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MODELING THE EFFECTS OF DISINFORMATION SPREAD ON MULTI-COMMODITY NETWORKS

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Abstract

Disinformation has become a more common weapon amidst growing social media platforms and users, targeting consumer behavior to affect physical infrastructure. Understanding how disinformation could attack a multi-commodity network and how to minimize its spread will help alleviate stress on systems during attacks. This research integrates an epidemiological model (SIR) with a mixed integer programming (MIP) model to minimize weighted shortage across commodities, evaluating the change over time dependent on disinformation spread β and recovery γ. It is then applied to a multi-commodity Swedish railway network carrying 14 goods over 200 nodes. Results demonstrated how different spread and recovery rates change the degree and timing of shortage.

Chapter 1: Introduction & Motivation

As technology drives a global transition to the digital world and convenient access to the internet increases, the amount of information readily available for public access has become more abundant. The prevalence of sharing platforms, such as Twitter, Facebook, Instagram, TikTok, and Snapchat have further contributed to the spread of information access, allowing people to create, share, comment, and push content on an individual level. While greater access to information has many benefits, such as the ability for people to more easily research important issues or local and national news to reach relevant audiences faster than previously possible, it has also opened a door for false information to be rapidly spread, making it difficult to decipher between fact and fiction.

Information can be categorized into different groups covering a spectrum from entirely true to entirely false. Bias and situational framing are other measures to be considered in defining accuracy, as well as the intent behind the creation and repeated spread of information [1]. Generally, information that is deemed to be largely untrue will fall into two categories: misinformation and disinformation [1, 2]. The key difference is the motivation behind the creation and subsequent passing of information. Misinformation is considered to be innocent, often resulting from miscommunication, misunderstanding, or based on an individual's perception or opinion that conflicts with truth or is based on no factual evidence. Disinformation is instead deliberately false, with the intention of harming an individual or community [3]. This may be to further a political agenda, argument, or even as a form of terrorism with short term or long term objectives. Being able to model information spread is crucial to limiting the damage of both misinformation and disinformation. Because each has a unique set of parameters that should be modeled independently, the scope of this paper will focus on the spread of disinformation specifically.

Though originally formulated to model epidemics, the SIR (susceptible-infected-recovered) model can be used to model many kinds of spread across populations [4]. It divides a given population into three categories (susceptible, infective, recovered), with a few basic assumptions such as fixed population, immunity after recovery, a fixed rate of infection and recovery, a negligible incubation period, and uniformly mixed groups [4]. This was adapted to fit the scenario of disinformation spread across social media, where the susceptible population describes all social media users, the infected population describes users who react to disinformation, and the recovered population describes users who either read disinformation and do not react or who previously were infected but have become aware the information is false and no longer react [5].

In the aforementioned model, the spread of disinformation was applied to a single commodity network (electric power grid); this work modifies the existing model, applying it to a multi-commodity system (rail network) carrying goods of varying importance. Disinformation could target the railway in several ways. First, it could increase short-term demand of a specific commodity through tactics such as a falsely advertised promotion encouraging consumers to buy more (ex. buy 2 get 1 free) or the use of a product as a miracle treatment for an illness (ex. ivermectin during the COVID-19 pandemic) [45, 46, 47]. As supply works to compensate for heightened demand, it could lead to delays in the delivery of other goods, as items need to be loaded and unloaded onto trains in the railway, increasing time at each node. An increase in supply could mean the railway reaches capacity by either weight or volume, resulting in shortage of one or several commodities. Alternatively, disinformation could aim to delay deliveries, resulting in shortages or even damage to the physical rail infrastructure. An attacker may use disinformation to convince an audience a rail car is carrying an explosive device, or divert a rail car away from a certain node for the same reason. Many examples of a threat like this being used can be found, such as red-line train stoppage in Chicago and an attempted plane diversion by Belarusian state officials [48, 49]. This could delay supply as searches are conducted, meaning goods do not arrive at their destination at the expected time and a shortage occurs. Disinformation could also lead to railway damage if an individual or group of individuals decided to take action by blocking or damaging tracks. In 2022, a group calling themselves the *Freedom Convoy* have caused supply chain issues by blocking the US-Canadian border in protest to a COVID-19 vaccine requirement when crossing national borders [50]. Similarly another group calling themselves the *People's Convoy* has caused significant traffic disruption by traveling cross-country in a large pack of trucks at slow speeds to protest COVID-19 related requirements [51]. Many of these concerns stem from incorrect information or conspiracy regarding vaccination, some initiated before the vaccine had even been developed, and ultimately taking root in this type of extreme reaction, and perpetuated through internet narratives, memes, and commentary, fueled by both fear and entertainment [52]. These situations demonstrate the vulnerability of a multi-commodity system like a rail network to be targeted by disinformation, likely leading to supply chain disruption.

