can send its message in multiple waves on each network n if time allows, with a minimum reset time l_m between two consecutive waves and a capacity p_m in each wave. Accordingly, a subset of p_m nodes (i.e., nodes to be targeted) needs to be determined corresponding to each wave of message m from its source. This process is the same as in Figure 4.2. Individuals' redistribution behaviors are modeled using time delays called user share delay and user transfer delay for sharing and transferring messages respectively. User share/transfer delay represents the time between message arrival at a user's device (e.g., PC, cell phone, iPad, etc.) and when the user shares/transfers the message. It is assumed to be specific to the individual node, the message and the social media network(s) through which the message is being shared/transferred, and denoted by matrix D, in which $d_{imnn'} \in D$ represents the delay of node i for message m on network n (note that message propagation through the same social network is considered when $n = n'$). Message transmission delay, which represents the digital transmission time between devices, is used to reflect network conditions (e.g., known outages, intentional hacks, etc.). Transmission delay is assumed to be specific to the network, and is denoted by matrix DM, in which $dm_n \in DM$ represents the transmission delay on network n. This delay could be non-negligible in emergency events due to cell phone tower damages and/or excessive load within a short period that prevents a given message's delivery. A user node i is considered active after receiving all messages (a message can be received on any of the networks), and the message dissemination outcome is defined as the weighted sum of the activation status of all individual nodes over the planning horizon, which essentially encourages wider and sooner message reception on the networks.

Now the MM-SMMDP can be formally stated as follows: Given social media networks $G_n = (I, A_n),\ n \in N$, message set M, planning horizon T, source messaging capacity matrix $P(M)$, source reset time matrix $L(M)$, user delay matrix $D(I, M, N, N)$, and message transmission delay matrix $DM(N)$, MM-SMMDP optimizes the message dissemination outcome by determining a sequence of subsets, each containing at most p_m nodes, to be targeted for each message m on each network n. Problem formulation is presented in section 5.2.

5.2. Problem Formulation

5.2.1. Sets and parameters

I = the set of user nodes

M = the set of messages

N = the set of social media networks

T = the set of time periods

T'_m= the set of time periods eligible for the source of m to send messages

N_{ni} = the set of nodes j such that $\langle j, i\rangle \in A_n$

w_{it} = the reward for node i being active at time t

p_m = the source messaging capacity for message m

$d_{imnn'}$ = the share delay of node i for message m on network n if $n = n$. Otherwise, the transfer delay of node i for message m from network n to network n'.

dm_n = the message transmission delay on network n

5.2.2. Decision variables

$z_{it} = 1$ if node i is active at time t, 0 otherwise

$x_{imnt} = 1$ if node i is targeted for message m on network n at time t, 0 otherwise

$y_{imnt} = 1$ if node i is active for message m on network n at time t, 0 otherwise

5.2.3. Formulation

$$max \quad \sum_{i\in I}\sum_{t\in T} w_{it}z_{it}. \tag{5.1}$$

s.t.

$$\sum_{i\in I} x_{imnt} \leq p_m, \quad \forall\, m \in M, n \in N, t \in T'_m. \tag{5.2}$$

$$y_{imnt} \leq \sum_{l\leq t} x_{imnl} + \sum_{j\in N_{ni}} y_{jmn(t-dm_n-d_{jmnn})}$$

$$+\sum_{j\in N_{ni}}\sum_{n'\in N\setminus\{n\}} y_{jmn'(t-dm_n-d_{jmn'n})}, \;\forall\, i \in I, m \in M, n \in N, t \in T \tag{5.3}$$

$$z_{it} \leq \sum_{n\in N} y_{imnt}, \quad \forall\, i \in I, m \in M, t \in T. \tag{5.4}$$

$$y_{imnt} \leq y_{imn,t+1}, \;\forall\, i \in I, m \in M, n \in N, t \in T. \tag{5.5}$$

$$z_{it} \leq z_{i,t+1}, \;\forall\, i \in I,\; t \in T. \tag{5.6}$$

$$x_{imnt}, y_{imnt}, z_{it} \in \{0,1\}, \;\forall\, i \in I, m \in M, n \in N, t \in T. \tag{5.7}$$

The objective function (5.1) optimizes the message dissemination outcome (i.e., maximizing the total reward for message reception over all user nodes within the planning horizon). For each node i, the weight w_{it} is a decreasing function of time t, which serves to encouraging early reception. In this way, the ultimate goal of the objective is to encourage wider and earlier message reception on the networks. Constraint (5.2) enforces the messaging capacity of the sources on each network. Note that for any message m, set T'_m is developed based on T and l_m. Constraint (5.3) states that, node i is active for message m on network n at time t, if it received the message either from the source node on network n prior to t, or from a friend node j on network

n who shared the message previously on network n, from a friend node j on network n who transferred the message previously from some network n' to network n. The lead times for the sharing and transferring are d_{jmnn} plus dm_n and $d_{jmn'n}$ plus dm_n, respectively. Constraint (5.4) enforces a message aggregation effect at the user end (i.e., a node has to receive all the messages to become active). Note that message reception is not network-dependent, so it does not matter which social media network the user receives content from. Constraints (5.5) and (5.6) preserve node status over time, and Constraint (5.7) imposes binary restriction on all decision variables.

5.3. Computational Experiments

In this section, we present the computational experimentation on MM-SMMDP. In particular, this analysis illustrates how decision parameters affect computational performance, message dissemination outcomes and targeting decisions. The factors being tested include length of planning horizon ($|T|$), source messaging capacity (P), source messaging interval (L), network structure (density), and network condition (DM). We use 100-node networks in these computational experiments and consider three unique messages and two social media networks (i.e., $|I|$ = 100, $|M|$ = 3, $|N|$ = 2). In order to obtain networks that are more representative of social media networks, we generate four sub-networks from the social media site Twitter and use their combinations as test networks. These Twitter sub-networks are generated through a Metropolis-Hastings Random Walk (MHRW) on Twitter, each using a different, randomly selected Twitter user as Node 0 in the random walk. All networks are treated as undirected where two nodes are connected with an edge if they have a friend/follower relationship originally or they have at least one common friend/follower. The summary of these Twitter sub-networks and visualizations of them can be found in Table 4.1 and Figure 4.4 respectively.

5.3.1. Experimental design

Table 5.1 provides the factors and levels for the implemented experimental design. For the purposes of our experimentation, we assume the basic time unit to be hours (we note that such an assumption may easily be changed to adapt the MM-SMMDP for different extreme event circumstances/scenarios).

Source messaging capacity and messaging interval are assumed to be identical for all message sources on each network (i.e., $p_1 = p_2 = p_3 = p$ and $l_1 = l_2 = l_3 = l$, though this is not a requirement of the model). Message transmission delay is assumed to be constant, as discussed in section 5.1. Individual's share and transfer delays are assumed to be independent, so the delay matrix D is randomly generated, in which each element $d_{imnn'} \in D$ is an integer sampled from $Uniform(1,10)$. The reward coefficient w_{it} in the objective function is assumed to be $w_{it} = 1/t$ for any node $i \in I$ and $t \in T$.

We define a problem scenario as a combination of decision parameters $(p, l, |T|, (N1, N2), (DM1, DM2))$, in which $(p, l, |T|)$ can represent an emergency manager's considerations and $((N1, N2),\ (DM1, DM2))$ reflects network structure and conditions. Based on the factors and levels given in Table 5.1, there are 1,280 unique

Table 5.1 Experimental factors and levels for MM-SMMDP

Factors	Levels
Networks ($N1, N2$)	(0.09,0.11), (0.11,0.14), (0.09,0.22), (0.14,0.22)
Messaging capacity (p)	1, 2, 3, 4, 5
Planning horizon ($\|T\|$)	1, 2, 3, 4, 5, 6 ,7 ,8
Messaging interval (l)	1, 2
Transmission delay ($DM1, DM2$)	(1,1), (1,3), (3,1), (3,3)

problem scenarios. To better capture the impact of random user behavior, we generate 10 replications for each scenario in terms of the delay matrix D to capture the variations. This results in 12,800 test instances in total. Given that MM-SMMDP introduces some new features that haven't been studied in SS- and SM-SMMDP (i.e., multiple networks and message transfer between networks), we create different cases to get some insights into their impact on message dissemination outcomes and model performance through comparisons. Specifically, in each test instance, we consider 4 cases, including a case without message transfer, a case without message transfer and two single-network multi-message cases, which are denoted as $N1 + N2\ w/o\ TF$, $N1 + N2\ w/\ TF$, $N1\ Only$, and $N2\ Only$ in the following analysis.

All the test instances are solved using ILOG Concert Technology with C++/CPLEX 12.4 on a Dell OptiPlex 755 computer (Inter Core 2 Duo E8500 3.17GHz, 4GB RAM and Windows 7 System), and the solution time are capped at 1,800 seconds for each test instance. Computational results and analysis are presented in the following.

