Generating Synthetic but Realistic Human Trafficking Networks for Modeling Disruptions through Transdisciplinary and Community-Based Action Research

Daniel Kosmas\(^1\), Christina Melander\(^2\), Emily Singerhouse\(^2\), Thomas C. Sharkey\(^3\), Kayse Lee Maass\(^4\), Kelle Barrick\(^5\), and Lauren Martin\(^2\)

\(^1\)Department of Mathematics, Rensselaer Polytechnic Institute, NY 12180, USA
\(^2\)School of Nursing, University of Minnesota, Minneapolis, MN 55455, USA
\(^3\)Department of Industrial Engineering, Clemson University, Clemson, SC 29634, USA
\(^4\)Department of Mechanical and Industrial Engineering, Northeastern University, Boston, MA 02115, USA
\(^5\)RTI International, Research Triangle Park, NC 27709, USA

Abstract

One of the major challenges associated with applying operations research (OR) models to disrupting human trafficking networks is a limited amount of reliable data sources readily available for public use, since operations are intentionally hidden to prevent detection, and data from known operations are often incomplete. To help address this data gap, we propose a network generator for domestic sex trafficking networks by integrating OR concepts and qualitative research. Multiple sources have been triangulated to ensure that networks produced by the generator are realistic, including law enforcement case file analysis, interviews with domain experts, and a survivor-centered advisory group with first-hand knowledge of sex trafficking. The output models the relationships between traffickers, so-called “bottoms”, and victims. This generator allows operations researchers to access realistic sex trafficking network structures in a responsible manner that does not disclose identifiable details of the people involved. We demonstrate the use of output networks in exploring policy recommendations from max flow network interdiction with restructuring. To do so, we propose a novel conceptualization of flow as the ability of a trafficker to control their victims. Our results show the importance of understanding

*Corresponding author (kosmad@rpi.edu).
how sex traffickers react to disruptions, especially in terms of recruiting new victims.

Keywords: sex trafficking, data generation, transdisciplinary research, network interdiction

1 Introduction

Human trafficking is human rights abuse and documented both in the United States and abroad. Although the magnitude of the problem is difficult to determine (Farrell & De Vries 2020, Fedina 2015), estimates suggest that nearly 40 million people were victims of human trafficking in 2016 (de Cock & Woode 2014). Human trafficking involves the use of force, fraud, or coercion in order to exploit a person for the purposes of labor or services (labor trafficking) or sexual exploitation (sex trafficking) (Carpenter & Gates 2016, Martin & Lotspeich 2014, Polaris Project 2017, Preble 2019). Despite the growing awareness of the problem, there has been limited research into developing quantitative tools to address the problem of human trafficking (Caulkins et al. 2019, Dimas et al. 2021, Konrad, Trapp, Palmbach & Blom 2017). This is partially due to a lack of readily-usable data to appropriately populate these tools. Since these networks are illicit in nature, their operations are hidden to avoid detection (Farrell & De Vries 2020, Fedina 2015, Konrad, Trapp & Maass 2017, Konrad, Trapp, Palmbach & Blom 2017). Current data for analytic approaches often comes from case files, scraped web data on sex advertisements, or data pertaining to massage parlors (Keskin et al. 2021, Mayorga et al. 2019, White et al. 2021). This data can be viewed as the “forward-facing” aspects of the operations of sex trafficking networks in terms of how they interact with the outside world, thus it is (somewhat) publicly accessible. However, there are data gaps around the more internal-facing operations and social connections between traffickers and victims. We seek to begin filling some of these gaps.

There are some data sources that can be investigated regarding domestic sex trafficking networks, including case file analysis and interviews with those who have been a part of, or victimized by, these networks. However, no single source will have the full information necessary to perform a proper analysis of the network structure. For example, data collected by law enforcement is known to be incomplete. This is because the focus of law enforcement is on proving the occurrence of a specific crime and, thus, may ignore details that do not help this goal, but would be relevant to construct the full extent of the trafficking network (Cockbain et al. 2020). Additionally, extracting
the relevant information from the case files to produce the network takes a significant amount of
time. Traffickers and survivors of sex trafficking are valuable sources of information on sex traffick-
ing networks, but there are numerous challenges associated with gathering data from them. These
include ethical and logistical challenges, as well as issues regarding the generalizability of the data
(Gerassi et al. 2017, Weitzer 2014).

1.1 Background on Sex Trafficking Networks

Analytical tools that can seek to understand and disrupt the operations of sex trafficking networks
could be quite powerful, assuming their consequences are analyzed by domain experts. We can
consider sex trafficking networks as mathematical networks. Networks consist of nodes, representing
the entities, and arcs, representing the connections between nodes. A common example is a social
network, where the nodes represent people and the arcs represent the different connections between
people. Many models in operations research (OR) involve networks, since they can be used to
model the connections between entities and how people and goods can move between different
locations or states. Operations researchers have begun to explore how network models can be used
to disrupt sex trafficking networks, and have experienced difficulty in obtaining high quality data
(Dimas et al. 2021, Mayorga et al. 2019, Tezcan & Maass 2020).

Cockbain (Cockbain 2018) provides a comprehensive analysis of networks of victims and traffick-
ing in case file records from six law enforcement investigations into domestic minor sex trafficking
the United Kingdom (UK). She analyzes police operational files, court records, and prosecution
case files, and interviews convicted traffickers, police investigators and prosecutors to explore the
demographics of the traffickers and victims in these cases, as well as the tactics used by traffickers
to recruit and retain victims. She also produces the social networks of the victims and of the traf-
flackers from these analyses. However, her work does not discuss how to generalize the structures of
these networks to systematically create different instances of a domestic sex trafficking network.

Dank et al. (Dank et al. 2014) conducted a comprehensive analysis of the prevalence of sex
trafficking in eight major cities in the United States of America (USA). As part of this study, they
investigated the operations of sex trafficking, as well as how victims are recruited and managed.
They also qualitatively describe how traffickers are socially connected to share information. They
noted, from interviews with both traffickers and law enforcement, that traffickers are highly net-
worked socially, but rarely form business partnerships. This work helps to set the foundation for creating realistic domestic sex trafficking networks.

Veldhuizen-Ochodnicanova and Jeglic (Veldhuizen-Ochodničanová & Jeglic 2021) explore sex trafficking networks with female traffickers by analysing publicly available federally prosecuted case files. Their work identifies operational characteristics, including the number of victims and traffickers, their ages, and whether or not victims are domestic or international, for 44 sex trafficking operations in the US. They also explore the roles and duties that women take on in sex trafficking networks. Their work does not, however, include the social and operational connections between traffickers and victims.

