Human Trafficking Interdiction with Decision Dependent Success

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Abstract

This paper presents a bi-level network interdiction model to increase the effectiveness of attempting to disrupt a human trafficking network under a resource constrained environment. To model the behavior of the trafficker, we present a new interpretation of the traditional maximum flow network problem in which the arc capacity parameter serves as a proxy for the trafficker's desirability to travel along segments of the network. The objective for the anti-human trafficking stakeholder is to invest resources in detection and intervention efforts throughout the network in a manner that minimizes the trafficker's expected maximum desirability of operating on the network. Interdictions are binary, and their effects are stochastic (i.e., there is a positive probability that a disruption attempt is unsuccessful). We present a multi-stage version of the model, which incorporates the effect of interdictions becoming more or less successful over time. Using a genetic algorithm that uses a pseudo-utility ratio for the repair operation, we solve multiple problem instances for a case study of the road network in the Eastern Development Region of Nepal and multiple grid networks. We then discuss observations regarding the impact of probabilistic interdiction success and the implications it has for optimal policies to disrupt a human trafficking network with limited resources.

keywords: maximum flow network interdiction, human trafficking, genetic algorithm

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1 Introduction

Human trafficking is a human rights violation affecting millions of people worldwide and international efforts to prevent, detect, and disrupt these exploitative operations have been growing in recent years. While the precise definition of human trafficking differs from country to country, and even among jurisdictions within the same country, the most widely recognized definition stems from the Palermo Protocol, which was adopted by the United Nations in 2000. In it, human trafficking is defined as "the recruitment, transportation, transfer, harbouring or receipt of persons, by means of the threat or use of force or other forms of coercion, of abduction, of fraud, of deception, of the abuse of power or of a position of vulnerability or of the giving or receiving of payments or benefits to achieve the consent of a person having control over another person, for the purpose of exploitation" (UN General Assembly, 2000). While human trafficking sometimes involves moving victims from one location to another, it is noteworthy to highlight that the definition of human trafficking does not require movement.

Although human trafficking is globally acknowledged, its US$150 billion annual global industry is far from being significantly disrupted (International Labour Office (ILO), 2017). Human trafficking prevalence estimates are notoriously difficult to obtain due to the varying jurisdictional definitions and illicit nature of the crime (Busch-Armendariz et al., 2017). However, the most reliable global estimates indicate that 25 million people were being trafficked on any given day in 2016 for labor and/or sex (International Labour Office (ILO), 2017).

While a substantial amount of human trafficking research has been conducted in the social sciences, most of the prior research has focused on empirical and qualitative insights to describe victim vulnerabilities, public health implications, and law enforcement responses to trafficking (e.g., Chisolm-Straker & Stoklosa (2017); Ortiz (2016); Nichols (2016); Farrell & Kane (2020); Weitzer (2014)). While critically important in its own right, this social science literature has also informed an emerging body of operations research literature aimed at providing actionable insight into optimal mechanisms of disrupting human trafficking operations (Mayorga et al., 2019; Konrad et al., 2017; Caulkins et al., 2019). These papers specifically identify the opportunity for network interdiction models to be used to disrupt human trafficking networks. Conversely, a recent publication identifying emerging areas of network interdiction research also identifies human trafficking as an application area requiring methodological advancements (Smith & Song, 2019).

Network interdiction models can be used to gain insights into the best ways to disrupt a human trafficking network and can be used in contexts in which human trafficking is occurring with or without movement. For example, in the former, network models can be used to represent financial transactions, social connections, and communication patterns. In the latter, network interdiction models can be used to disrupt human trafficking that involves traffickers and/or victims moving throughout a physical network. The model we develop in this paper can be used to disrupt both movement and non-movement network related aspects of human trafficking operations. However, we present the model in the context of disrupting the physical movement involved in human trafficking operations.

For instance, migration has been identified as a system condition that enhances an individual's vulnerability to being trafficked (Seo-Young, 2015). The United Nations Office on Drugs and Crime (2013) states that two-thirds of migrants (not all are being trafficked) in the East Asia and Pacific region use informal crossing points such as rivers and accessible points of the coasts. As we will discuss in the case study presented in this paper, similar informal crossing also occurs along the Nepal/India border. Due to the many border crossing locations, it can be difficult to monitor all possible crossing points in the region for human trafficking activity. This motivates the usefulness of network interdiction models in resource constrained environments.