5.3.2. Results and analysis on CPU time

Table 5.2 provides a summary of CPU time of all the test instances in the experiments, listed by Networks ($N1, N2$). In the table, % $Optimal$ gives the percentage of instances solved to optimality in 1,800 sec solution time. AVG, $StDev$, MIN, and MAX mean the average, standard deviation, minimum and maximum of the CPU times of instances. With AVG reflecting the average levels and $StDev$ reflecting the variations, RSD, relative standard deviation which is given by $RSD = StDev/AVG$, can reflect the degree of variation in respect to the average level of each case.

Given that 100% of CPU times are within 1,800 sec and about 40 sec on average, we can conclude that the MM-SMMDP model is tractable for 100-node Twitter sub-networks, although in some extreme case(s) it may take 1,116 sec to solve. Overall, AVG and $StDev$ increase by 26% and 31% respectively when considering message transfer ,which indicates the introduction of message transfer on the multiple-network scenario will cause more difficulties in getting the optimal solutions (probably because there are more decision variables). We also observe an overall decreasing trend in computational difficulty as the total density of networks increases, as shown in Figure 5.2, in which the columns and bars represent AVG and $StDev$ respectively. It is clear

Table 5.2 A summary of CPU times in the MM-SMMDP experiments

Networks	Instances	% Optimal	N1+ N2 w/o TF					% Optimal	N1+ N2 w/ TF				
			AVG	*StDev*	*MIN*	*MAX*	*RSD*		*AVG*	*StDev*	*MIN*	*MAX*	*RSD*
(0.09,0.11)	3,200	100.00%	36.910	61.584	0.047	917.630	1.668	100.00%	48.236	78.264	0.047	1115.800	1.623
(0.11,0.14)	3,200	100.00%	29.665	41.221	0.047	789.800	1.390	100.00%	42.325	63.580	0.016	869.300	1.502
(0.09,0.22)	3,200	100.00%	25.021	33.788	0.047	496.270	1.350	100.00%	28.547	39.413	0.047	969.340	1.381
(0.14,0.22)	3,200	100.00%	23.332	31.130	0.047	808.900	1.334	100.00%	25.275	33.635	0.031	582.600	1.331
Overall	12,800	100.00%	28.732	43.912	0.047	917.630	1.528	100.00%	36.096	57.473	0.016	1115.800	1.592

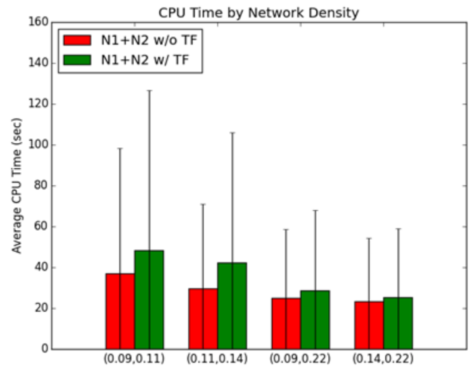


Figure 5.2 CPU time by networks ($N1, N2$)

that increasing network density can help reduce the average and variation observed in CPU time, and that it may also reduce the gap observed between problems that allow message transfer and problems that prohibit message transfer (by comparing the columns of (0.09,0.22) and (0.14,0.22) to (0.09,0.11) and (0.11,0.14)). This property should be noticed and potentially utilized by emergency managers in the planning phase (e.g., encouraging people in a community or neighborhood to use social media and connect to each other).

It is noticeable from Table 5.2 and Figure 5.2 that in each set of networks, $StDev$ is much larger than AVG (RSD is higher than 1.52 on average and is almost 1.67 in some case(s)), which means some other factors also affect the computational performance significantly. Figure 5.3 shows the impacts of length of planning horizon, source messaging capacity, network condition (transmission delay) as well as source messaging interval. Overall, the length of planning horizon has the most significant impact on CPU time among all the factors being considered. On one hand, AVG grows exponentially as the increase of $|T|$, which is true for both cases ($w/o\ TF$and w/TF). One the other hand,

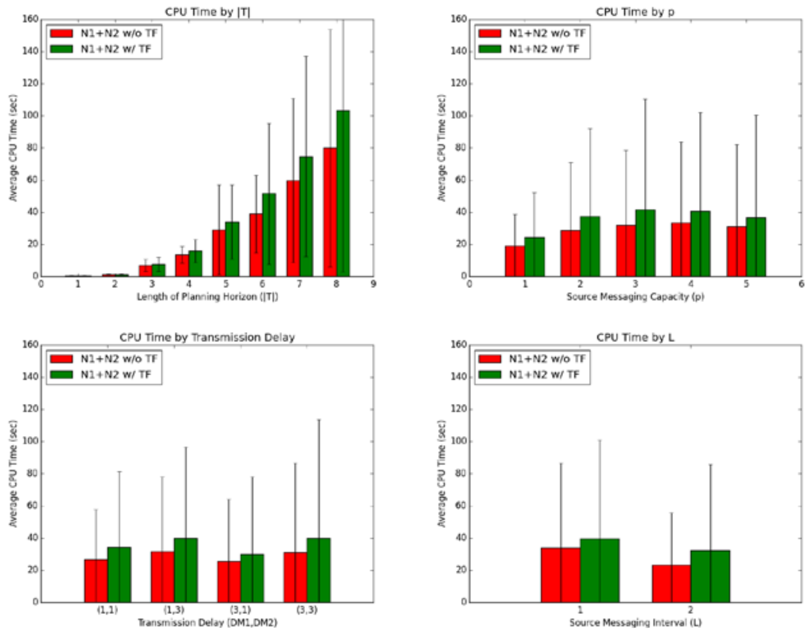


Figure 5.3 CPU time by factors

$RSD < 1$ holds for each planning horizon length $|T|$, which cannot be observed for any realization of other factors. Compared to length of planning horizon, other factors' impact on overall computational performance is much less significant. As for source messaging capacity, largest AVG is observed at $p = 4$ and $p = 3$ for two cases, respectively, but the gaps between them and the others are not significant. Regarding network condition, larger AVG and $StDev$ can be observed when the condition of the second network (the one with higher density in $(N1, N2)$) is bad (i.e., $DM2 = 3$), which is also true for both cases. As for source messaging interval, larger AVG and $StDev$ are observed at $l = 1$ for both cases. When the messaging interval is short (i.e., $l = 1$), message sources are able to send more waves of messages (i.e., this leads to more active decision variables and constraints in the model) and therefore causing more difficulty in obtaining the solutions. But as mentioned previously, the gaps are not significant from the overall scale.

Figure 5.4 shows the combined effects of length of planning horizon $|T|$, source messaging capacity p as well as network density $(N1, N2)$ on average CPU time AVG. In particular, we are interested in the changes of AVG as p increases and how $(N1, N2)$ and $|T|$ affect these changes. Here we just show $|T| = 5, \dots, 8$ because the lines are flat and overlapping with each other when the planning horizon is short. First, we see that it takes much longer time (at least twice) to solve multi-network instances than single-network instances, and we might expect larger gaps between them for networks of larger size. The CPU times of the single-network instances are also insensitive to the increase of p, compared to those of the multi-network instances. Second, the CPU times of both multi-network cases fluctuate more drastically as the increase of p when the networks are sparse and the planning horizon is long (i.e., $(N1, N2) = (0.09, 0.11)$ and $|T| = 8$), as shown in the bottom right corner, while the opposite can be seen in the top left corner, where $(N1, N2) = (0.14, 0.22)$ and $|T| = 5$. The implication here for the emergency managers is that when they are dealing with sparse social media networks (which is the case in reality oftentimes), they should be expecting large variations in the computational efforts required to examine different alternatives in terms of how many nodes they target at a time. And from the other way, encouraging more connections between social media users of a certain area may allow the emergency organizations and agencies to evaluate more message targeting alternatives in their planning phase.