1.2 Background on OR Modeling of Sex Trafficking Networks

OR models for societal challenges can be supplemented with insights from domain experts from a wide array of disciplines, such as qualitative researchers. Transdisciplinary research is necessary to conduct appropriate research related to human trafficking networks and seeks to address complex societal challenges through the integration of knowledge and methods of different disciplines (Lotrecchiano & Misra 2018). Because of the complexities of the lived experiences of survivors of sex trafficking, domain expertise is necessary to ensure that any analytical tools developed for the purpose of understanding and disrupting sex trafficking networks appropriately consider the human element of these networks. There are many challenges with building a transdisciplinary research team, but the time and effort put in to build such a team can result in scholarly works better grounded in the application area (Sharkey et al. 2021). We have applied a transdisciplinary approach in creating the proposed network generator by collaborating with domain experts, who have been investigating human trafficking for over 10 years (see Martin & Lotspeich 2014, Martin et al. 2017, 2014), and a survivor-centered advisory group.

Incorporating domain expertise in the application of OR is critical since it allows the created models to focus on the true underlying problems faced in the application area. This is especially important when the system cannot be directly observed. Morris (Morris 1967) discusses the types of tasks necessary to inform models while Willemain (Willemain 1994, 1995) discuss the process by which experts create models when faced with a practical problem. However, less research has been done on how to integrate domain expertise, both within other academic disciplines and from
practitioners, on socially-sensitive, hidden issues, like human trafficking. Caulkins et al. (Caulkins et al. 2019) discuss the potential types of insights that can be obtained by using engineering models to understand human trafficking and discuss the need to partner with human trafficking domain experts. Sharkey et al. (Sharkey et al. 2021) present a high-level approach for how to integrate this expertise into the modeling process. A critical observation of Sharkey et al. (Sharkey et al. 2021) is that data is one of the key areas where experts need to inform the modeling process.

Researchers are currently considering investigating two different perspectives for sex trafficking networks. One perspective considers how sex trafficking networks interact with different locations. Mayorga et al. (Mayorga et al. 2019) used web scraping from an online escort service to model the movement of sex trafficking networks between different cities. Keskin et al. (Keskin et al. 2021) proposed a process of grouping online advertisements to predict the movement of sex trafficking networks based on where related advertisements appear. White et al. (White et al. 2021) used web scraping to gather data on illicit massage parlors, and determines potential contributing factors for where illicit massage parlors may be located. These works use a visible, forward-facing part of the sex trafficking networks, the advertisements, to perform their analysis. Yet, advertisements are not the same as number of victims or people in the network and it is unclear exactly how advertisements map to the underlying phenomena of trafficking itself. The other perspective considers the relationships of the individuals within the sex trafficking network. Cockbain (Cockbain 2018) performs social network analysis traffickers and victims in six sex trafficking operations in the UK that law enforcement disrupted. We seek to augment the social network perspective by incorporating the insights of domain experts and people with lived experiences in sex trafficking networks, elucidating hidden aspects of domestic sex trafficking networks that may not be able to be determined by advertisements or law enforcement investigations.

1.3 Our Contributions

We propose a novel network generator that outputs network configurations that are representative of domestic sex trafficking networks in the real world and that account for realistic variation among operations. This generator takes the number of desired trafficking operations for use in analysis as an input, then produces the operational and social connections between the participants in the network. We also describe the process by which our generator was developed. Our generator is
the product of triangulating multiple data sources, including case file analysis, interviews with people who have domain expertise, and validation with a survivor-centered advisory group. The networks produced by the generator can be used for various analytical models without the need for researchers to collect and validate their own data. We note that the development process for the network generator is iterative. The more the generator is used alongside domain experts, the more it can be refined, expanded and further validated for improved accuracy.

Additionally, we propose a novel conceptualization of flow for sex trafficking networks; we model flow as the ability of the traffickers to control their victims. Thus, the maximum flow through the network is the total number of victims the traffickers victimize at a particular moment in time. We demonstrate how max flow network interdiction can be applied to these networks and discuss policy recommendations for when the traffickers are able to restructure their operations after the interdiction decisions have been implemented.

The paper is organized as follows. Section 2 outlines our objectives when developing the network generator and the process of triangulating data sources to develop the generator. Section 3 addresses the assumptions of the network generator and analyzes sample outputs. Section 4 focuses on a responsible use case study of the generator that focuses on applying a novel network interdiction model to disrupt the operations of generated sex trafficking networks. Section 5 discusses limitations of our network generator and proposes directions for future qualitative research to improve the applicability of the network generator. Section 6 concludes the paper and discusses directions for improvements.

2 Development of the Network Generator

2.1 Goals

The generator focuses on the social and operational connections of the people within domestic sex trafficking networks with specific operational characteristics. In this work, we recognize that these networks are abstractions of the true operations of sex trafficking. Therefore, the proposed network generator cannot appropriately capture all of the complexities of the lived experiences of trafficking victims and survivors, nor can it account for the human rights abuses and violence that occur in sex trafficking networks. This is a limitation of any analytical approach to understanding the issue
For our network generator, we focused on the social and operational connections of the participants in domestic sex trafficking networks with certain operational characteristics. The nodes represent the people in the network, and arcs represent the connections between them. The participants we consider are the traffickers, so-called “bottoms”, and victims. The term “bottom” is used in the literature and in some operations to refer to someone who was a victim, but has gained trust and responsibility from the trafficker and thus has additional responsibilities within the trafficking operation (Belles 2018). They might be viewed as the highest ranking former victim and function as a sort of right-hand person in the operation. However, there is a gray area in that bottoms may experience varying degrees of force and coercion since there is always a chance they will lose this status and be forced to trade sex. Likewise, a trafficker can expect or force some bottoms to exploit other victims (Roe-Sepowitz 2019, Belles 2018). For purposes of the generator, victims are split into two groups based on age, either minor or adult. We do this because published research and insights from our survivor-centered advisory group suggest that there are operational differences in how traffickers interact with minors versus adults due to developmental differences and a legal distinction where trafficking of minors results in much higher penalties (Marcus et al. 2014).

In order to clarify the distinction between the activities of a specific trafficker and the activities of all traffickers, we additionally define the distinction between an operation and network. Henceforth, when we refer to an operation, we are referring to a single trafficker, their bottom (if they have one), and their victims. The network refers to all operations generated, where the number of operations is a user-specified input. We can view the network as all operations in a given geographical region. We also want to provide a distinction to connections that are necessary for the function of a trafficking operations, as opposed to connections that are purely social, although we recognize that social connections may help further the activities of a trafficking operation. We define an operational arc as an arc that is necessary for the functions of the trafficking operation. An example of this is an arc between a trafficker and a victim, as that connection represents that the trafficker is able to control the victim. We define a social arc as an arc that does not necessarily have a function associated with them. An example of this is an arc between two victims. Such a connection may not be necessary for the act of sex trafficking.
2.2 Transdisciplinary Research Approach: Creation and Validation

We sought to utilize different data sources to guide the development of the network generator. All data sources focused on trafficking operations in the Midwest region of the USA. For this first phase of development of the network generator, data analysis focused on smaller operations with only one trafficker. Table 1 denotes the number of each type of data source.