The objective of this model is to minimize the weighted shortage of commodities; doing so will account for supply and demand sets of different commodities within the same node. Through this pre-existing research, we are able to gain a better understanding of how disinformation spread can affect supply chains and as a result, the surrounding community. If an attacker chose to target a specific commodity with disinformation, impacts may extend beyond just that individual product. It is understood that higher demand results in higher price to compensate for shortage, and if the demand shift is rapid enough, it may impact availability of substitute products as well [6]. This can create a feeling of resource scarcity which subsequently may result in panic buying, further disrupting the supply chain and putting stress on the system [7, 8]. Some commodities may have direct implications on the production of others as well. For instance, oil and natural gas are often used in production, so an increased price as a response to heightened demand resulting from a disinformation attack could increase the price of other manufactured goods [9, 10]. Another implication of targeted disinformation is the creation of uncertainty, as products that were once readily available at a given price are now difficult to find. In response, consumers may attempt to exert control over uncertainty through control-restoration, like what was seen during COVID-19 through the stockpiling of toilet paper [11, 12]. This highlights the importance of controlling disinformation spread, as the presence of uncertainty often leads to shifts in consumer behavior, ultimately capable of severe supply chain disruption [13]. Another result of disinformation could be an increased mistrust in public entities perceived to be responsible. For example, a city may be responsible for a multimodal transportation system including a high-speed train, bus, bike sharing program, and taxis. A disinformation attack may incentivize citizens to take the train home one day through false advertisement a year-long free pass for all transportation modes, for riders of the train that evening. This could lead to delayed arrival and departure times, broken-down train cars resulting from exceeded weight capacity, or a mass casualty event if attackers executed a secondary attack with the goal of harming riders. It may also impact the use of the other transportation modes, dissuading individuals from utilizing any of the transportation vehicles, and creating mistrust for city government as a consequence. By modeling disinformation spread on a multi-commodity system, we can better understand how to minimize the effects.

The rest of this paper is organized as follows. In Chapter 2, other models and applications of disinformation spread found in literature are explored. In Chapter 3, the SIR model and mixed integer programming model, which are both used during implementation, are presented. In Chapter 4, the models are applied to a dataset to illustrate computation and efficacy. In Chapter 5, results from the application are discussed, noting any potential errors or assumptions that may impact conclusions. In Chapter 6, concluding remarks are made along with recommendations for future research.

Chapter 2: Literature Review

The effects of disinformation are widespread, resulting in negative consequences, like mass shortage of a commodity, or generalized harm, such as increased mistrust in government. Though disinformation has been largely propagated by the virtual world, the effects frequently take place in physical infrastructure. Raman et al. investigated the result of disinformation spread on a city's power grid [14]. Participants were shown a message claiming the cost of electricity was being reduced by 50% within a two hour period and were asked to specify the likelihood of changing their electricity-use patterns and sharing this message with others. The follow-through rates were then tracked until the network state remained unchanged in two consecutive time steps. The impacts were shown to be city blackouts, affecting 5.6% to 100% of city residents, depending on the follow-through rate range of 9.4% to 26.8%, respectively, demonstrating how manipulation via disinformation is likely to harm at least a small portion of a city's population and could potentially take down the entire system. Another example of disinformation effects taking place in physical systems comes in the form of traffic disruption; by spreading false information, routes taken by vehicles could be changed to direct drivers in a particular direction. Waniek et al. similarly measured the impact by evaluating follow-through rates by asking participants to assess the likelihood they redirect a route based on alerts to take another path due to an accident or follow a road sign [15]. A 6/10 or higher likelihood of following through with traffic redirection was given by 89% of participants for a traffic alert and 97% of people for road signs. The potential consequences of disinformation to target and disrupt physical aspects of society is expansive, further demonstrating the importance of being able to identify and trace sources and spread.