While the potential benefit of using network interdiction models for human trafficking intervention is suggested in the aforementioned recent operations research literature, to the best of our knowledge, our work is the first to begin to tailor network interdiction models to the nuances of human trafficking on a physical network. The model we present draws assumptions and incorporates nuances of human trafficking from the current social science literature. Yet, information regarding the structure and operations of human trafficking networks is currently limited, and as such, so is the data to populate network interdiction models. Therefore, our model serves as an illustration of the benefit network interdiction models could have for human trafficking disruption efforts and motivates further interdisciplinary collaborations between social scientists and operations researchers to pursue research that identifies robust input parameters and additional factors that need to be incorporated into network interdiction models.

Specifically, we present a bi-level network interdiction model in which there are two players who are self-optimizers based on the other player's actions. Players in our model include the interdictor—who takes an initial action seeking to disrupt the human trafficking network—and the trafficker—who observes the interdictor's actions and operates on the resulting network. We modeled the trafficker's movement using the maximum flow problem where the traditional arc capacity parameters are a proxy for the desirability of a trafficker to operate along that arc rather than a literal interpretation of flow; the interdictor desires to minimize this maximum flow, thereby minimizing the trafficker's desirability of operating on the network. Interdiction decisions are binary and attempt to reduce the capacity of an arc to zero. However, the result of the decision is stochastic; there is a positive probability that an interdiction decision on an arc is unsuccessful and doesn't have any effect on the arc capacity. Additionally, our model is multi-staged and interdiction decisions affect the probability of successful interdiction in future stages. This assumption is inspired by human trafficking literature that states the training and information gained from previous interdictions give interdictors signals about how traffickers operate in an area (**?**). On the other hand, traffickers adapt their operations over time in response to interdictions to avoid detection (Surtees, 2008). This adjusted success probability dynamic results in nonlinearities within the model, motivating us to use a genetic algorithm with a novel repair function to solve the model.

We illustrate the impact network interdiction models can have on disrupting human trafficking operations through a case study involving census data and the road network from the Eastern Development Region of Nepal. Due to the available data, this paper primarily focuses on law enforcement as interdictors. However, we note that there are many types of non-law enforcement related interventions to human trafficking that could be considered by other types of interdictors, including basic needs provision, prevention efforts, increasing access to human trafficking hotlines and services for survivors, training healthcare staff to recognize potential signs of trafficking, and labor inspections. Thus, nonprofit organizations, healthcare providers, public health officials, policy makers, and government agencies can also be viewed as interdictors. Indeed, recent human trafficking research discusses the need to consider human trafficking interventions outside of the criminal justice system and acknowledges that this multi-faceted approach may yield better outcomes (Farrell, Bright, & de Vries, 2019; Farrell & Kane, 2019; Farrell, Dank, et al., 2019). This highlights the need for additional social science research that focuses on non-law enforcement disruption mechanisms and their efficacy that could also serve as inputs into our model.

The motivating example for this model is non-governmental organization Love Justice International's human trafficking transit monitoring operations in Nepal (Hudlow, 2015). Due to the high trafficking flow between Nepal and India's open border, Love Justice International trains staff to identify possible cases of human trafficking along the border and at key transit points throughout Nepal. These staff don't have the authority to physically interdict the traffickers or stop potential human trafficking victims from crossing the border. However, they can ask screening questions to travellers and notify local law enforcement if they observe indicators of trafficking or connect potential victims to resources to lessen their vulnerability to trafficking. Thus, the transit monitoring approach is a human trafficking disruption mechanism.

Our contributions with this work include: providing one of the first network interdiction models to address human trafficking, creating a multi-stage network interdiction model with decision dependent interdiction success probabilities with the objective of minimizing the maximum flow, re-framing arc capacity parameters as proxies for arc desirability, and developing a novel repair function for a genetic algorithm to solve the resulting nonlinear model.

The remainder of the paper is organized as follows. Section 2 provides a literature review of related network interdiction models. In Section 3, we present the multi-stage stochastic network interdiction model with decision dependent interdiction probabilities. The genetic algorithm for solving the resulting nonlinear model is discussed in Section 4, and Section 5 presents a case study for the Eastern Development Region of Nepal. Finally, in Section 6, we summarize our results and discuss the practicality of the model. We also propose extensions for the model and solution framework.

2 Literature Review

Network interdiction models allow us to analyze human trafficking disruption efforts by modeling both the trafficker's and the interdictor's policies, behaviors, timing, and level of information about the other player. Network interdiction typically models two opposing decision makers on the same network. One decision maker, the defender, is trying to operate on the network as effectively as possible, while the other, the interdictor, takes actions to interrupt the ongoing operation (Smith & Song, 2019). Classical examples consider the defender as a player who desires to protect the network from damage and the interdictor as a player who aims to optimally impair the defender's infrastructure to reduce network utilization (Smith et al., 2013). In the human trafficking case, human traffickers are the defenders that seek to operate their trafficking networks without disruption, while law enforcement and other anti-trafficking stakeholders are the interdictors that attempt to disrupt the trafficking network. As previously mentioned, in this paper, we will refer to law enforcement as the interdictors and traffickers as the defenders.