Table 1: Data sources synthesized to help produce the network generator

| Data Source                                                      | Number |
|-----------------------------------------------------------------|--------|
| Publicly Available Federal Case Files                           | 13     |
| Key Informant Interview                                         | 10     |
| Secondary Analysis of Interviews from Previous Studies ([Martin et al. 2017, 2014]) | 246    |

We began the development of our network generator by first investigating publicly available federal case files of domestic sex trafficking cases. These case files consisted of relevant information needed to prosecute the trafficker(s), include the people involved, locations visited, online presence, and connections between them. However, these case files only contain the information necessary to prove a crime has been committed, which may omit key details regarding the network structure.

The data contained in these case files focused on the victims identified by law enforcement and the actions performed by the trafficker that would be necessary to prove that sex trafficking had been committed, and anything needed to perform those actions. Since the case files focused on proving a crime had been committed, they often had too much and too little information. For example, the case files included details connecting people to cell phones. While communications between the people using the phones is important for modeling connections between individuals, capturing how many phones each person uses and how phones move from person to person would be difficult to generalize in the network generator. Additionally, only considering the details necessary to prove the elements of the crime provides an inaccurate picture of the full number and roles of people involved in the network. Figure 1, a visualization of all connections between people, places and things in one of the case file, demonstrates this. Most notably, there was no record in the case file connecting the trafficker (T1) with their bottom (B1), which is a connection we would expect to see and was commented on by our advisory group when this network was presented to them. However, such a connection would not be necessary to prove that the person trading sex (PTS1) had been victimized by either T1 or B1. Moreover, these case files spanned a short duration of
time, thus only capturing a small snapshot of the trafficker’s operation in that moment in time. In the case of the network from Figure 1, the recorded operations only spanned a week.

![Sample Network from Case File Analysis](image)

**Figure 1: Sample Network from Case File Analysis**

The second source of data we investigated was transcripts of interviews conducted with people who have first-hand knowledge of sex trafficking networks, including survivors, support people, and law enforcement. These interviews guided how to determine the size of networks, as well as how to determine social connections between victims.

From triangulating these sources, we devised a basis for network generation. We devised rules from consistencies across multiple data sources, such as the distribution of number of victims within an operation, and used statistics and qualitative descriptions to estimate parameters for these rules. Once all necessary parameters were determined, we generated a set of networks to review with domain experts on the research team, as well as a list of questions and observations to discuss. We reviewed these networks and engaged in discussions to clarify what seemed to be accurate based on their expertise. After the discussions, the domain experts were provided the outputs to further discuss. They wrote a memo that critiqued the outputs with the known literature on domestic sex trafficking and then discussed how to improve the generator. Some topics the domain experts commented on included adjusting parameters for determining whether a bottom is in the network and how victims are connected to traffickers and bottoms. Adjustments to the rules and parameters were made based on the suggestions in the memo. This process of reviewing networks produced by the generator with the domain experts was repeated multiple times. Figure 2 displays the probability distribution of the number of victims in a trafficking operation after it was critiqued.
by the domain experts and adjusted to better reflect their knowledge.

Figure 2: Probability Distribution of Number of Victims in a Trafficking Operation, Validated with Domain Experts

After converging to output networks of the generator that reflected the knowledge of the domain experts on the research team, we then presented the networks to a survivor-centered advisory group. As part of the research team’s approach to transdisciplinary research, the advisory group was familiarized with the concept of networks prior to these presentations. The basis for the network generator was presented to validate if the underlying rules for network generation seemed accurate based on their knowledge, and sample output networks were presented for members of the advisory group to discuss. The researchers also solicited feedback on if there were other factors that should be incorporated into the network generator, both for immediate adjustments and directions for future versions of the generator. After this presentation, adjustments were made, and new output networks were presented to domain experts on the research team. In particular, discussions with the advisory group led to a new method to determine social connections between victims. To the best of our knowledge, very little literature explores social connections between victims [Cockbain 2018]. Conversations with the advisory group shed some light on these connections, such as smaller groups of victims being housed together and separated from the rest of the victims. After implementing this new method, the domain experts were able to refine the choice of parameters for this method.
2.3 Details of the Network Generator

For single trafficker operations, we first generate the number of victims a trafficker has in their operation. The distribution we sample from is based on statistics gathered and validated by the domain experts. Based on the number of victims, we randomly determine if there is a bottom in the network. The probability of a bottom in the network grows significantly with respect to the number of victims, with a bottom almost surely present when there are at least six victims. If it is determined there is a bottom in the network, a new node is added to be the bottom, as the statistics collected for number of victims did not include a bottom as a victim. These observations were made based on a secondary analysis of previously collected interview data (Martin et al. 2014, 2017).

We next determine how a trafficker is managing the victims within their operation. We do so by partitioning the victims into “pods” (Melander et al. n.d.). Pods can be thought of as groups of victims who were recruited roughly at the same time, or live in the same location. Each victim in a given pod is connected to every other victim in the same pod, i.e., a pod forms a clique in the operational network. We generate all feasible partitions of the number of victims where each part has at most six victims, then randomly select from this set (Melander et al. n.d.). Feedback from the advisory group provided insights on how to determine the probability of selecting different partitions. When there is more than one pod, we randomly determine the age group (i.e., minor or adult) of the victims for the entire pod, as opposed to determining the age group for victims individually. The exception to this is when a pod consists of two victims, which we allow for one victim to be a minor and one victim to be an adult. This is representative of a situation where a pair of victims may be family members (e.g. mother and daughter) or where there is a parental-type relationship. These choices regarding ages and pods were suggested by the advisory group.

We then determine how the trafficker (and bottom) interact with the pods. If there is a bottom, we first determine how the victims are connected to the trafficker and bottom, as all victims are not necessarily connected to both the trafficker and the bottom. We randomly determine which pods are connected to the trafficker, then which pods are connected to the bottom. Similarly, if the trafficker (or bottom) is not randomly assigned any pods, they will be assigned to the largest pod. The probability of a pod being assigned to the trafficker and bottom varies based on the age of the
victims in the pod. This is due to a trafficker potentially not wanting to have direct contact with a victim who is a minor, as prosecuting a sex trafficking case is easier if the victim is a minor, and the minimum punishments are more severe (Marcus et al. 2014). If there is no bottom, all victims are connected to the trafficker. If there is a single pod, then age and connections to trafficker and bottom are determined individually, as if each victim were in their own pod.

We then expand upon the social network amongst victims within the operation. Partitioning the victims into pods provides an initial set of arcs for the social network amongst victims. We then determine any social connections between victims in different pods. For each pair of victims in different pods, we randomly determine if an arc between them should be added to the network. The probability of an arc being added between them is dependent on the age of the victims, since minor victims tend to be recruited into trafficking via their social network (Marcus et al. 2014).

This procedure is repeated for the number of operations desired. After all operations are generated, we generate the social network amongst traffickers. From Dank et al. (Dank et al. 2014), we know that traffickers are connected to share information about profitable locations and law enforcement activity. Since little further is known about how traffickers are connected socially, we use the Watts-Strogatz model to generate the social network amongst traffickers (Watts & Strogatz 1998). The Watts-Strogatz model is a random graph generation model that is often used for social networks since it produces networks with the “small world phenomena,” which indicates that the shortest paths between pairs of nodes include a small number of arcs and that nodes tend to be grouped into clusters, with a larger number of arcs between nodes in the same cluster than between nodes in different clusters. After the trafficker social network is generated, we then generate social connections between victims in different trafficking operations. Again, we impose a higher likelihood of two victims who are minors being connected over adult victims. Parameters regarding social connections were validated by the domain experts and advisory group.