Efforts to model the spread of disinformation are becoming more common in research studies. Rabb et al. categorized disinformation as a social contagion, with the assumption that once misinformation has been adopted by an individual, this view is unlikely to change [16]. Here, they use cognitive cascade models, as opposed to an epidemiological model, which factors in an individual's current beliefs. Instead of infection being only based on a threshold, identity-based belief is considered, resulting in an application of techniques from network and cognitive science and a demonstration of how even simple cognitive cascade models can better simulate belief propagation [17]. Results demonstrated that with purely threshold-based models, populations are affected differently even with the same initial conditions and beliefs being spread. Using the cognitive model, more robust results were achieved, better fitting opinion data, showing individuals are very unlikely to have an updated belief if the information strays too far from their current belief. Murayama et al. model disinformation with a focus on the use of social media, specifically Twitter [18]. In this model, disinformation is initially posted and spread as a news story, and later uncovered as false, with a second news story correcting the original being shared, meaning two cascades occur. The Time-Dependent Hawkes process is utilized to represent users and aging information cycles, such as with the sequence and timing of tweets and retweets. The results of this model outperformed both of the baseline models (linear regression and reinforced Poisson process), accurately predicting the true correction time between the initial story and follow up, through applications to datasets. Disinformation spread may also be modeled by taking concepts from the echo chamber phenomenon, in which the virality of information is affected by opinion and network polarization. Tornberg developed a network simulation model to show how information spreads more easily when a network has an echo chamber, with results indicating a possible connection between the presence of echo chambers and disinformation spread, via an emergent network effect [19]. By combining opinion and network polarization, the clusters of users with the same differing perspective are seen to affect virality, potentially brought on by the algorithm information filtering within social media platforms and tendency for users with similar worldviews to cluster.

For many epidemiological studies, the SIR model is used to simulate pandemics and disease spread. Neves and Guerrero used an A-SIR model to predict the spread of COVID-19 across Europe, which builds from the original model to account for individuals who are asymptomatic [20]. Given the likelihood these individuals ignore their condition, they are likely to infect a larger group of people, compared to those who are symptomatic and isolated once symptoms develop. Chowdhury et al. modified the SIR model by considering infection and removal rates as time-dependent parameters to predict a herd immunity threshold [21]. In this case, the herd immunity threshold is also a function of time, changing as the number of current infections fluctuates. It is observed that the spread prevention is most successful by forcing the herd immunity threshold below the herd immunity of the population, often accomplished through widespread isolation or quarantine, but has the consequence of easy re-outbreak. Similar to modeling infection, Laguzet and Turinici modeled vaccinations against disease, to determine if equilibrium exists, applying the model to the 2009-2010 H1N1 vaccination campaign in France [22]. This study analyzed how individuals view the risk of vaccination and the shift of vaccination choice to an egocentric view, versus a community-oriented view. Findings demonstrated the existence of an equilibrium, even when individuals only choose to vaccinate out of self-interest, as opposed to protecting the greater community. In this case, the choice to vaccinate is driven by an individual threshold, based on one's own assessment of risk between vaccinating or not.

Outside of traditional epidemiological studies, the SIR model has also been applied to model other scenarios. Wang et al. used it to model the impact of government policy on the expansion of new, intelligent manufacturing technologies [24]. A new state *E* is introduced to represent the decision-making state. In this case, the disease is considered to be the adoption of smart manufacturing technology, modeling the effects of policy on the industry development. Applying SIR to information spread has also previously been studied. Oktaviansyah and Rahman use the SIR model to predict hoax spread in Indonesia [25]. S is defined as the group able to be persuaded by false information, I as the number of information spreaders, and R as the number of fact-checkers. Using pre-existing data collected between 2017 and 2019 regarding behavior response to trending news, a simulation was run to show the population within each of the SIR groupings shifts over time, including where peak and equilibrium balance occur.

Chapter 3: Model

The SIR model has been adapted to demonstrate the spread of disinformation on social media, and the effects on a multi-commodity system, using both the predictive SIR model and a network flow optimization model, which will aim to minimize the effects of disinformation on the system. In this case particular case, the weighted shortage of commodities from a Swedish rail network will be minimized over time, where disinformation targets the supply and demand of a specific commodity [26].

When disinformation is initiated through a social media platform, there are several things that may occur. Users may read the content and react to it by changing their habits and/or sharing it with others, they may read content but ignore it, they may read content and recognize it as disinformation, potentially creating a secondary post discrediting the original content, or they may never see the content. In the context of the rail system, disinformation could target a particular node, where the community surrounding that node would be led to over-purchase a highly important commodity, resulting in a shortage.

Users are grouped into three groups: S users who are susceptible to adopting the disinformation, I users who saw and reacted to disinformation, and R users who saw the disinformation and did not react. The overall population is assumed to be fixed, with the proportion of these groups modeled using the homogeneous SIR compartmental model, and explained mathematically by a system of differential equations 1-3, and constrained by equation 4. Index $i \in V$ describes each node within the system, assumed to also contain a community of individuals affecting the supply and demand of commodities at a particular node, index $k \in K$ describes each of the 14 given commodities, and index $t \in T$ describes a point in time.