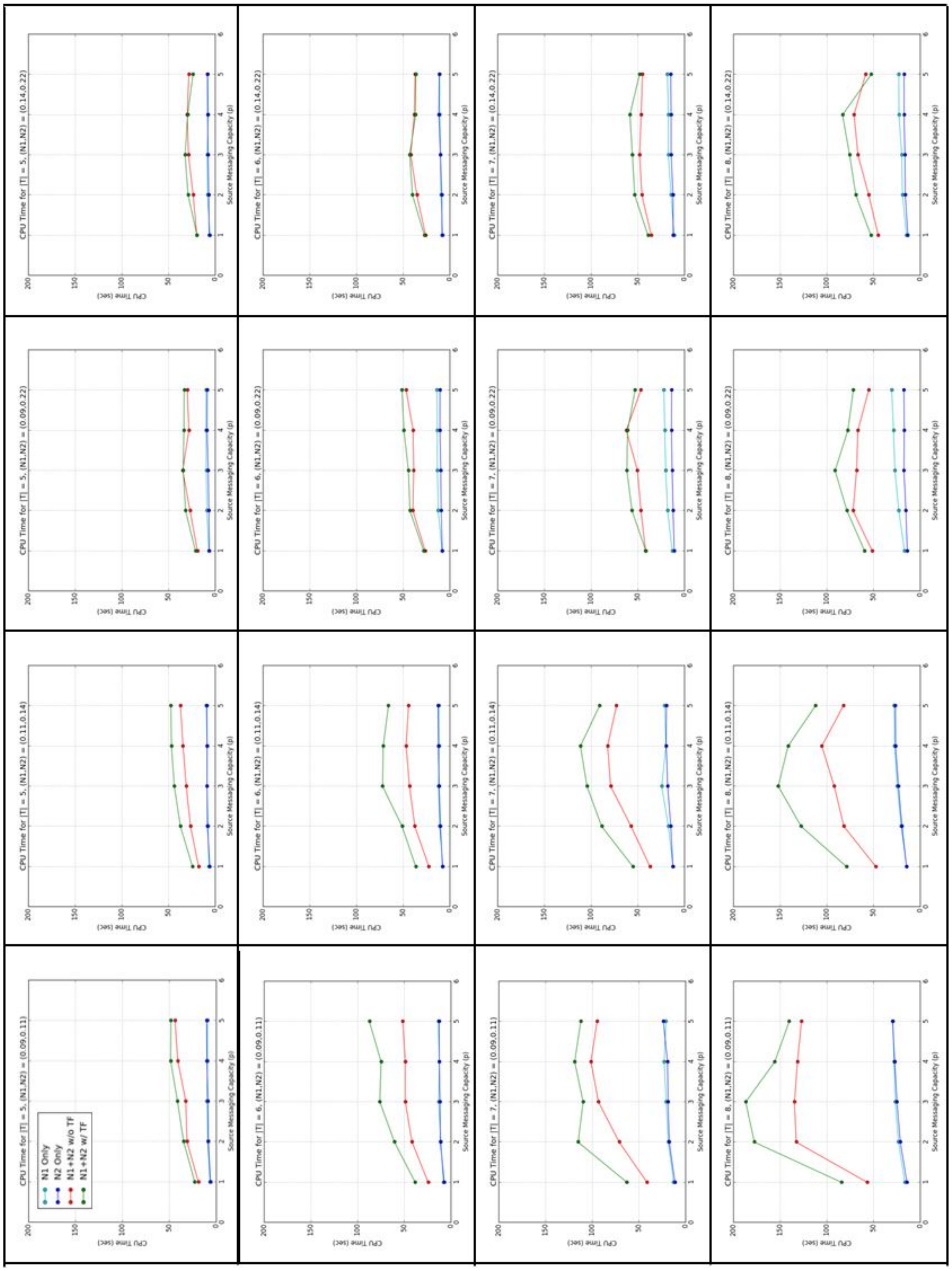


Figure 5.4 CPU time by p under combinations of $(N1, N2)$ and $|T|$

5.3.3. Results and analysis on objective values

The objective function for the MM-SMMDP is defined as the weighted sum of the activation status of all individual nodes over the planning horizon, which essentially encourages wider and earlier message reception on the networks. It is worth noticing that the maximum objective value possible depends on the length of planning horizon $|T|$, as the way the objective function is set. Given any specific $|T|$, a larger objective value implies a better overall message dissemination outcome, and the maximum objective value is reached when every node becomes active in the first time period. As a baseline for interpreting the objective, here we first provide these values in Figure 5.5. In the following analysis, we use AVG, $StDev$, and $RSD = StDev/AVG$ to represent the average, standard deviation, and relative standard deviation of objective values of instances, respectively.

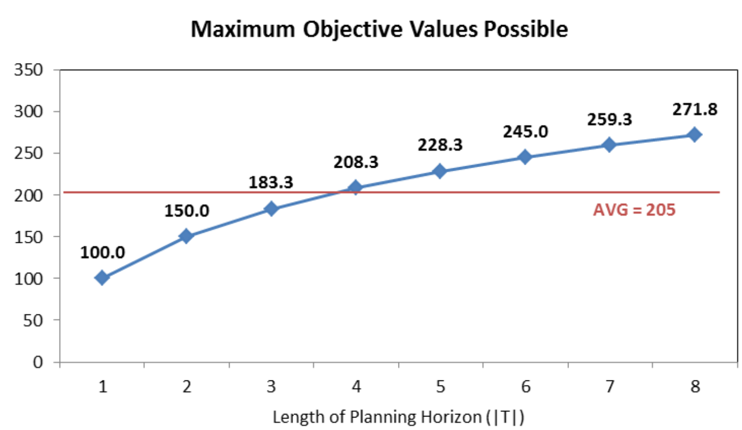


Figure 5.5 Maximum objective values possible

5.3.3.1. Objective values at the overall scale

Figure 5.6 provides a comparison of average objective values between the 4 cases we developed in the experiments. Same as before, the columns and bars represent AVG and $StDev$, respectively. Although the comparison is about overall average for each case, the increase in AVG from one-network cases to two-network cases is significant. For example, the percentage of increase is 57% from $N2\ Only$ to $N1 + N2\ w/o\ TF$ and is as large as 133% from $N1\ Only$ to $N1 + N2\ w/\ TF$, which is much larger than the 13% increase in two-network cases by introducing message transfer. The implication here for emergency management organizations and agencies is that they should set up accounts on multiple social media sites, especially on those most popular ones including Facebook and Twitter, in order to improve the overall message dissemination outcome.

As the impact of length of planning horizon on objective value is dominating, the impact of other factors still needs to be examined. Figure 5.7 shows AVG and $StDev$ versus source messaging capacity p, network condition $(DM1, DM2)$, network density $(N1, N2)$ as well as source messaging interval l. Among these four factors, p and

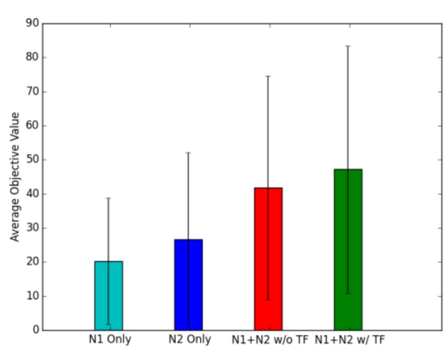


Figure 5.6 Average objective values

$(DM1, DM2)$ have more significant impact than $(N1, N2)$ and l. As source messaging capacity p increases, the objective values tend to increase linearly, and the degree of variations decreases. From a strategic standpoint, emergency management organizations and agencies could achieve better and more robust message dissemination outcomes by increasing the number of nodes they are able to target each time. Similar observation can be made for network condition as well. When the condition of both networks is good (i.e., $(DM1, DM2) = (1, 1)$), the dissemination outcomes tend to be good and robust, while the condition of both networks is bad (i.e., $(DM1, DM2) = (3, 3)$), the outcomes appear the opposite. Therefore, emergency managers should be fully aware of these effects when assessing situations and making decisions for social media message dissemination in disasters and extreme events. Message dissemination outcomes tend to get better on denser networks, however, the improvement is mild. Same thing for source messaging interval, which we are not going to mention again. Note that here we analyze the impact of individual factors on AVG and $StDev$ at the overall scale, and we are aware that such impact may vary in specific problem scenarios. Therefore, we provide Table 5.3, which contains detailed selected results from selected problem scenarios and cases, and present analysis based on problem scenarios in section 5.3.3.2.

5.3.3.2. Objective values by problem scenarios

As discussed previously, we define a problem scenario as a combination of decision parameters $(p, l, |T|, (N1, N2), (DM1, DM2))$, in which $(p, l, |T|)$ can represent an emergency manager's considerations and $((N1, N2),\ (DM1, DM2))$ reflects network structure and conditions. Here we further define the maximum messages possible (MMP) for the message sources, as the maximum number of messages a source can send within the planning horizon. It is given by $MMP = \lceil |T|/(l+1) \rceil \times p$ and reflects the maximum messaging (targeting) capability given their choice of $(p, l, |T|)$. Now we are interested in the relationship between this capability and message dissemination outcome of each problem scenario (i.e., AVG and $StDev$ of the objective values over 10 replications). AVG can reflect the average level of message dissemination outcomes in a problem scenario, while $StDev$ can reflect the degree of variation (stability) of the outcomes under the variations in user information sharing behaviors.