3 Outputs

We now present sample output networks from our domestic sex trafficking network generator and compare them to sex trafficking networks constructed in previous research. Figure 3 displays five sample operations generated by the network generator. Trafficker nodes are squares, bottom nodes
are triangles, and victims nodes are circles. Nodes representing victims who are adults are a darker shade of gray than nodes representing victim who are minors. Arcs are solid if they are representing an operational arc (e.g. trafficker to victim), or dashed if they are representing a social arc. We include arcs between victims in the same pod as an operational arc.

![Network Diagrams](image)

(a) Sample Operation 1  (b) Sample Operation 2  (c) Sample Operation 3  (d) Sample Operation 4  (e) Sample Operation 5

Figure 3: Sample operations within a generated human trafficking network

In these five operations, all but one operation has a bottom. In 25 generated outputs, 20 operations have bottoms, and every operations with more than 5 victims had a bottom. Of the eight operations with 4 victims, only one operation does not have a bottom. Of the four operations with 3, half of them have a bottom. Both networks with 2 victims do not have a bottom. Additionally, of the 25 operations, 5 have one pod, 16 have two pods, 2 have three pods, and 1 has four pods.
In the operation with four pods, three of them are isolated victims. The median pod size has 2 victims, with a maximum pod size of 5 victims.

We compare centrality measures of the output operations in Figure 3 against those listed in Cockbain (Cockbain 2018). We exclude Operation Retriever, as the number of victims in that network is significantly higher than the other networks in the text. We note that this analysis is comparing operations from two different locations (Midwest USA versus UK), and so trafficking networks may be structured differently between the two locations.

Table 2: Comparison of centrality measures between operations produced by the network generator and the operations studied in Cockbain (Cockbain 2018)

| Operation | Number of Victims | Arc Density | Degree Centralization | Betweenness Centralization |
|-----------|-------------------|-------------|-----------------------|---------------------------|
| 1         | 3                 | 0.6667      | 0.3333                | 1                         |
| 2         | 3                 | 0.6667      | 0.3333                | 1                         |
| 3         | 6                 | 0.7333      | 0.2667                | 0.2                       |
| 4         | 3                 | 1           | 0                     | 0                         |
| 5         | 5                 | 0.9         | 0.1                   | 0.0278                    |
| Engage    | 2                 | 1           | n/a                   | n/a                       |
| Central   | 4                 | 1           | 0.0                   | 0.0                       |
| Span      | 5                 | 0.5         | 0.4                   | 0.2                       |
| Chalice   | 6                 | 0.4         | 0.6                   | 0.3                       |

The number of victims in operations produced by the network generator is similar to the number of victims in the operations investigated by Cockbain. Additionally, the arc densities and degree centralization scores of the synthetic operations all fall in the range of arc densities and degree centralization scores of the real operations. Excluding operation 4, operation Engage, and operation Central, which are all complete networks, the arc densities of the synthetic networks are higher than that of operations Span and Chalice, while the degree centralization scores of the synthetic networks are lower than the real networks. This is likely due to the pod structure in the synthetic networks. In operations with larger pods, the arc density will be larger and the degree centralization will be smaller. The pod structure also likely explains the significant difference in the betweenness centralization scores between the synthetic and real networks. While operation 3 has a betweenness centralization score similar to operations Span and Chalice, operations 1 and 2 have betweenness centralization scores of 1. This is because these two networks have the same structure: one pod

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1Centrality scores can only be calculated in networks with at least three nodes.
with two victims, and one isolated victim, with a single arc from the isolated victim to one victim in the pod. These results suggest that although there is variation in the synthetic generators, they do share similarities with those produced through case file analysis on sex trafficking networks. This is important as the generator is able to create more synthetic networks for OR analysis.

Once the generator has produced the desired number of operations, the social network amongst traffickers is generated to create the full sex trafficking network. Figure 4 displays a sex trafficking network with the five operations in Figure 3. At this point, OR models, such as network interdiction could be applied to the full network with appropriate modifications to the data.

4 Responsible Use Case Study: Network Interdiction

We now present a case study on how an output of the network generator can be used as data for OR tools. We consider interdiction prescriptions via the max flow network interdiction problem (MFNIP) [Wood1993]. In a network $G = (N, A)$, with source node $s \in N$ and sink node $t \in N \setminus \{s\}$, and capacities on the arcs $u : A \to \mathbb{R}_{\geq 0}$, the max flow problem seeks to find the total amount of flow from $s$ to $t$ such that the flow on each arc is at most the capacity of that arc, and the amount of flow into a node is the same as the amount of flow leaving that node. The max flow network interdiction problem converts that problem to a two player game, where one player, known as the attacker, seeks to minimize the maximum flow through the network by choosing a subset of arcs...
to reduce their capacity to zero, subject to a budget and other constraints. The other player, the
defender, then operates the network as per the max flow problem. Max flow network interdiction
has successfully been applied to disrupting illicit drug trafficking networks (Baycik et al. 2018,
Malaviya et al. 2012, Shen et al. 2021, Kosmas et al. 2020), and has been identified as an analytical
tool to help address sex trafficking (Smith & Song 2020). Some max flow network interdiction
models have been proposed for disrupting human trafficking (Mayorga et al. 2019, Tezcan & Maass
2020). We apply the model of Kosmas et al. (Kosmas et al. 2020), max flow network interdiction
with restructuring (MFNIP-R), to sample outputs of our network generator. Their model accounts
for how drug traffickers will respond to disruption efforts. This response is also a key aspect for
disrupting sex trafficking, not merely displacing it. Accounting for responses from traffickers is vital
to responsible policy recommendations, as research suggests that removing individual victims from
a trafficking situation, while clearly necessary, might paradoxically result in more victims being
recruited into trafficking after an interdiction (Caulkins et al. 2019, Martin & Lotspeich 2014).
This paradox aligns with the theoretical analysis in Kosmas et al. (Kosmas et al. 2020), where
they observed that current law enforcement policy typically recommended interdicting participants
in drug smuggling networks that would trigger restructuring arcs that would cross the minimum
cut. We find that a similar situation occurs for our conceptualizations of sex trafficking networks,
thus indicating that both disrupting current operations and their ability to restructure (especially
recruit) is critical.

Kosmas et al. (Kosmas et al. 2020) defines MFNIP-R as the following. Given a network $G = (N, A)$
with source node $s$, sink node $t$, set of restructure-able arcs $A^R$, and node and arc capacities
$u : N \cup A \cup A^R \to \mathbb{R}_{\geq 0}$, let $Y$ be the set of feasible interdiction plans and let $Z(y)$ be the set of
feasible restructurings dependent on the chosen interdiction plan. First, the attacker chooses an
interdiction plan $y \in Y$, setting the capacity of the interdicted nodes to 0. Next, the defender
chooses a restructuring plan $z \in Z(y)$ to add arcs to the network, increasing their capacity from 0.
Lastly, the defender operates the network to maximize flow through the network.