Users are all initially categorized in group S at t = 0. After, they may remain in group S, transfer from group S to group I, or transfer from group S to group R. Once in group I, users may either remain or eventually move from I to R, but can never move backwards. The movement between groups occurs at a uniform rate. Users in group S transfer to group I at rate β and may move from S to R or I to R at rate γ. Rather, disinformation spreads at a rate of β and is recovered at a rate of γ.

$$\frac{dS_{it}^{a}}{dt} = -\beta S_{it}^{a} I_{it}^{a}, \forall i \in V, \forall a \in A, \forall t \in T \tag{1}$$

$$\frac{dI_{it}^{a}}{dt} = \beta S_{it}^{a} I_{it}^{a} - \gamma I_{it}^{a}, \forall i \in V, \forall a \in A, \forall t \in T \tag{2}$$

$$\frac{dR_{it}^{a}}{dt} = \gamma I_{it}^{a}, \forall i \in V, \forall a \in A, \forall t \in T \tag{3}$$

$$S_{it}^{a} + I_{it}^{a} + R_{it}^{a} = 1, \forall i \in V, \forall a \in A, \forall t \in T \tag{4}$$

The rail network is modeled with a set of nodes V representing the stations which incorporate supply and demand of a given community, connected through a set of rails. A mixed integer programming (MIP) model is used to track the effects of disinformation on the Swedish rail system, with the goal of minimizing the weighted shortage of commodities across nodes.

$$\min_{x,h,e,d,I,g} \sum h_{it}^{a} w^{a} \tag{5}$$

s.t.

$$\sum_{j \in V^{in}} x_{jit}^{a} - \sum_{k \in V^{out}} x_{ikt}^{a} + sh_{it}^{a} - e_{it}^{a} + q_{it}^{a} - d_{it}^{a} = 0, \forall i \in V, \forall a \in A, \forall t \in T \tag{6}$$

$$x_{ijt}^{a} \leq m_{ijt}^{a}, \forall i \in V, \forall j \in V, \forall a \in A, \forall t \in T \tag{7}$$

$$d_{it}^{a} = p_{it} d_{it}^{a} \{(1 - I_{it}^{a}) + \{I_{it}^{a}[r_{it}^{ap}(1 + \rho_{it}^{a}) + (1 - r_{it}^{ap})]\}\}, \forall i \in V, \forall a \in A, \forall t \in T \tag{8}$$

$$I_{it+\bar{t}_t}^{a} = I_{it}^{a} + \dot{I}_{i,t+\bar{t}_t}^{a}(1 - r_{it}^{a} g_{it}), \forall i \in V \setminus \{|V|\}, \forall a \in A, \forall t \in T \tag{9}$$

$$\sum_{i \in V} g_{it}^{c} \leq n_{t}^{p} \tag{10}$$

$$x_{ijt}^{a}, h_{it}^{a}, e_{it}^{a} \in R_{\geq 0}, \qquad d_{it}^{a}, I_{it}^{a} \in R_{\geq 0}, \qquad g_{it}^{a} \in \{0,1\} \tag{11}$$

$$\sum w^{a} = 1, \forall a \in A \tag{12}$$

The objective function in Eq. 5 minimizes the weighted shortage of commodities over time, meaning commodities of higher importance will be prioritized. Constraint 6 balances the supply and demand with shortage and surplus of commodities. Constraint 7 restricts the demand from exceeding the capacity for a commodity at a given node. Constraint 8 relates the responsive change in demand as a result of disinformation spread to equal the baseline demand of a commodity at a given node. Constraint 9 accounts for the secondary spread of information correcting the disinformation. Constraint 10 restricts the number of nodes from which a secondary spread of correcting information may be disseminated. Constraint 11 defines the nature of each of the decision variables. Constraint 12 balances the weights of the commodities.