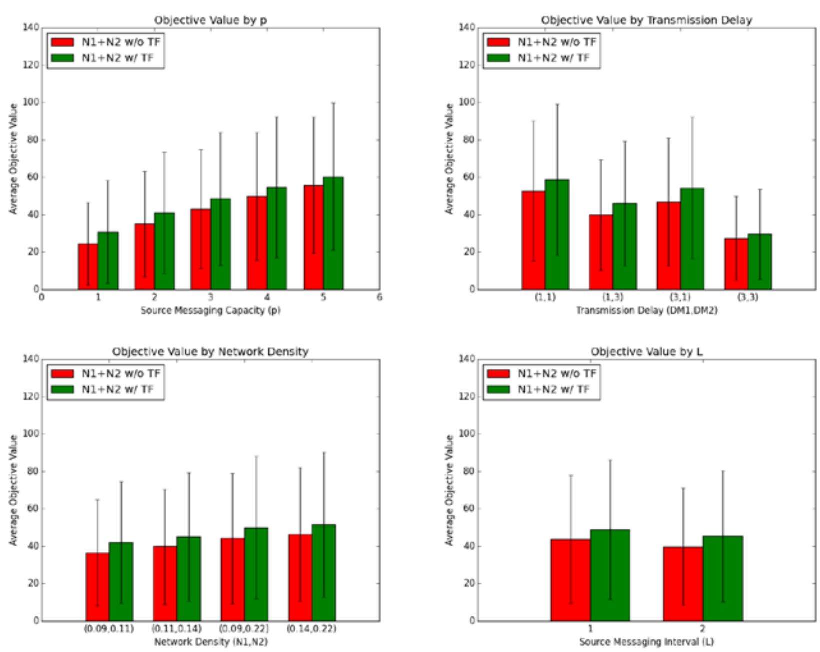


Figure 5.7 Objective values by factors

Table 5.3 Selected objective values from MM-SMMDP experiments

p	|T|	l	DM1	DM2	N1+N2 w/o TF								N1+N2 w/ TF							
					(0.09,0.11)		(0.11,0.14)		(0.09,0.22)		(0.14,0.22)		(0.09,0.11)		(0.11,0.14)		(0.09,0.22)		(0.14,0.22)	
					AVG	*StDev*	*AVG*	*StDev*	*AVG*	*StDev*	*AVG*	*StDev*	*AVG*	*StDev*	*AVG*	*StDev*	*AVG*	*StDev*	*AVG*	*StDev*
1	4	1	1	1	22.692	2.754	24.808	4.507	30.108	3.252	32.875	3.502	25.442	2.273	31.717	2.675	39.283	4.122	40.475	2.974
1	4	1	1	3	14.517	2.550	17.892	2.602	13.142	2.622	17.875	4.233	19.408	2.473	21.800	2.367	19.517	2.330	26.625	4.518
1	4	1	3	1	16.750	3.555	17.667	4.044	25.742	5.276	21.742	4.514	22.892	1.314	25.550	3.781	41.000	4.458	35.650	4.546
1	4	1	3	3	5.333	0.000	5.333	0.000	5.333	0.000	5.333	0.000	5.333	0.000	5.333	0.000	5.333	0.000	5.333	0.000
1	4	2	1	1	20.200	2.869	25.983	3.408	28.583	4.143	32.042	3.913	23.208	1.999	29.483	4.222	38.575	4.658	39.617	3.953
1	4	2	1	3	11.742	2.342	15.092	3.483	12.508	2.820	16.417	1.813	17.508	1.573	20.658	2.525	18.308	2.476	24.675	3.596
1	4	2	3	1	14.700	2.674	16.408	2.899	25.325	7.262	20.034	5.009	20.808	2.609	24.533	3.236	38.667	4.190	36.725	5.397
1	4	2	3	3	4.667	0.000	4.667	0.000	4.667	0.000	4.667	0.000	4.667	0.000	4.667	0.000	4.667	0.000	4.667	0.000
1	8	1	1	1	62.379	5.059	73.887	6.136	85.398	5.566	90.988	4.753	77.268	4.636	87.180	3.600	102.300	4.667	102.373	5.157
1	8	1	1	3	47.161	4.431	55.771	3.765	53.886	5.477	62.985	5.038	61.073	4.181	64.460	4.564	63.615	3.465	76.041	4.587
1	8	1	3	1	52.384	3.869	61.920	5.612	75.629	9.397	73.981	5.243	61.520	3.547	73.942	6.580	93.380	6.366	94.861	6.481
1	8	1	3	3	30.088	2.511	35.572	3.259	38.020	4.176	45.162	4.106	36.490	2.280	38.741	2.483	49.288	2.620	52.193	3.925
1	8	2	1	1	57.210	4.343	69.181	4.239	74.610	6.482	82.808	8.044	72.954	2.744	81.945	2.048	97.388	6.103	99.278	3.755
1	8	2	1	3	41.832	3.970	47.127	4.240	48.866	2.797	56.936	5.087	52.509	3.471	58.735	3.878	57.959	2.265	71.612	4.614
1	8	2	3	1	45.278	5.582	53.956	6.877	69.971	7.445	74.682	7.488	56.406	3.885	67.065	6.335	93.024	6.658	95.697	4.150
1	8	2	3	3	26.098	2.466	31.162	3.322	35.133	2.618	37.472	3.567	31.074	1.607	36.764	1.768	47.250	2.813	45.108	3.435
3	4	1	1	1	41.650	2.815	47.150	2.547	53.892	1.910	57.033	1.780	48.883	1.771	53.742	2.265	61.275	1.003	62.208	0.815
3	4	1	1	3	32.475	1.165	33.167	2.334	33.758	2.494	39.167	4.470	39.733	1.643	40.725	3.147	39.725	1.360	46.800	2.816
3	4	1	3	1	33.433	2.221	36.550	4.147	48.517	2.910	48.717	4.045	40.875	2.132	45.225	2.134	58.675	1.600	57.258	2.031
3	4	1	3	3	16.000	0.000	16.000	0.000	16.000	0.000	16.000	0.000	16.000	0.000	16.000	0.000	16.000	0.000	16.000	0.000
3	4	2	1	1	36.600	3.611	40.725	4.029	51.525	3.312	51.642	3.271	43.083	1.378	48.067	2.464	57.808	1.289	56.942	1.846
3	4	2	1	3	26.342	3.645	30.758	3.924	27.708	3.473	35.608	3.134	34.175	3.089	37.642	2.800	33.817	2.695	42.317	1.852
3	4	2	3	1	30.133	2.743	34.542	3.440	46.133	5.686	46.808	3.743	35.700	1.583	42.033	2.747	54.600	2.063	54.967	1.629
3	4	2	3	3	14.000	0.000	14.000	0.000	14.000	0.000	14.000	0.000	14.000	0.000	14.000	0.000	14.000	0.000	14.000	0.000
3	8	1	1	1	97.983	4.386	103.666	2.408	116.079	4.437	122.416	2.557	111.016	2.411	115.181	2.399	124.045	1.484	126.103	1.359
3	8	1	1	3	81.956	5.503	88.009	2.823	85.992	4.017	96.479	3.305	95.886	3.749	97.996	2.043	96.061	3.296	107.289	2.908
3	8	1	3	1	83.539	4.103	95.806	4.976	110.868	6.820	114.163	3.023	96.709	3.254	106.023	2.244	121.887	1.690	122.631	1.504
3	8	1	3	3	58.827	1.573	64.946	2.838	71.235	3.165	72.917	2.123	66.226	1.843	70.667	1.878	76.891	1.010	77.326	1.014
3	8	2	1	1	90.415	4.752	98.135	3.420	113.798	5.549	112.162	5.439	105.240	3.202	109.051	2.738	121.554	2.348	121.517	1.292
3	8	2	1	3	71.365	3.768	78.533	3.413	81.771	2.768	88.189	2.912	87.584	1.905	92.896	1.900	90.997	3.016	97.374	2.030
3	8	2	3	1	73.683	4.531	83.261	4.348	107.035	6.917	105.541	5.410	87.931	3.871	96.825	2.638	116.110	3.072	116.222	2.074
3	8	2	3	3	52.032	2.268	57.037	2.808	65.704	2.334	66.790	2.676	59.383	1.610	62.894	3.013	71.158	1.630	72.166	1.703
5	4	1	1	1	55.725	3.062	60.750	2.807	68.400	1.746	69.308	1.635	64.858	0.494	66.808	0.713	72.925	0.633	73.133	0.427
5	4	1	1	3	47.858	2.359	48.092	2.985	44.608	5.082	53.917	2.517	53.817	2.845	55.192	2.521	54.967	2.728	61.200	2.134
5	4	1	3	1	47.908	2.348	54.933	2.791	63.350	4.937	64.667	3.372	55.992	1.898	61.958	1.353	70.900	1.308	71.433	1.571
5	4	1	3	3	26.667	0.000	26.667	0.000	26.667	0.000	26.667	0.000	26.667	0.000	26.667	0.000	26.667	0.000	26.667	0.000
5	4	2	1	1	50.567	3.082	55.567	2.372	63.650	2.858	62.933	2.415	58.367	2.372	62.275	1.010	69.217	1.379	69.042	0.819
5	4	2	1	3	39.383	2.486	41.433	2.876	39.750	1.585	47.100	3.269	47.167	2.990	48.717	3.226	47.392	1.500	53.725	2.029
5	4	2	3	1	42.633	2.352	48.458	3.330	59.867	4.020	58.325	4.066	48.317	1.870	55.992	1.819	65.500	3.275	65.617	2.052
5	4	2	3	3	23.333	0.000	23.333	0.000	23.333	0.000	23.333	0.000	23.333	0.000	23.333	0.000	23.333	0.000	23.333	0.000
5	8	1	1	1	118.920	2.934	124.961	3.209	132.021	2.605	134.271	1.740	127.295	2.223	130.895	2.779	136.215	0.708	136.690	0.300
5	8	1	1	3	105.489	3.296	108.377	3.775	107.598	3.544	115.588	3.330	116.952	2.539	119.044	1.916	118.948	2.494	124.591	2.268
5	8	1	3	1	106.799	4.198	115.834	2.395	127.132	3.653	130.225	2.985	117.730	3.311	124.733	1.790	134.405	1.230	135.154	1.335
5	8	1	3	3	83.394	1.722	86.145	1.728	88.729	1.518	89.692	0.757	88.099	1.180	89.286	1.004	90.119	0.000	90.119	0.000
5	8	2	1	1	110.595	1.843	115.797	3.238	127.089	3.034	127.626	2.708	120.673	1.327	124.988	1.978	132.169	1.791	132.336	1.251
5	8	2	1	3	92.541	3.963	96.904	2.692	97.952	2.463	107.281	2.138	107.258	3.184	109.237	3.031	108.894	2.678	115.178	1.915
5	8	2	3	1	95.354	3.835	105.985	2.633	122.600	2.098	122.750	4.372	107.146	3.420	115.416	2.895	128.687	2.257	128.779	2.223
5	8	2	3	3	71.455	3.786	74.628	2.833	83.719	1.501	82.639	1.328	78.706	2.425	81.506	1.433	86.361	0.457	86.248	0.499