We now summarize the literature related to illicit network interdiction and broader applications of multi-stage min max flow network interdiction models that incorporate uncertainty.

2.1 Illicit Network Interdiction

While the current literature regarding network interdiction models tailored to the human trafficking context is limited to general overview papers (Caulkins et al., 2019; Mayorga et al., 2019; Smith & Song, 2019; Konrad et al., 2017), network interdiction models have been applied to other illicit network applications, such as drug trafficking and nuclear smuggling. The complex nuances of interdicting illicit networks motivate the need for the extending network interdiction theory, as described in a survey of recent advancements in network interdiction models and algorithms (Smith & Song, 2019).

In recent years, network interdiction models have been used to disrupt drug trafficking (Malaviya et al., 2012; Baycik et al., 2018), nuclear smuggling (Morton et al., 2007; Michalopoulos et al., 2013; Dimitrov et al., 2011; Morton & Pan, 2005), and strengthen border control (Zhang et al., 2018). While, collectively, these papers have considered multi-stage, stochastic extensions to the classic network interdiction model in which players gain information over time, none of the models incorporate all of the features in a maximum flow network interdiction model as we do in this paper.

In Malaviya et al. (2012), the authors model an illegal drug supply chain as a deterministic hierarchical social network and solve a maximum flow network interdiction problem. The authors assume that criminals in the upper echelons of the drug supply chain can only be interdicted if the lower-level criminals are first interdicted to gain more information about the upper-level criminals. This is captured through what the authors refer to as “climbing the ladder” constraints and causes the model to use a multi-stage approach.

While Morton et al. (2007) consider stochastic source and sink nodes to model the lack of knowledge about a smuggler’s operations, the model is a stochastic shortest path network interdiction model rather than a maximum flow network interdiction model. Additionally, the formulation allows the interdictor/leader to increase the resilience of the network by taking monitoring actions on the selected arcs while the smuggler/follower is solving their shortest path problem. Ramirez-Marquez et al. (2010) consider both maximizing the shortest path and minimizing the interdiction strategy cost and therefore come up with a bi-objective approach.

A wide variety of network types have also been considered in illicit network applications. For example, in Malaviya et al. (2012) the network on which interdictions are being made is a social hierarchical drug network where the interdictor climbs up the hierarchy. Kosmas et al. (2020) also consider a social network of a drug trafficking and human trafficking networks to model how an illegal organization can continue to operate after interdictions if the illicit network can replace interdicted arcs or nodes. However, physical networks have also been considered; Morton et al. (2007) consider interdicting nuclear smuggling on a physical network and Baycik et al. (2018) uses a layered drug network which consists of both information and physical networks. The model we present in this paper focuses on interdicting physical networks.

2.2 Multi-stage Min Max Flow Interdiction with Uncertainty

The maximum flow network interdiction problem that serves as the basis for our work is one type of network interdiction model in which the interdictor seeks to minimize the maximum amount of flow the adversary can send through the network (Wood, 1993; Smith, 2010). The deterministic interdiction assumption of the traditional maximum flow network interdiction problem is relaxed by Cormican et al. (1998) to allow stochastic interdictions such that the success of the interdiction is not certain. In other words, the decision to interdict may not result in a successful change to the network. The main case that Cormican et al. (1998) studied is the binary interdiction realization case where an interdiction attempt on an arc either makes the flow capacity for that arc zero or does not affect the capacity at all. Since Cormican et al. (1998), many network interdiction models have focused on minimizing the maximum flow (Smith, 2010), including versions that include uncertainty (Smith et al., 2013; Smith & Song, 2019; Janjarassuk & Linderoth, 2008; Sadeghi & Seifi, 2019). Also, evolutionary algorithms have been investigated for the stochastic network interdiction problem (Ramirez-Marquez et al., 2009).

Uncertainty can arise in network interdiction models in various places. Held & Woodruff (2005) consider interdiction decisions where the underlying network topology is not known with certainty. Morton et al. (2007) aim to find sensor locations on a network that minimizes the expected maximum reliability path for a potential evader. They consider a case where the source-pair of the evader is not known with certainty but according to a distribution. Zhang et al. (2018) are also interested in finding sensor locations on a physical network against evaders with an uncertain source-sink pair, with the goal of minimizing the expected shortest path.