Table 1: Sets, parameters, and decision variables

Notation	Description
Sets	
V	Set of railway nodes
E	Set of infrastructure network links
T	Set of periods
Parameters	
$\bar{t}_t$	Time interval between periods
q_{it}^{a}	Supply of commodity a ∈ A from each node i ∈ V at time t ∈ T
m_{ijt}^{a}	Capacity of arcs between nodes i and j for commodity a ∈ A at time t ∈ T
p_{it}	Population surrounding node i ∈ V at time t ∈ T
d_{it}^{ac}	Per capita demand of commodity a ∈ A of the population surrounding node i ∈ V at time t ∈ T
r_{it}^{ap}	Proportion of the consumption of commodity a ∈ A surrounding node i ∈ V at time t ∈ T that is price dependent
ρ_{it}^{a}	Estimated elasticity of the consumption of commodity a ∈ A surrounding node i ∈ V at time t ∈ T
$\dot{I}_{it}^{a}$	Local derivative of the proportion of the population surrounding node i ∈ V targeted by disinformation at time t ∈ T
r_{it}^{a}	The proportion at which $\dot{I}_{it}^{a}$ changes by spreading counter information regarding commodity a ∈ A to the population surrounding node i ∈ V at time t ∈ T
n_{t}^{a}	Total number of locations informed by counter information regarding commodity a ∈ A at time t ∈ T
w_a	Importance weight of commodity a ∈ A
Decision Variables	
x_{ijt}^{a}	Flow of commodity a ∈ A from node i ∈ V to node j ∈ V at time t ∈ T
h_{it}^{a}	Shortage of commodity a ∈ A from node i ∈ V at time t ∈ T
e_{it}^{a}	Excess of commodity a ∈ A from node i ∈ V at time t ∈ T
d_{it}^{a}	Nominal demand of commodity a ∈ A at node i ∈ V at time t ∈ T
I_{it}^{a}	Proportion of population surrounding node i ∈ V at time t ∈ T that adopted disinformation
g_{it}	= 1 if counter information is released to node i ∈ V at time t ∈ T = 0 otherwise

Chapter 4: Application

This multi-commodity disinformation model is applied to a Swedish railway network, with data collected from publicly available sources, originally compiled by Svegrup and Johansson [26]. The network is an interconnected system of stations and tracks operated by both the public and private sector, containing 1363 stations and carrying 20 different categorical commodities. Each node has varying supply and demand values for the commodity set and a different community size. Due to the size of the dataset, only 14 commodities and 200 nodes were included in the model application, listed in Table 2.

Model parameters were determined through estimates based on existing data. Supply, demand, and link capacity were given with the Swedish railway data. The link capacity refers to the maximum transportation of goods on the rail system, constrained by factors like rail speed, tracks, volume, and cost. The community size p_{kt} of each node, ranging from 5,000 to 1,515,017, was simulated based on population data from cities in Sweden, then randomly assigned to nodes [43]. It is then assumed that only 89% of the population surrounding each node may be influenced by disinformation, due to social media access [44]. Price dependent demand r_{ikt}^{p}, describing the how much of a commodities demand may change due to price, was assumed to be 0.9 for all commodities. Due to the broad aggregation of commodities and sensitivity between regions, the elasticity ρ_{ikt}, which evaluates to what extent a price shift alters demand for each commodity, is a rough estimate, and is primarily for demonstrative purposes.

Weights were taken from Whitman et al. where commodities were aggregated according to the freight categories from the dataset [27]. The GDP value for each aggregated set was divided by the summation of the GDP values for all commodities.

Table 2: Commodity categories and weights by GDP [27]

Index	Commodity	Total Usage	Weight
1	Agriculture, forest, fishing	130,329	0.048
2	Coal, crude oil, natural gas	91,241	0.033
3	Ore	91,241	0.033
4	Food, beverage, tobacco	222,790	0.082
5	Textile, leather	58,167	0.021
6	Wood, cork, pulp, paper	237,093	0.087
7	Petroleum products	190,674	0.070
8	Chemicals, rubber, plastics	316,821	0.116
9	Other non-metallic mineral	47,472	0.017
10	Fabricated metal products	180,394	0.066
11	Machinery and equipment	718,996	0.263
12	Transport equipment	308,902	0.113
13	Furniture, other manufactured	81,663	0.030
14	Return materials and recycling	57,265	0.021

Table 3: Global model parameters

$\boldsymbol{r_{it}^{a}}$	$\boldsymbol{n_{t}^{p}}$	$\boldsymbol{r_{it}^{ap}}$	$\boldsymbol{\bar{t}_{t}}$
0.2	8	0.9	24

Table 4: Elasticity parameter by commodity

Index	$\boldsymbol{\rho_{it}^{a}}$
1	-0.4 [28]
2	-0.2 [29]
3	-0.3 [30]
4	-0.4 [28, 31]
5	-0.5 [32, 33]
6	-0.9 [34, 35]
7	-0.3 [36]
8	-0.6 [37]
9	-0.4 [38]
10	-0.4 [38]
11	-0.5 [39]
12	-0.3 [40]
13	-0.7 [41]
14	-0.1 [42]

Chapter 5: Results

The parameters β and γ refer to the rate of disinformation spread and counter-spread, respectively. A higher β value indicates a higher number of targeted individuals per time period, thus a higher γ value equates to a higher counter-spread of information, correcting the initial disinformation attack. The Julia programming language and Gurobi Optimizer were used to solve the SIR model in conjunction with the MIP model where shortage was recorded for each commodity at each time period, then iterated for different combinations of β and γ, demonstrating how a change in the proportion of users can affect the speed of disinformation spread.