Figure 5.8 provides the objective values versus MMP for multi-network case without message transfer (left) and with message transfer (right), respectively. Each dot in the charts shows the average of objective values of a specific problem scenario, reflecting the average level of message dissemination outcomes in that scenario. The

best and worst message dissemination outcomes (i.e., highest and lowest average objective values) are plotted for each of the capability levels, denoted as MAX and MIN in the figure. It is interesting to see the best and worst outcomes can be fitted well using logarithm functions and linear functions respectively, which is true for both cases. If we further examine these dots, we can find the MAX and MIN points are typically associated with largest and smallest possible $|T|$ for each capability level, which suggests that the length of planning horizon is a strong determinant for message dissemination outcome. From the perspective of the networks, we can find the MAX points are typically associated with $(DM1, DM2) = (1, 1)$ and $(N1, N2) = (0.14, 0.22)$, and the MIN points with $(DM1, DM2) = (3, 3)$ and $(N1, N2) = (0.09, 0.11)$. This shows network structure and condition also affect the message dissemination outcomes when the messaging capability of the sources is set. Such observations and relationships could be potentially utilized by emergency managers in evaluating and assessing message dissemination outcomes on the networks. Given a choice of $(p, l, |T|)$, they could get the estimated best and worst message dissemination performances, which could provide a powerful support in their social media messaging decision making process.

Figure 5.9 provides the relative standard deviation values versus MMP for multi-network case without message transfer (left) and with message transfer (right), respectively. Each dot in the charts shows the RSD of a specific problem scenario, reflecting the stability of message dissemination outcomes under the variations in user information sharing behaviors in that scenario. All the problem scenarios are plotted in

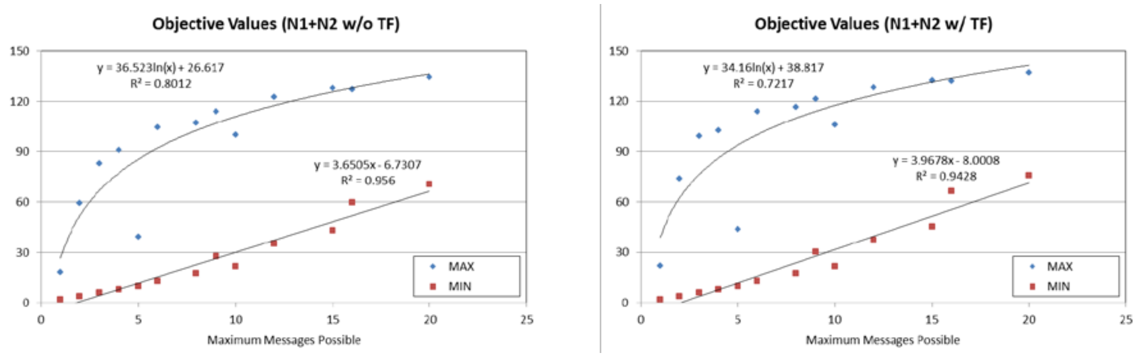


Figure 5.8 Objective value vs. MMP

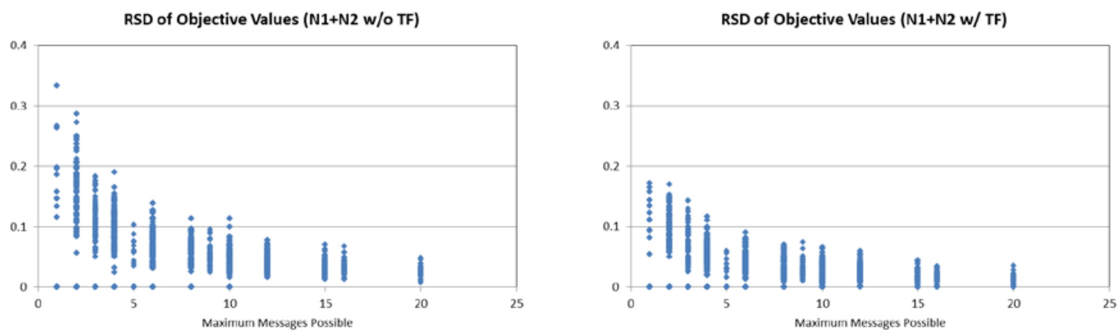


Figure 5.9 Relative standard deviation (RSD) vs. MMP

the figure. Generally speaking, increasing source messaging capability within the planning horizon is helpful to reduce the degree of variation, which can be seen in both cases. In particular, larger messaging capability tends to result in smaller range of the degree of variation (i.e., smaller gap between largest and smallest values corresponding to each capability level). Moreover, comparing the dots for two cases, the largest degree of variation corresponding to each source capability level is significantly reduced as a result of introducing message transfer, especially when source messaging capability is low (e.g., 0.34 to 0.18 at $MMP = 1$). In both cases, the largest degree of variation for each messaging capability level can be fitted well using a logarithm function (with $R^2 > 0.9$), as shown in Figure 5.10 and Figure 5.11. As a summary, increasing source messaging capability within the planning horizon contributes to stabilize the message dissemination outcomes under the variations in user behaviors, and message transferring behavior can further strengthen such effect. Therefore, to achieve more robust message dissemination outcomes, emergency management organizations and agencies should try to target as many nodes as possible within the planning horizon by planning early, building more reliable connections with the population, and/or applying more powerful technologies. At the same time, they should also encourage users' message transfer behaviors between networks and adapt their messages to make the transfer operation more convenient for them.

Now we move the attention to the most unstable problem scenarios, each of which has the largest RSD value for a specific messaging capability level. In particular, we are interested in how network condition and network density affect the instability. Figure 5.10 and Figure 5.11 show the RSD versus MMP, grouped by network condition and density respectively. For a given messaging capability level, each dot gives the largest RSD over the problem scenarios of a specific group, and the dot $Overall$ circles the largest RSD for that messaging capability level. From Figure 5.10, it is clear that the highest instability is always associated with the scenarios with $(DM1, DM2) = (1, 3)$ or $(3, 1)$ (with only one exception in the right-hand-side chart at $MMP = 8$, where the largest RSD is from $(DM1, DM2) = (3, 3)$, but its value very close to $(1, 3)$). This implies that the message dissemination outcomes are most influenced by the variations in user behaviors when the conditions of the two networks are different (i.e., one's condition is good and the other's is bad). And when the conditions are both good or both bad, the message dissemination outcomes are not likely to be affected significantly by user behaviors.

Similar observation can be made for the impact of network density, as shown in Figure 5.11. Networks with lower density tend to create more ground for the highest instability given a specific messaging capability level, since largest RSD is found associated with $(N1, N2) = (0.09, 0.11)$ in 38% of the capability levels (5 out of 13 capability levels), same for both cases. On the other way, networks with higher density are less likely to lead to highest instability. That is, 8% (1 out of 13) and 23% (3 out of 13) of the largest RSD is found associated with $(N1, N2) = (0.14, 0.22)$ for the case without message transfer and with message transfer, respectively. As an implication, the emergency managers should be fully aware that network density and condition can significantly affect the stability of the message dissemination outcomes given that the users' information sharing behaviors on social media are unpredictable and subject to changes in disasters and extreme events, and they could reduce such instability by increasing their messaging capability within the planning horizon and taking measures to encourage users' message transfer behaviors between networks.