4.1 Modeling Sex Trafficking with Max Flow

Compared to drug trafficking, it is less clear in sex trafficking networks of traffickers and victims
what an interdiction might seek to restrict in terms of flow. The function of a drug trafficking
network is to move and eventually sell a product (i.e. drugs) to a user. Thus the flow is the drugs. In a sex trafficking network, flow is more complex. The “product” begin sold in sex trafficking is people and a sexual experience (Martin et al., 2017, 2014). The commercialization and sale of sex to a sex buyer may in some ways be analogous to the sale of drugs since both are commodities. The flow within the network is not the same because people (and their labor) are not equivalent to drugs. Much more work is needed to conceptualize how this concept of “flow” should best be applied to sex trafficking networks. Thus, we posit a novel interpretation of the maximum flow problem as it pertains to traffickers and victims of trafficking within a sex trafficking operation. Flow could represent the ways traffickers exhibit control over victims and the sex acts that victims are forced to perform. Thus flow is exerted through control over trafficking victims in order to make them (and their labor) a product to sell (Martin et al., 2014). This is a preliminary exploration; much more empirical research is needed to verify and extend modeling to understand the specificity and nuances of trafficking for sexual exploitation. Further, it must be noted that the flow that is being modeled is exerted through violence, manipulation, and harm. For this discussion, we will focus on control within the network and on situations in which a trafficker needs to maintain control over a certain number of victims. We postulate, for the sake of this model, that a trafficker has a specific number of victims they wish to have under their control at any given time.

In the max flow network interdiction setting, we consider a model where nodes are interdicted, as opposed to arcs, so that interdictions are representative of removing traffickers and victims from the network. An equivalency between node interdiction and arc interdiction has been demonstrated in (Malaviya et al., 2012). This relies on the standard network expansion technique of replacing each node with two nodes and an arc between them, where all arcs coming into the original node flow into one of the expanded node, an arc goes to the second expanded node, and then all arcs leaving the original node leave the second expanded node. In this case, capacities are assigned to the nodes as well.

To convert an output of the network generator to a network usable in max flow network interdiction, we need to add in a source node and sink node. We add arcs from the source node to each trafficker and bottom node with infinite capacity, and arcs from each bottom and victim node to the sink with capacity one. All arcs incident to the trafficker are directed out of the trafficker, and all arcs incident to the bottom and a victim are directed out of the bottom and into the victim.
Arcs between victims are replaced with a pair of arcs between the victims, one in each direction. The capacity of each trafficker node is the number of victims they can control, the capacity of each victim node is one, and the capacity of each bottom node is the number of victims they can control plus one. This is to recognize that bottoms are victims too, and that their role in sex trafficking networks does not make them any less of a victim than the other victims. Note that it is not necessary to directly model the control of a bottom with an arc from the trafficker to them as the arc from the source can model this control. For ease of notation, we define $T$ to be the set of traffickers, $B$ to be the set of bottoms, and $V$ to be the set of victims. Capacities for the traffickers and bottoms are chosen in such a way that the maximum flow through the network is the total number of victims currently in the network (including bottoms). The arcs between traffickers are only used to determine restructure-able arcs, and are assigned capacity 0.

We now define the set of restructure-able arcs $A^R$. For the set of restructure-able arcs, we allow for traffickers to recruit each other’s victims, traffickers to give or take victims from their bottom, the recruitment of new victims, back-up traffickers to take over an interdicted trafficker’s operation, the promotion of a new bottom, and traffickers to give victims to their newly promoted bottom.

We start with $A^R$ consisting of the set of arcs between traffickers and the victims of traffickers they know. More precisely, for $i \in T$ and $j \in V$, $(i, j) \in A^R$ if there exists a $k \in T$ such that $(i, k) \in A$ and $(k, j) \in A$. To allow for a trafficker $i$ to assign a new victim $k$ to their bottom $j$, we include $(j, k) \in A^R$ if $(j, k) \notin A$. Likewise, we allow for a trafficker $i$ to take a victim $k$ from their bottom $j$ by including $(i, k) \in A^R$ if $(i, k) \notin A$.

To model the recruitment of new victims, we introduce an additional set of nodes $V^R$. We include an arc from each of these nodes to the sink node in the arc set $A$. We then randomly determine a subset of traffickers that can restructure to each recruitable victim node, and add arcs between the traffickers and the recruitable victim to $A^R$. This results in these nodes having no arcs into them in the initial network, meaning no flow can pass through them, but flow can pass through them if an arc ending at the recruitable victim is restructured by a trafficker. To model the an operation having a back-up trafficker, we introduce an additional set of nodes $T^R$ be the set of back-up traffickers for certain operations, which is represented by ordered pairs $(i, j)$, where trafficker $i$ can be replaced by back-up trafficker $j$ if trafficker $i$ is interdicted. We add arcs from the back-up trafficker $j$ to all of trafficker $i$’s victims, and include an arc $(s, j)$ in the set of
restructure-able arcs. As with recruitable victims, there are no arcs into back-up trafficker \( j \) in the initial network, so no flow can pass through the node, but restructuring the arc \((s, j)\) allows for flow to pass through the node. To model the promotion of new bottoms, we define the set \( B^R \) as the set of victims which may be eligible to be promoted to the role of bottom, which is represented by ordered pairs \((i, j)\), where victim \( j \) may be promoted if bottom \( i \) was interdicted. If victim \( j \) is promoted to the role of bottom, their capacity is increased by \( \tilde{u}_j \), allowing flow to pass from victim \( j \) to the victims that they are adjacent to. An arc \((s, j)\) is added to the set of restructure-able arcs, mimicking the inclusion of arcs to back-up traffickers. We also allow for a trafficker \( i \) to assign a victim \( k \) to the newly promoted bottom \( j \) by including arc \((j, k)\) \( \in A^R \) if \((j, k) \notin A \) that can only be restructured if \((s, j)\) has been restructured.

We now define the necessary components for MFNIP-R. Let \( x_{ij} \) be the amount of flow through arc \((i, j)\), and \( x_i \) be the amount of flow through node \( i \). Let \( y_i \) be the indicator of whether or not node \( i \) has been interdicted, setting its capacity to 0, with \( Y \) being the set of feasible interdiction decisions. As in Kosmas et al. (Kosmas et al. 2020), we define the variables on restructuring to represent which node is enabling the restructuring to occur. An “out” restructuring would be representative of a trafficker restructuring to a new victim after having one of their victims interdicted. An “in” restructuring would be representative of a victim being recruited into a new operation after their trafficker has been interdicted. Let \( z^\text{out}_{ij} \) be the indicator of restructuring arc \((i, j)\) from node \( i \), and let \( z^\text{in}_{ij} \) be the indicator of restructuring arc \((i, j)\) from \( j \), with \( Z^\text{out}(y) \) and \( Z^\text{in}(y) \) being the sets of feasible restructuring decisions from \( i \) or \( j \), respectively, with respect to the interdiction decision \( y \). We note that we restrict the set of restructuring decisions to be dependent on the implemented interdiction decisions because we are specifically interested in how the traffickers will react to the interdictions. Additionally, we define sets of restructure-able arcs \( A^R,\text{out} \) and \( A^R,\text{in} \), based on whether a restructure-able arc in \( A^R \) is initiated by a trafficker or by a victim. Restructure-able arcs between an existing trafficker and existing victim are included in \( A^R,\text{in} \), while all restructure-able arcs are included in \( A^R,\text{out} \). Note that \( A^R,\text{in} \subset A^R,\text{out} = A^R \) in our model.