Figure 1 shows the change in shortage over time is plotted for all 14 commodities, providing a better understanding of where shortage may peak. The raw data was normalized to better compare the change in shortage across commodities. This was done by dividing the average shortage at each time period by the average initial shortage, since all commodities saw shortage at given nodes prior to the simulated disinformation attack.

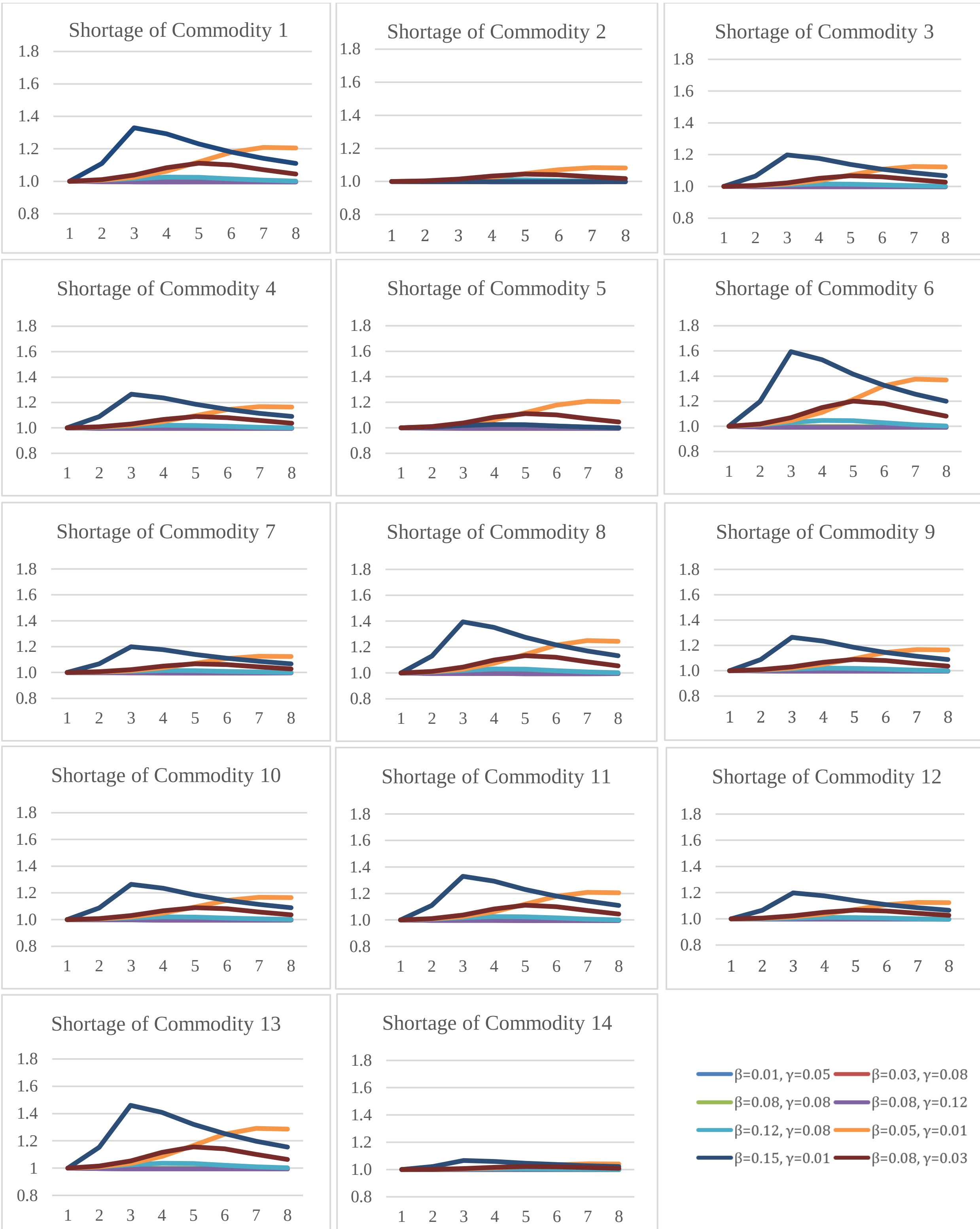

Figure 1. The change in shortage over time at varying levels of γ for each commodity are shown. The x axis ranges from 1- 8 to show time steps of 24 hours and the x axis is the normalized average shortage of a given commodity.