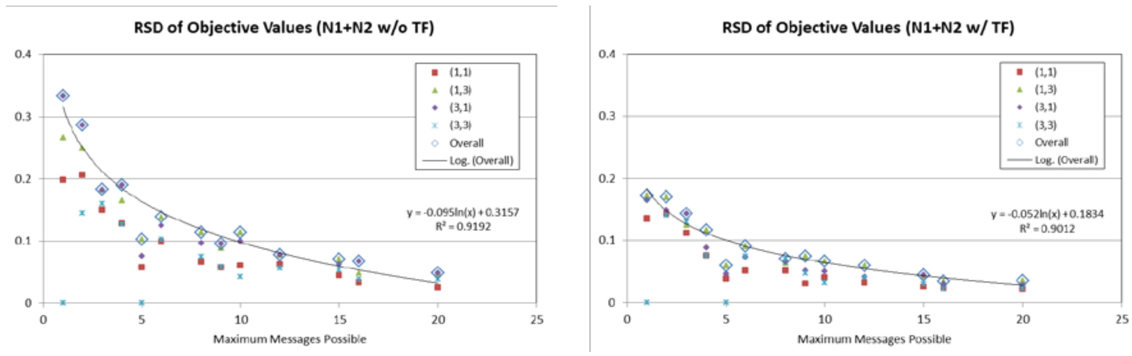


Figure 5.10 RSD vs. MMP grouped by network condition

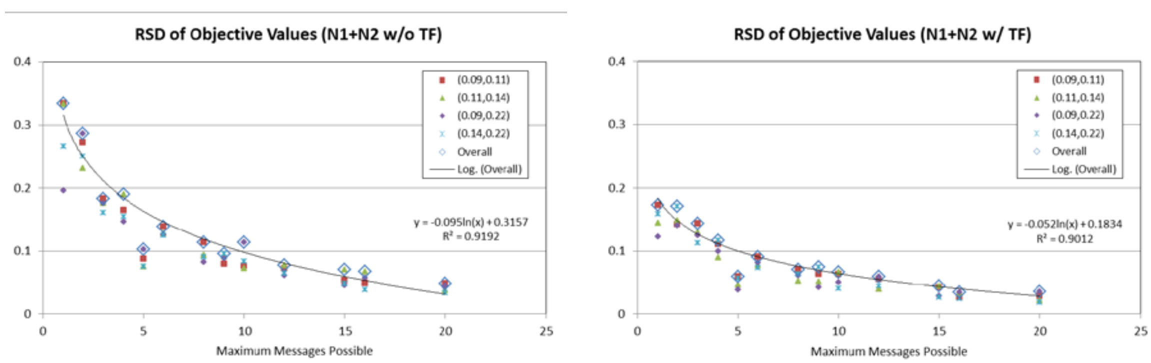


Figure 5.11 RSD vs. MMP grouped by network density

5.3.4. Results and analysis on node activation

Based on the analysis from Chapter IV, node degree has a major impact on individual node's activation (i.e., message reception). In general, nodes with higher degree are more likely to be active at the end of the planning horizon, and they tend to become active sooner in the planning horizon. Here we explore such relationships in the presence of multiple networks and message transfer.

5.3.4.1. Node activation at the overall scale

We are interested in the relationships between node degree and activation status at the end of the planning horizon/the activation time in the planning horizon. Note that in the presence of multiple networks (two networks in the experiments here), there are multiple degree values (two degree values here) associated with each node, so we consider the min, max, and sum of these degree values for each node in this analysis. To study the relationship between node activation status and node degree, we count the times that a specific node is active at the end of the planning horizon over all test instances and define the probability of activation (POA) of a node i as

$$POA_i = \frac{\#\ active}{\#\ instances}$$

where $\#\ active$ is the number of times node i is active at the end of the planning horizon and $\#\ instances$ the total number of instances that node i is involved in. To study the relationship between node activation time and node degree, we sum up all the time periods at with a specific node becomes active over all test instances and define the average activation time (AAT) of a node i as

$$AAT_i = \frac{total\ act\ time}{\#\ instances}$$

where $total\ act\ time$ is the sum of activation times for node i and $\#\ instances$ the total number of instances in which node i is active eventually. With POA_i and AAT_i defined, we calculate the values for each node in each of the four sets of networks accordingly, and this results in 400 POA and AAT values respectively for each case. The detailed analysis is presented in the following.

We create scatterplots for POA and AAT values versus min, max and sum of node degree in two networks to explore their relationships. Interestingly, these relationships can be fitted well with logarithm functions, compared to linear, exponential, power and polynomial functions. And among these logarithm functions, largest R^2 values can be observed when versus sum of degree, which indicates an individual's activation status at the end of the planning horizon and activation time in the planning horizon are significantly more dependent on the total number of connections she has on both networks rather than a single one of them. The fitted lines are given in Figure 5.12, which shows activation status on the left and activation time on the right. These results are inspiring in that they would potentially empower emergency organizations and agencies to predict message reception as well as message delivery time in a given population solely based on node degree information, which is easily accessible through collaborations with social media service providers like Facebook and Twitter.

5.3.4.2. Node activation by network density

Here we examine the relationships discussed in section 5.3.4.1 more carefully by dividing the nodes based on the network density. Specifically, we fit the POA and AAT values versus sum of degrees for two cases on each of the four sets of networks and examine the R^2 values associated with the fitting. The results are plotted in Figure 5.13.

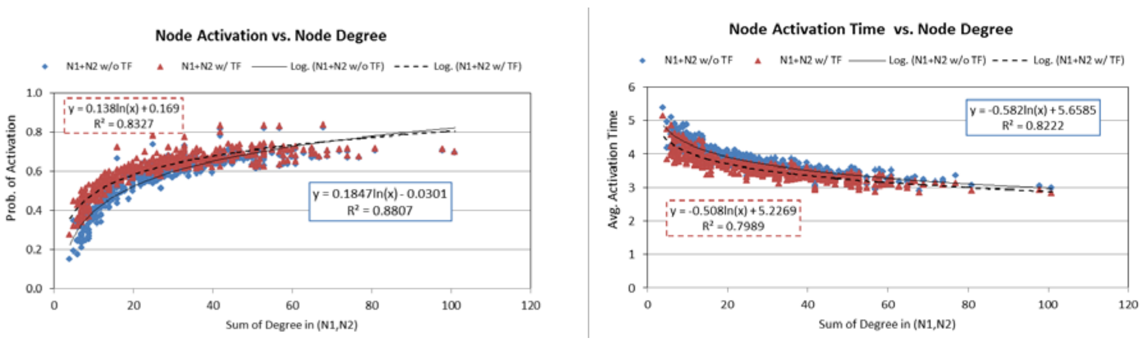


Figure 5.12 Node activation status (left) and activation time (right) vs. sum of degree

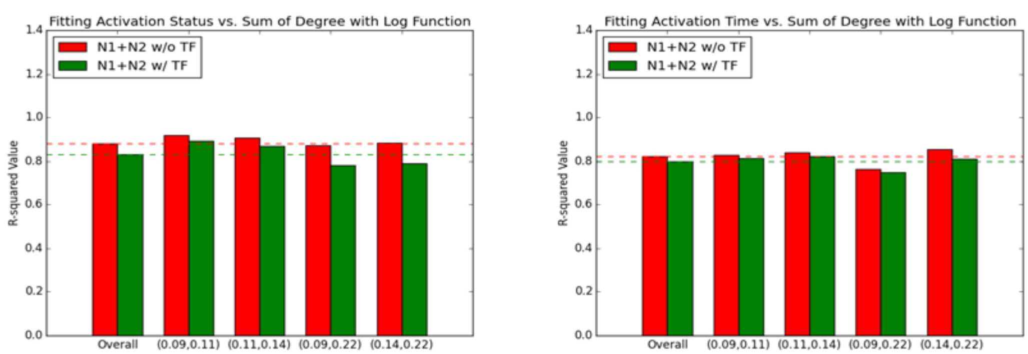


Figure 5.13 R^2 values of the fittings by networks

We can see that the case with message transfer always has higher R^2 values. When messages can be transferred between networks, the nodes actually have more virtual connections (that are not directly reflected in their node degree), so the activation status and activation time are less dependent on their degree on the networks. For activation status, larger R^2 values can be found associated with networks with low density for both cases, which indicates a stronger dependency of activation on degree when the networks involved are relatively sparse. For activation time, smallest R^2 values can be found associated with $(N1, N2) = (0.09, 0.22)$ for both cases. This implies that activation time may have more variations and thus becomes less predictable when the networks involved are unbalanced in terms of density. In summary, these results could help emergency managers predict message reception and delivery in the population at risk in real-world applications, which has been a major challenge they have been facing, and the implications could be considered to improve social media messaging decisions.

5.3.5. Results and analysis on node targeting

As discussed previously in this dissertation, a social media messaging strategy with node targeting could help emergency management organizations and agencies significantly improve their communication efficiency by delivering their messages to the population at risk in a wide and timely manner. On the other way, the nodes targeted by these organizations and agencies should possess some features (compared to untargeted nodes) that contribute to wider and faster message dissemination in disasters and extreme events. Therefore, we examine the subset of targeted nodes in the experiments here in order to find how and to what degree decision parameters, including length of planning horizon, network density as well as network conditions, affect node targeting decisions. We are particularly interested in the role that node degree information can play in helping emergency managers identify the subsets of nodes to target. The reason we choose node degree information is that it is easily accessible to these organizations and agencies and the characteristics of node degree are relatively stable in emergency settings, compared to user behaviors that are more unstable and unpredictable. The results and findings are presented below.