In this case study, instead of assigning a global budget for restructuring, we assign each trafficker a budget. We choose to limit the number of action each trafficker can take, as the actions of one trafficker may not prevent the actions of the other traffickers. For ease of defining constraints, we
further partition $A^R_i$ into sets based on which trafficking operations are involved. Let $A_i^{R_{\text{out}}}$ be the set of restructure-able “out” arcs that can be restructured by trafficker $i$, and $A_i^{R_{\text{in}}}$ be the set of restructure-able “in” arcs that involve trafficker $i$. We note that these sets are disjoint between different traffickers, i.e. $A_i^{R_{\text{out}}} \cap A_j^{R_{\text{out}}} = \emptyset$ for $i, j \in T$ and $i \neq j$, and $A^{R_{\text{out}}} = \bigcup_{i \in T} A_i^{R_{\text{out}}}$.

Let $c^i_{jk}$ be the cost for trafficker $i$ to restructure the arc $(j, k)$, and let $b^i$ be the budget of trafficker $i$. For a fixed attacker solution $\bar{y}$, we can define the defender’s problem as:

$$\max_{x, b} \sum_{i \in N \setminus \{i\} \subseteq A \cup A^{R_{\text{out}}}} x_{ii}$$

s.t.

$$\sum_{(h, i) \in A \cup A^{R_{\text{out}}}} x_{hi} = x_i$$

$$x_i = \sum_{(i, h) \in A \cup A^{R_{\text{out}}}} x_{ih}$$

$$x_{ij} \leq u_{ij}$$

$$x_{ij} \leq u_{ij} z^i_{jk}^{\text{out}}$$

$$x_{ij} \leq u_{ij} (z^i_{jk}^{\text{out}} + z^i_{jk}^{\text{in}})$$

$$x_i \leq u_i (1 - y_i)$$

$$x_j \leq u_j (1 - y_j) + u_j z^i_{jk}^{\text{out}}$$

$$\sum_{(j, k) \in A^{R_{\text{out}}}} c^i_{jk} z^i_{jk} + \sum_{(j, k) \in A^{R_{\text{in}}}} c^i_{jk} z^i_{jk} \leq b^i$$

$$\sum_{j \in V} z^i_{jk} \leq \sum_{h \in V \cap (i, h) \in A} \bar{y}_h$$

$$\sum_{h \in T \cap (i, h) \in A} \bar{y}_h$$

$$\sum_{(i, j) \in R^T} z^i_{jk} \leq \bar{y}_i$$

$$\sum_{(j, i) \in R^B} z^i_{jk} \leq \bar{y}_i$$

$$z^i_{jk} \leq 1 - \bar{y}_j$$

$$\sum_{(j, k) \in B^R \cap (i, j) \in A} z^i_{jk} \leq 1$$

$$\sum_{k \in V \cap (j, k) \in A^{R_{\text{out}}}} (z^i_{jk}^{\text{in}} + z^i_{jk}^{\text{out}}) \leq 1$$

$$\sum_{i \in T \cap (j, i) \in R^{R_{\text{out}}} \cap A^{R_{\text{in}}}} (z^i_{jk}^{\text{in}} + z^i_{jk}^{\text{out}}) \leq 1$$

$$x \geq 0$$

$$z^i_{jk} \in \{0, 1\}$$

$$b^i \in \{0, 1\}$$

for $i \in N$ (1)

for $i \in N$ (2)

for $(i, j) \in A$ (3)

for $(i, j) \in A^{R_{\text{out}}} \setminus A^{R_{\text{in}}}$ (4)

for $(i, j) \in A^{R_{\text{in}}}$ (5)

for $i \in N \setminus \{j \in V : \exists h \in B \text{ with } (h, j) \in B^R\}$ (6)

for $j \in V \text{ s.t. } \exists i \in B \cap (i, j) \in B^R$ (7)

for $i \in T$ (8)

for $i \in T$ (9)

for $j \in V$ (10)

for $i \in T$ (11)

for $i \in B$ (12)

for $j \in V \text{ s.t. } \exists i \in B \cap (i, j) \in B^R$ (13)

for $i \in T$ (14)

for $i \in T$ (15)

for $j \in V$ (16)

for $(i, j) \in A^{R_{\text{out}}} \cap A^{R_{\text{in}}}_i$ (17)

(18)

(19)

(20)

(21)
The objective function of the MILP is maximizing the amount of flow out of the source node. Constraints (1)-(2) are flow balance constraints. Constraints (4)-(7) enforce the flow through an arc or node is at most the capacity of that arc or node, as adjusted by interdictions and restructurings. In particular, constraint (7) incorporates the decrease in flow through a victim node from interdiction and increase from being promoted to the role of bottom. Constraint (8) enforces the restructuring budget for each trafficker. Constraint (9)-(10) allow for restructurings from the traffickers or bottoms based on the implemented interdictions. Constraint (11) allows for a back-up trafficker to be restructured to if the trafficker has been interdicted, and constraint (12) allows for a victim to be promoted to bottom if the operation’s bottom has been interdicted. Constraint (13) prevents an interdicted victim from being promoted to bottom, and constraint (14) enforces that at most one victim can be promoted to bottom. Constraint (15) allows for the trafficker to give victims to the newly promoted bottom. Constraint (16) prevents a victim from being recruited into more than one operation. For arcs in \( A_i^{R,\text{out}} \cap A_i^{R,\text{in}} \), constraint (17) prevents both \( z^{\text{out}} \) and \( z^{\text{in}} \) from being nonzero. Constraint (18) enforces that the flow variables are non-negative, and constraints (19) and (20) enforces that the restructuring variables are binary.

The attacker is assigned a budget \( b^a \) to interdict the network, limiting their ability to disrupt the network. Each node \( i \) is assigned a cost \( r_i \) that must be expended to interdict that node. In drug trafficking, “climbing the ladder” constraints are used to emulate how law enforcement would pursue prosecuting cases against participants in the drug trafficking network [Malaviya et al. 2012]. In disrupting sex trafficking networks, it is not necessary to interdict victims in order to interdict traffickers; however the cooperation of victims can assist in the successful prosecution of traffickers. To model this, the cost of interdicting a trafficker node is reduced by a fixed amount based on whether or not their bottom has been interdicted, as well as the number of their victims that have been interdicted. Let \( d_k^i \) be the decrease in interdiction cost of trafficker \( i \) be interdicting node \( k \). Additionally, let \( r_i^{\text{min}} \) be the minimum the cost to interdict trafficker \( i \), and define the variable \( \tilde{r}_i \) be the adjusted cost of interdicting trafficker \( i \).