The average shortage follows a similar trend across commodities for each β and γ combination. It is seen that for almost every instance when $\beta = 0.15$ and $\gamma = 0.01$, the highest shortage occurs, with a peak at $t = 3$, demonstrating the effectiveness of a rapid attack where disinformation targets at high volumes in a short amount of time. In a less extreme example, when $\beta = 0.8$ and $\gamma = 0.03$, a similar trend is seen across commodities, where shortage peaks about $t = 5$ then tapers off, but peak is not as sharp as seen previously, and provides more time for counterinformation to take effect and the shortage to be minimized. In another instance, when $\beta = 0.05$ and $\gamma = 0.01$, the growth in shortage is steadier, but results in a greater final shortage at $t = 8$. This would be the case if disinformation is slowly introduced and spread, allowing it to reach greater final values than other combinations, as it goes nearly unchecked by counterinformation, spreading at a rate that may not initially raise concern. In instances where β and γ are equal or γ is higher than β, the change in shortage is insignificant. Figure 2 further demonstrates the relationship between β and γ and the effect on relative total shortage.

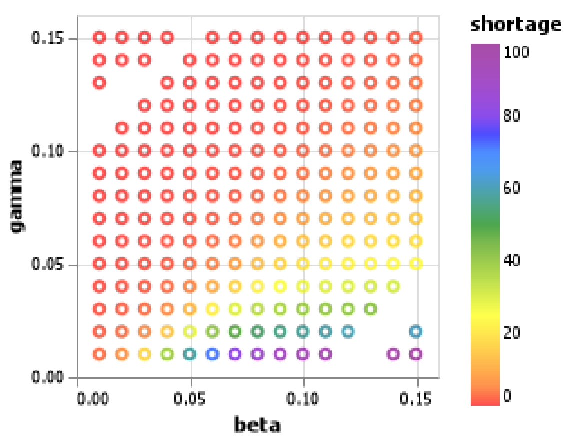

Figure 2. The change in shortage across all commodities with all combinations of β and γ is visualized.

In all instances where γ is higher, shortage is near 0. This does not mean that true shortage is 0 at all nodes, as the spectrum has been normalized so the minimums are treated as 0 and the maximums are treated as 100. It is observed that low γ values result in the highest shortage, especially at the minimum where most β values will lead to shortage near the maximum.