Recall that there are two degree values associated with each node in our experiments. When a node is targeted by any of the message sources, we consider the degree on the network where it is targeted (target network) as well as the sum of degree on both networks. Figure 5.14 shows the weighted average of degree on target network and sum of degree on both networks respectively for all the targeted nodes in the experiments. In particular, we divide these targeted nodes by the wave they belong to. Wave 1 includes the nodes targeted in the first time period and Wave 2 in the second or third time period (based on messaging interval l). The weights are given by frequency (i.e., the number of times a node is targeted in a certain wave). The lines called $mean$ and $median$ represent the mean and median of node degree values based one (left) or two (right) networks, added as baseline information. In both charts, Wave 1 nodes are highly distinct from others for their higher-than-average degree values, which cannot be observed for nodes in other waves. And from the comparison of Wave 1 columns between the left and right charts, it appears that the nodes targeted in Wave 1 are

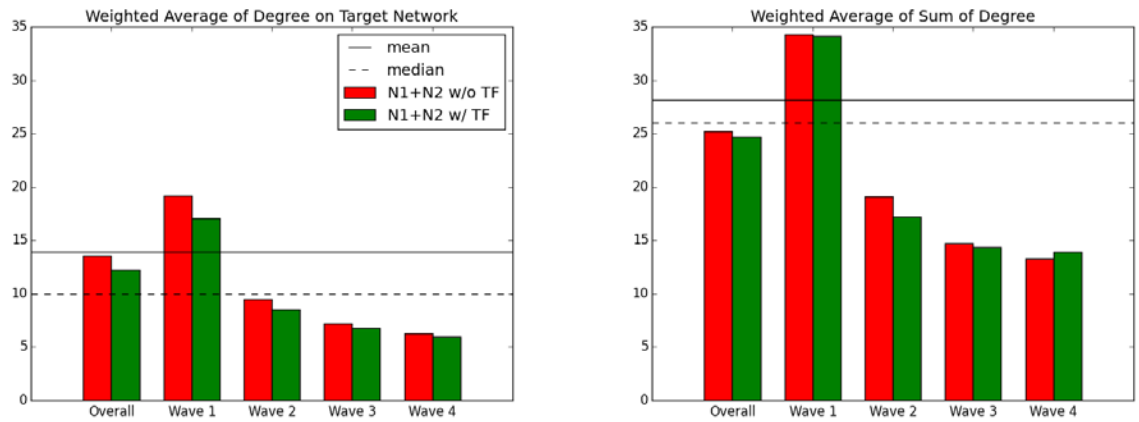


Figure 5.14 Overall degree characteristics of targeted nodes

associated with high sum of degree, in the presence of message transfer. As an general implication for emergency managers, they could consider targeting the high-degree nodes on the network especially in the initial period of the planning horizon to achieve a good message dissemination outcome, and when message transfer behavior is common among the users, the degree on both networks (potentially all networks involved) should be considered.

From here we move the attention to the nodes targeted in Wave 1 and examine these nodes by specific problem scenarios. Specifically, we calculate the weighted average of degree and sum of degree values for all the targeted nodes in each problem scenario, and aggregate these results by decision parameters including length of planning horizon and network condition. We observe the average (AVG) and standard deviation ($StDev$) of these aggregated values in order to examine the targeting decisions under different decision parameters. Figure 5.15 and Figure 5.16 give the characteristics of the targeted nodes in Wave 1 by planning horizon length and network condition, respectively. Through the comparison between left-hand side and right-hand side, it is still the case that sum of degree values is more important in the presence of message transfer behavior. When $|T| = 5, \dots, 8$, the degree characteristics (AVG and $StDev$) of the two cases, red columns/bars on left-hand side and green columns/bars on right-hand side, are almost the same on each set of networks. This may imply that when the planning horizon is relatively long, the targeting decisions could be more stable and robust (i.e., such decisions don't have to be changed significantly as planning horizon gets longer). Considering the size of such Wave 1 nodes is relatively small, emergency management organizations and agencies could manage them with less effort. Same findings can be made in Figure 5.16 as well, in which the red columns/bars on left-hand side (reflecting the targeting decisions for the case without message transfer) and green columns/bars on right-hand side (reflecting the targeting decisions for the case with message transfer) do not exhibit any significant differences when network conditions change. As a summary and a general implication, the degree characteristics of the targeted nodes in the initial period of the planning horizon are relatively stable under the changes of planning horizon length as well as network condition and insensitive to network density, therefore emergency managers could potentially identify and maintain a core subset of users and make sure they receive (and share) messages timely in order to achieve good dissemination outcomes under the changes of network structure, density as well as condition in disasters and extreme events.

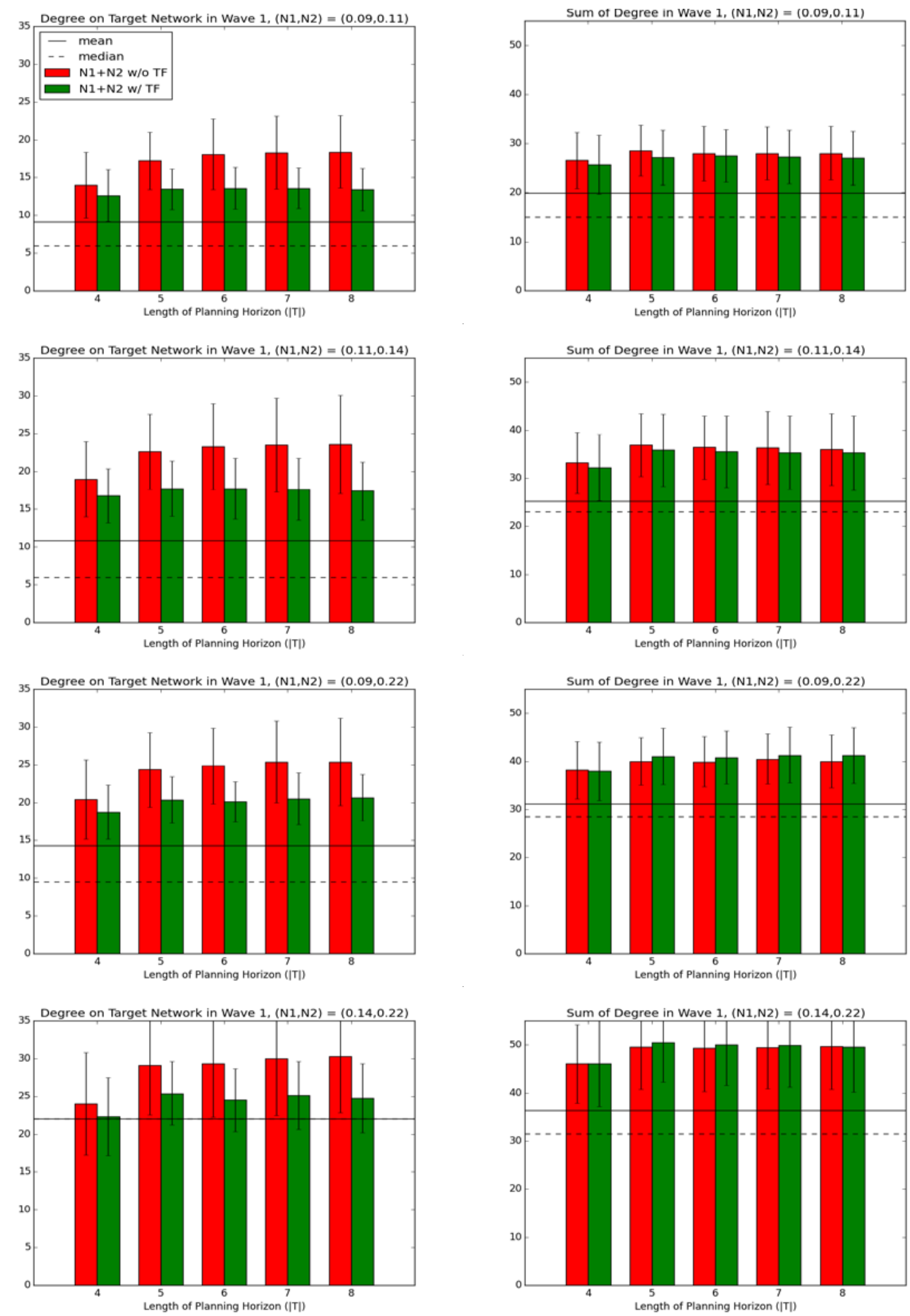


Figure 5.15 Degree characteristics by problem scenarios and planning horizon length