We can define the attacker’s problem as:

\[
\min_{y,f} \max_{\tilde{r},x} \sum_{i \in N, \{s,i\} \in A \cup A^{R,\text{out}}} x_{si} \\
\text{s.t.} \quad \text{Constraints (1) - (21)}
\]
\[ \sum_{i \in T} \tilde{r}_i y_i + \sum_{j \in B \cup T} r_j y_j \leq b \]

(22)

\[ \tilde{r}_i \geq r_i^{\text{min}} \quad \text{for } i \in T \]

(23)

\[ \tilde{r}_i \geq r_i - \sum_{k \in B \cup V} \bar{d}_k y_i \quad \text{for } i \in T \]

(24)

\[ y \in \{0, 1\}^{|N|} \]

(25)

Constraint (22) is the budget of the attacker. Constraints (23) and (24) adjust the cost to interdict the traffickers. Constraint (25) enforces that the interdiction variables are binary. We note that, as qualitative research on the operations of sex trafficking networks is furthered, this model can be refined to provide more accurate insights regarding disrupting sex trafficking networks.

Note that \( \tilde{r}_i y_i \) is a bilinear term. This can be linearized by replacing it with a new variable \( \tilde{y}_i \) and including the McCormick inequalities in the set of constraints \cite{McCormick1976}. Since \( y_i \) is binary, the McCormick inequalities will result in \( \tilde{y}_i = \tilde{r}_i y_i \).

We apply the method of Kosmas et al. \cite{Kosmas2020} to solve this model. Their method is a column-and-constraint generation (C&CG) method, where, when a previously visited restructuring plan is infeasible with respect to the currently interdiction plan, the feasible components in that restructuring plan are used in place of the full plan to determine a lower bound on the true objective value. This method has been shown to be effective in solving their model faster than standard C&CG methods, particularly when new participants are able to be recruited.

### 4.2 Computational Results

We implement this interdiction model on five generated networks, each with five operations. Table 3 reports the number of nodes, and number of bottoms and victims, in each network.

| Network | Number of Traffickers | Number of Nodes | Number of Bottoms | Number of Victims |
|---------|-----------------------|----------------|-------------------|------------------|
| 1       | 28                    | 5              | 3                 | 20               |
| 2       | 32                    | 5              | 4                 | 23               |
| 3       | 35                    | 5              | 5                 | 25               |
| 4       | 35                    | 5              | 4                 | 26               |
| 5       | 27                    | 5              | 4                 | 18               |

We set the cost of interdicting a trafficker to be 8, the cost to interdict a bottom to be 4, and the cost to interdict a victim to be 2. Interdicting a bottom reduces the cost of interdicting their
trafficker by 3, and interdicting a victim reduces the cost of interdicting their trafficker by 1. Each trafficker has a budget of 8 to restructure their operation. The cost to restructure to a victim currently in the network is 1, as is the cost to take a victim from their bottom or give a victim to their bottom. The cost to recruit a new victim not currently in the network is 2. The cost for a back-up trafficker to come into the operation is 4. The cost to promote a new bottom is 5, and the cost for the trafficker to give them a victim is 2. We set the number of recruitable victims to be 40% of the number of victims in the network. A trafficker will have a back-up trafficker if they have at least than four victims (including a bottom). If a trafficker has a bottom, the number of victims that can be promoted to become a bottom is at half of the number of victims the trafficker is connected to (minimum one).

We set a solve time limit of 2 hours. All instances solved within the time limit. We model the problem in AMPL with Gurobi 9.0.2 as the solver. Experiments were conducted on a laptop with an Intel® Core™ i5-8250 CPU @ 1.6 GHz - 1.8 GHz and 16 GB RAM running Windows 10. Figure 5 demonstrates the flow through the network over different attacker budgets. In this figure, the dotted black represents the total number of victims (including bottoms) in the network. The hollow circles represent the interdicted flow determined by solving MFNIP. The stars represent the flow after optimally restructuring the network in response to MFNIP’s recommended interdictions. The diamonds represent the interdicted flow determined by MFNIP-R. Note that network 1 is the network in Figure 4.

In each network and across all budget levels, the traffickers are able to recover a significant amount of flow after restructuring in response to the MFNIP recommended interdictions. This is primarily due to being able to recruit new victims when victims are primarily interdicted, and being able to replace interdicted traffickers with back-up traffickers when traffickers are primarily interdicted. However, when we are able to account for how the traffickers will restructure in response to interdiction, we are often able to reduce the flow. Table 4 demonstrates the interdiction recommendations for the network in Figure 4. Results on other networks can be found in Appendix A. Columns 2 - 4 display the number of traffickers, bottoms, and victims that MFNIP recommends to interdict, and columns 5 - 7 display the number of traffickers, bottoms, and victims that MFNIP-R recommends to interdict.

A clear distinction between the two recommended plans is the number of bottoms that each
Figure 5: MFNIP-R flows over varying attacker budgets
## 5 Limitations and Directions for Future Qualitative Research

As the lack of data is the challenge we wish to address, our network generator has many limitations that a responsible user needs to be aware of. First and foremost, our network generator is built on sources about domestic sex trafficking cases within the Midwest of the USA, since the case file analysis focused on the cases in the Midwest and the advisory group’s experiences involve operations within the Midwest. As such, their experience is not necessarily representative of sex trafficking as a whole. It may be that biases based on their experience are built into the network generator. However, the more the network generator is used and feedback is provided regarding operations in

### Table 4: Interdiction recommendations from MFNIP and MFNIP-R for Network 1

| Attacker Budget | MFNIP Int Trafficker | MFNIP Int Bottom | MFNIP Int Victim | MFNIP-R Int Trafficker | MFNIP-R Int Bottom | MFNIP-R Int Victim |
|-----------------|----------------------|------------------|------------------|------------------------|-------------------|-------------------|
| 8               | 0                    | 2                | 0                | 0                      | 0                 | 4                 |
| 12              | 1                    | 1                | 0                | 0                      | 0                 | 4                 |
| 16              | 1                    | 2                | 1                | 1                      | 0                 | 6                 |
| 20              | 1                    | 2                | 3                | 1                      | 1                 | 6                 |
| 24              | 1                    | 3                | 3                | 1                      | 0                 | 10                |
| 28              | 1                    | 3                | 4                | 1                      | 2                 | 8                 |
| 32              | 1                    | 3                | 8                | 2                      | 1                 | 8                 |
| 36              | 1                    | 3                | 10               | 2                      | 1                 | 12                |
| 40              | 1                    | 3                | 12               | 2                      | 2                 | 10                |
more locations and contexts, the more accurate we will be able to make it over time. Users should collaborate with domain experts in their geographical location to understand how sex trafficking networks in their location may operate differently from that of the Midwest.