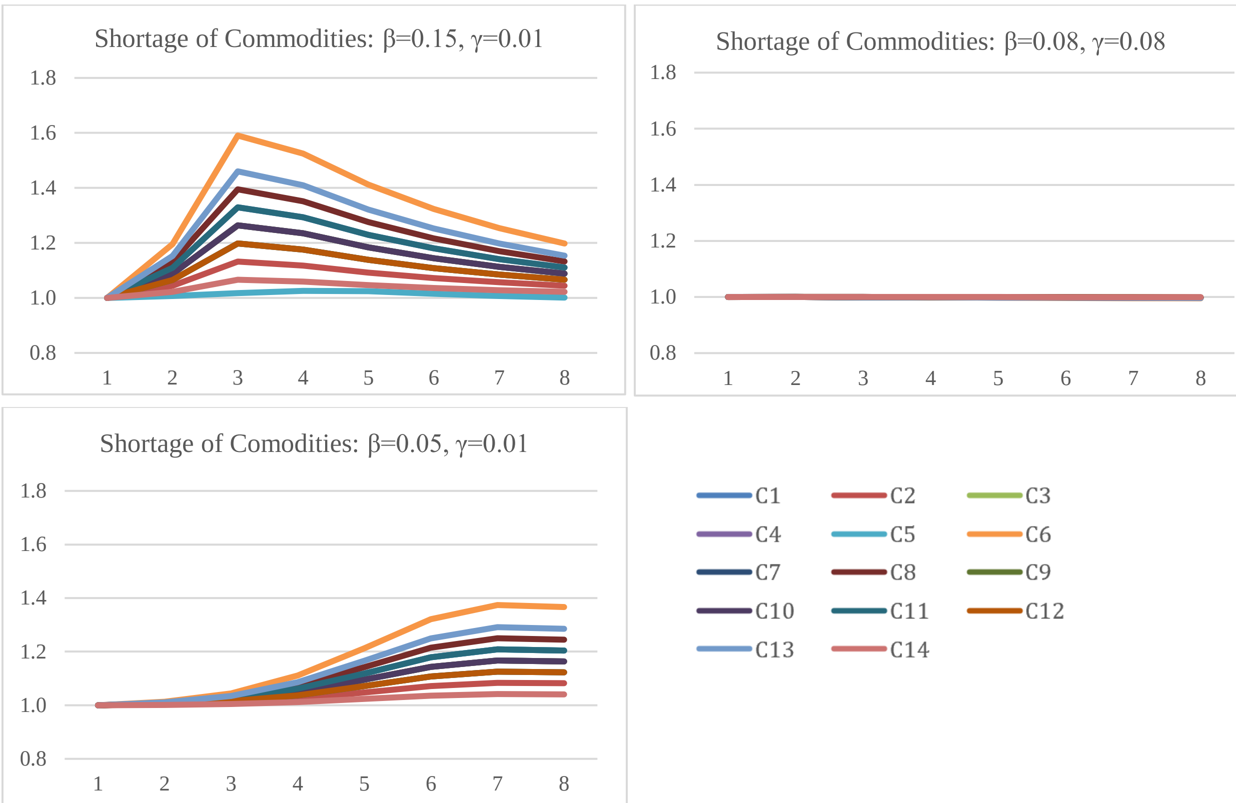

Figure 3. Commodities are directly compared at three combinations of β and γ, demonstrating how the speed of disinformation spread and recovery drastically impacts how shortage occurs over time. The x axis ranges from 1- 8 to show time steps of 24 hours and the x axis is the normalized average shortage of a given commodity.

Commodity 6 is impacted the most by shortage in both the β = 0.15, γ = 0.01 and the β = 0.05, γ = 0.01 cases, followed by Commodity 13 and Commodity 8. It is also clear how little shortage is affected when β = γ, as in the β = 0.08, γ = 0.08 case, which is the same for all instances when γ ≥ β.

Chapter 6: Discussion

Due to the broad aggregation of commodities, values such as price dependent demand and elasticity were estimates that are unlikely to be representative of individual goods. For example, Commodity 4 is labeled as food, beverage, and tobacco, but the elasticity of individual foods varies significantly. In addition, the size of the dataset was reduced in order to perform analysis and as a result, the average shortage was taken over a portion of the original data. Because of this, conclusions about the Swedish railway as a whole cannot be drawn, but the data used still provides an illustrative example to how the mathematical model can be applied.

Due to redundancy, a sample combination of β and γ values are shown, but data was collected for all combinations from 0.01 to 0.15. Trends for instances such as $\beta = \gamma$ did not differ significantly, so only one selection, $\beta = \gamma = 0.08$, was shown.

The weights assigned to commodities did not appear to influence shortage. This was because the capacity along each arc is constrained by commodity. As a result, the weight has no significant effect on the average shortage, since once the capacity for an arc has been reached, no more of that commodity may be carried, no matter how much higher the comparative weight may be. In applications where the capacity is a total constraint on an arc, instead of per commodity, it is likely that weights would have more adverse effects,

Chapter 7: Conclusion & Future Research

With the number of social media platforms and users increasing daily, it has become easier to create and distribute false information, which may ultimately harm physical systems and infrastructure. This paper provides a mathematical model to show how disinformation spreads through a multi-commodity system, using an both an epidemiological SIR model and an MIP model, with the goal of minimized the weighted shortage of a commodity. Doing so provides a better understanding of how quickly disinformation spread occurs from creation to peak impact and decline, as well as how to best propagate counter-information.

Through the application of the model to a multi-commodity Swedish railway dataset, results demonstrated how varying β and γ values affect the shortage of commodities. When γ is low, disinformation has a higher potential to create shortage, even when β is moderate, demonstrating the importance of counterinformation and the ability to recognize disinformation. As γ increases, the shortage is shown to quickly decrease, even as β increases. The combination of $\beta = 0.15$ and $\gamma = 0.01$ has the highest peak, with shortage increasing rapidly over the first 3 time steps, demonstrating the effectiveness of a thorough and swift attack. In any instance where γ is greater or equal to β, shortage has no significant change.

Future research should determine how changing capacity to a total constraint on each arc affects shortage for differently weighted commodities, evaluating sensitivity of weights as well. Investigating the effect of disinformation spread on more specific multi-commodity model, such as paper, food, or petroleum products, would also allow model parameters to be more precise and better model specific systems. In addition, analyzing the spread of disinformation on different social media platforms could provide more insight into the rate at which content is propagated, and how to best launch counter-information to minimize the effects. In this model, β and γ values do not change over time, but naturally, it is likely the proportion of counter-information would increase through each time period. Modifying the spread of counterinformation to increase proportionally could more accurately model spread. Finally, applying this model to a real case of disinformation spread to validate its accuracy would both verify which aspects may model a real-life system more closely, and highlight gaps for which this model could be improved.

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