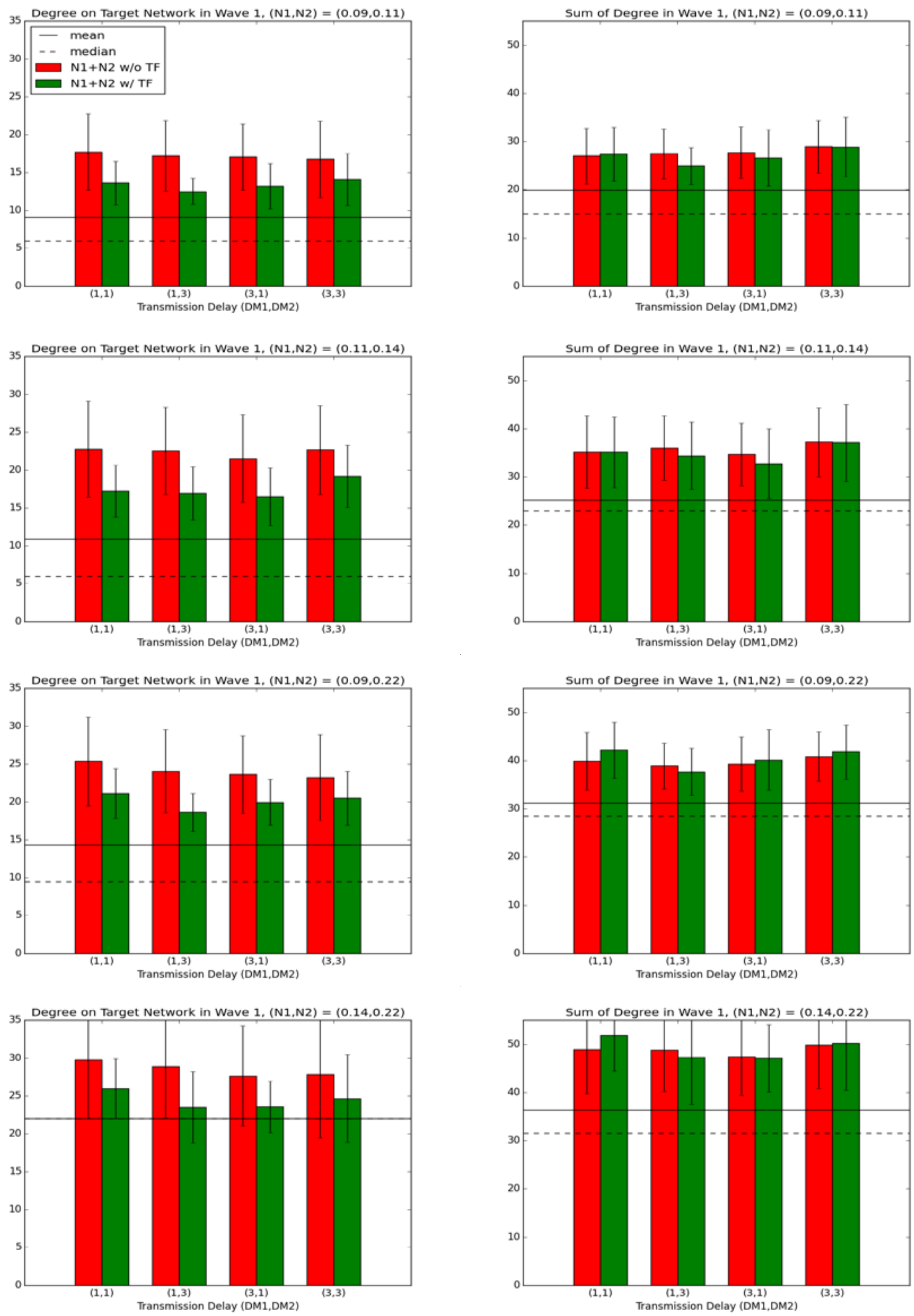


Figure 5.16 Degree characteristics by problem scenarios and network condition

5.4. Closing Remarks for MM-SMMDP

In this chapter, we examine the message dissemination application scenario in which multiple messages need to be disseminated to a population within a predefined planning horizon in the presence of multiple social media networks. In addition to sharing messages on a social media network, individual nodes could also transfer messages from the current network to other networks, subject to some delay constraints. These new features are captured in the MM-SMMDP model. Computational experiments are performed using small-scale Twitter sub-networks and on different cases to study this new dissemination scenario. We consider decision parameters, including length of planning horizon, source messaging capacity, source messaging interval, network density as well as network conditions, and examine their impacts on CPU time, objective values, node activation as well as node targeting decisions.

We find that planning horizon length affects CPU time significantly, compared to other factors, and the CPU time fluctuates more drastically as the increase of messaging capacity when the networks are sparse and the planning horizon is long. The objective value reflects the outcome of message dissemination in a specific problem scenario. We show that the best and worst-case outcomes can be predicted using the maximum targeting capability of the message sources in the whole planning horizon. We also demonstrate that network density and condition can significantly affect the stability of the message dissemination outcomes under the variations in users messaging behaviors on social media networks. In the presence of two networks, we find node activation status at the end of the planning horizon and activation time in the planning horizon are highly correlated to the sum of degree values on both networks, and the relationships can be fitted well using logarithms functions. We also show the performance of these functions depends on the density of the networks involved. For node targeting, we find that the nodes targeted in the first wave are associated with high degree. In particular, in the absence of message transfer, they have high degree on the network where they are targeted, while when message transfer is present, they exhibit high sum of degree values on both networks. We also find the degree characteristics of the targeted nodes in the initial period of the planning horizon are relatively stable under the changes of planning horizon length as well as network condition and insensitive to network density.

There are some limitations in this work that need to be addressed in order for a better use of the results and implications. First, we perform all the experiments on 100-node Twitter sub-networks. More studies needs to be done in the future on large-scale networks as well as different types of social media network to compare with the current results and trends. Second, we assume here individual's sharing and transferring behaviors are totally independent. However, such an assumption needs to be revisited whenever new research progress on that is available. Third, efficient algorithms need to be developed and tested for problems of real-world size, and effective heuristics may be considered for that purpose.

CHAPTER VI

CONCLUSIONS AND FUTURE RESEARCH

There has been an increasing use of social media in disseminating emergency messages by various governmental and non-governmental emergency management organizations and agencies in recent year. However, the knowledge about the impact of social media message propagation on individual message reception as well as the identification of strategies to facilitate message dissemination is too little under the complex environments in disasters and extreme events.

This research was motivated by these facts and takes a first step to conduct quantitative analysis on social media messaging strategies for emergency management organizations and agencies. We capture the message propagation process on social media networks by considering user information sharing behaviors and explore message targeting strategies under the constraints of the length of planning horizon, source messaging capability as well as network structure and conditions. We examine three message dissemination application scenarios, including a single-network single-message scenario, a single-network multi-message scenario, and a multi-network multi-message scenario, and perform computational experiments on smaller-scale random and Twitter networks.

We show the impacts of these factors on computational performance, message dissemination outcomes as well as node targeting decisions based on the computational results. All the factors are found to have some impact on the message dissemination outcome, but the degree of the impact varies over different application and problem scenarios. We also look into the combined effect of these factors and put them into two categories, one reflecting emergency managers' considerations (i.e., planning horizon length, source messaging capacity and interval as well as maximum source messaging capability), and the other reflecting network characteristics (i.e., network density and condition). The findings can provide valuable insights for emergency management organizations and agencies in developing social media messaging strategies under different scenarios and situations.

We particularly examine node degree characteristics for their potential to be used to predict message reception and message delivery time and to identify influential users to be targeted by message sources. The results are promising, although limited by the scale and range of the experiments. Compared to user information sharing behaviors, these characteristics are easily accessible to the emergency management organizations and agencies and relatively stable in emergency settings, so we expect the implications and strategies developed based on them to be more reliable for applications in disasters and extreme events.

Although inspired by the results and implications, we are aware of the limitations of this work that need to be addressed in future work. An immediate area of emphasis is on diversifying experimentation on social media networks of different sizes (e.g., 500, 1000, 5000, 10000, 50000, 100000-node networks and so on) as well as social media networks of different types (other than Twitter) to see whether the trends observed and implications derived in this research are still true. To do this, effective tools to acquire these large-scale networks are needed. Another future direction of this research is to revisit some of the assumptions we made in this research. In particular, we assume individual user's information sharing behaviors are independent and sample them randomly from some common distributions. This may not be true in reality. For example, a user's information sharing behaviors for different messages on a social media site might be correlated, and these behaviors for a specific message on different social media sites might be correlated too. This is a very complex problem, so more efforts are needed to get a better understanding. Also, we assume the message sources, FEMA, NWS, NOAA, etc. are independent in this research, while in reality they have been observed to have some kind of interactions between each other on major social media sites. While the scale and frequency of such interactions are unclear, their impact on message dissemination as well as targeting strategy making is worth noticing and examining.

Despite the limitations of this research, it conceptualizes the major components in the identification of social media messaging strategies in disasters and extreme events and develops a feasible solution framework to obtain such strategies with length of planning horizon, source messaging capability as well as network structure and conditions taken into account. This framework is adaptive, in that new research results (such as those on user information sharing behaviors) can be integrated very easily, and therefore it has the potential to assist emergency managers' social media messaging decision making in the short and long run. It is our hope that this research could motivate more research efforts into social media use in emergency communication especially into social media messaging strategies to improve dissemination performance of emergency messages. In some cases, this performance means life or death.

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