Another limitation is regarding the social connections between traffickers. It is known that some traffickers are connected socially with other traffickers, but there has been little research on what these social networks look like. This gap prevents us from developing more authentic trafficker social networks. Further research focused on how traffickers are connected, both socially and professionally, will allow for more accurate trafficker social networks to be produced.

How bottoms interact with the network is also an area where further research is needed. While their function in the network is known, little is known on how they are connected to other traffickers and victims outside of their operation. It is also not well known what causes a trafficker to want or need to have a bottom in their network. Here, we base the likelihood of there being a bottom on the number of victims in the trafficker’s operations. Future qualitative research can ascertain why a trafficker chooses to promote a victim to the role of the bottom and how having a bottom allows a trafficker to grow their business.

6 Conclusions

We presented our network generator for producing synthetic domestic sex trafficking networks. The networks produced include the operational and social connections between traffickers, bottoms, and victims. Data sources including publicly available federal case files and interviews were triangulated to determine the basis and parameters in the generator. The generator was further validated by domain experts, including a survivor-centered advisory group. As qualitative research furthers our understanding of the connections within sex trafficking networks, we can refine and advance the functionality of the generator in future iterations. An example of such research is on how traffickers communicate and collaborate, which would allow us to build multiple-trafficker operations. The network generator and generated networks in this study are available from the corresponding author upon reasonable request.

This generator allows for the OR community to engage in human trafficking research without needing to go through the time-intensive process of collecting and cleaning their own data. We
demonstrate how an OR tool, network interdiction, can be applied to networks produced by this generator. In particular, we proposed a novel conceptualization of flow which considers the ability of the traffickers to control their victims. Our results suggest that better understanding the roles of bottoms in maintaining operations after disruptions occur may be key to more impactful disruptions.

The advisory group has suggested three avenues of future research to improve the applicability of the network generator. The first avenue is to include a temporal component. From their insights, the victims in an operation can change rapidly (in some cases daily) depending on many different factors. Being able to account for a temporal component can allow for a better understanding of how long term disruption decisions can be made. The second avenue of future research is to include a spatial component. Trafficking operations may move to different locations based on profit and law enforcement activity. Understanding how trafficking operations move between different locations will be essential to effective disruption prescriptions. The third avenue of future research is to produce networks where multiple traffickers are collaborating in larger trafficking operations.

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Appendices

A Recommended Interdiction Plans

Table 5: Interdiction recommendations from MFNIP and MFNIP-R for Network 2

| Attacker Budget | MFNIP Int Trafficker | MFNIP Int Bottom | MFNIP Int Victim | MFNIP-R Int Trafficker | MFNIP-R Int Bottom | MFNIP-R Int Victim |
|-----------------|----------------------|------------------|------------------|------------------------|-------------------|-------------------|
| 8               | 0                    | 2                | 0                | 0                      | 0                 | 4                 |
| 12              | 0                    | 3                | 0                | 1                      | 0                 | 4                 |
| 16              | 0                    | 2                | 2                | 1                      | 0                 | 6                 |
| 20              | 1                    | 2                | 2                | 1                      | 1                 | 6                 |
| 24              | 2                    | 3                | 1                | 1                      | 1                 | 8                 |
| 28              | 2                    | 4                | 1                | 2                      | 0                 | 10                |
| 32              | 3                    | 4                | 0                | 2                      | 0                 | 13                |
| 36              | 3                    | 4                | 2                | 3                      | 1                 | 9                 |
| 40              | 3                    | 4                | 5                | 3                      | 2                 | 9                 |

Table 6: Interdiction recommendations from MFNIP and MFNIP-R for Network 3

| Attacker Budget | MFNIP Int Trafficker | MFNIP Int Bottom | MFNIP Int Victim | MFNIP-R Int Trafficker | MFNIP-R Int Bottom | MFNIP-R Int Victim |
|-----------------|----------------------|------------------|------------------|------------------------|-------------------|-------------------|
| 8               | 0                    | 2                | 0                | 0                      | 1                 | 2                 |
| 12              | 1                    | 1                | 1                | 1                      | 0                 | 4                 |
| 16              | 1                    | 2                | 1                | 1                      | 0                 | 6                 |
| 20              | 2                    | 2                | 1                | 2                      | 1                 | 3                 |
| 24              | 2                    | 3                | 1                | 2                      | 1                 | 6                 |
| 28              | 2                    | 2                | 5                | 3                      | 3                 | 1                 |
| 32              | 2                    | 3                | 5                | 2                      | 2                 | 8                 |
| 36              | 4                    | 4                | 0                | 3                      | 3                 | 5                 |
| 40              | 4                    | 4                | 2                | 4                      | 3                 | 5                 |
Table 7: Interdiction recommendations from MFNIP and MFNIP-R for Network 4

| Attacker Budget | MFNIP Int Trafficker | MFNIP Int Bottom | MFNIP Int Victim | MFNIP-R Int Trafficker | MFNIP-R Int Bottom | MFNIP-R Int Victim |
|-----------------|----------------------|------------------|------------------|------------------------|-------------------|-------------------|
| 8               | 0                    | 2                | 0                | 0                      | 1                 | 2                 |
| 12              | 1                    | 1                | 1                | 1                      | 0                 | 4                 |
| 16              | 1                    | 2                | 1                | 1                      | 0                 | 6                 |
| 20              | 2                    | 2                | 1                | 1                      | 0                 | 8                 |
| 24              | 2                    | 3                | 1                | 2                      | 1                 | 5                 |
| 28              | 2                    | 2                | 5                | 2                      | 1                 | 7                 |
| 32              | 3                    | 3                | 2                | 3                      | 2                 | 5                 |
| 36              | 3                    | 4                | 2                | 3                      | 3                 | 5                 |
| 40              | 3                    | 4                | 5                | 4                      | 3                 | 5                 |

Table 8: Interdiction recommendations from MFNIP and MFNIP-R for Network 5

| Attacker Budget | MFNIP Int Trafficker | MFNIP Int Bottom | MFNIP Int Victim | MFNIP-R Int Trafficker | MFNIP-R Int Bottom | MFNIP-R Int Victim |
|-----------------|----------------------|------------------|------------------|------------------------|-------------------|-------------------|
| 8               | 0                    | 2                | 0                | 0                      | 0                 | 4                 |
| 12              | 0                    | 2                | 2                | 0                      | 0                 | 6                 |
| 16              | 1                    | 2                | 2                | 0                      | 0                 | 8                 |
| 20              | 2                    | 2                | 1                | 0                      | 0                 | 10                |
| 24              | 2                    | 3                | 1                | 0                      | 0                 | 10                |
| 28              | 2                    | 3                | 3                | 1                      | 1                 | 10                |
| 32              | 2                    | 3                | 5                | 1                      | 0                 | 13                |
| 36              | 2                    | 4                | 5                | 2                      | 1                 | 12                |
| 40              | 2                    | 4                | 7                | 2                      | 1                 | 13                |