The type of uncertainty we incorporate into the present paper is decision-dependant uncertainty. In network interdiction models with decision-dependent uncertainty, scenario occurrence probabilities depend on the interdiction decision; therefore they are not independent of the model decisions. This makes calculations such as expectations and compound probabilities more complex as they can become nonlinear as scenario probabilities can become variables themselves. An example for this case can be seen in in Sadeghi & Seifi (2019). They first linearize a decision-dependent maximum flow interdiction model by using Laumanns et al. (2014)'s distribution shaping and then use Benders decomposition to solve a decision-dependent network interdiction problem where the inner problem is a maximum flow problem for a single stage. The uncertainty in their model lies in the outcome of an interdiction attempt. Other researchers have used probability chains to reformulate the model to allow decision-dependent probability calculations, such as O'Hanley et al. (2013) who use probability chains to reformulate Morton et al. (2007)'s problem of minimizing the expected maximum reliability path problem. Decision-dependent uncertainty is a more general concept observed in other stochastic programming problems outside of the network interdiction subfield as well, and we refer the authors to models in facility protection and network design for a broader understanding of decision-dependent uncertainty in such (Bhuiyan et al., 2020; Medal et al., 2016).

Another important aspect in a multi-stage model with uncertainties is the timeline of events and decisions. While some multi-stage network interdiction models assume that the interdictor wishes to make an interdiction decision, wait to observe the outcome of the interdiction decisions, and then adapt their strategy for future stages based on the outcome of the present stage (e.g., Ketkov & Prokopyev (2020); Borrero et al. (2016); Held & Woodruff (2005)), we do not assume such "sequential" decision making. Instead, our approach assumes the decision maker wishes to determine the interdiction decisions for all future time periods at once. This is a realistic assumption in many practical cases as creating a multi-time stage human trafficking disruption plan can take a significant amount of resources and time to coordinate. Other researchers have also considered multi-stage models in which the decision maker plans for all upcoming stages at time zero (e.g., Malaviya et al. (2012); Baycik et al. (2018)).

Table 1: A Summary of Relevant Literature

Paper	**Maximum Flow Inner Problem**	**Multi-Stage**	**Stochastic Success Probabilities**
Borrero et al. (2016)		X	
Held & Woodruff (2005)		X	
Janjarassuk & Linderoth (2008)	X		X
Ketkov & Prokopyev (2020)		X	
Malaviya et al. (2012)	X	X	
Morton & Pan (2005)			X
Morton et al. (2007)			X
O'Hanley et al. (2013)			X
Ramirez-Marquez et al. (2009)	X		X
Ramirez-Marquez et al. (2010)			
Sadeghi & Seifi (2019)	X		
Zhang et al. (2018)			X

As we describe above, network interdiction models have been used in disrupting illicit network operations. However, to the best of our knowledge, neither the illicit network interdiction nor the broader network interdiction literature captures all of the features we consider in this paper (see Table 1). Specifically, we consider a multi-stage min max flow problem with decision-dependent uncertainty. In our model, a scenario's occurrence probability depends both on the current stage's and the previous stage's interdiction decisions because of the probability updates we consider. Additionally, our model is one of the first to present a network interdiction model focusing on a human trafficking application and our reinterpretation of the network flow as desirability allows us to represent the decision maker's decision-making from a different point of view.

3 The Model

3.1 Model Description

With this work we aim to aid the prevention, detection, and intervention stages of current human trafficking efforts. Since human trafficking is difficult to identify, we've assumed that trained members of law enforcement have a higher chance of successfully interdicting human trafficking in their region. This assumption is in alignment with previous studies that show providing law enforcement personnel with human trafficking focused training is positively correlated to the number of human trafficking prosecutions (?).

Real world cases also indicate that communities that include survivor input were more successful at addressing human trafficking (Sebastian, 2018; Okech et al., 2012). Human trafficking survivors provide valuable information about trafficking networks, operations, and recruitment methods including how traffickers adapt to interdiction attempts.

In this research, we captured these two assumptions of human trafficking with a bi-level stochastic maximum flow network interdiction model with dynamic interdiction success probabilities. In our model we have two players, the interdictor, who we assume to be law enforcement, and the defender, who we assume to be the human trafficker. We use a maximum-flow to model the the trafficker's decision making process. Rather than a literal interpretation of flow capacity constraints on arcs as is common in most network interdiction literature, we reinterpret the arc capacity parameters to represent the desirability of a trafficker to operate along the arc. In other words, we are assuming the interdictor has expert knowledge about how the trafficker views the network. We amalgamate this information with the trafficker's inherent goal of profiting from factors such as desire for cheap labor and other pulling factors in one part of the network by exploiting vulnerabilities of others in another part of the same network.

In this paper we assume that both the trafficker and the interdictor have the same knowledge of network topology for the trafficking operation and there is no information asymmetry. An extension to the model we present could consider the case in which the anti-human trafficking decision maker doesn't know the trafficker's desirability of operating on each arc to capture more of the hidden/covert nature of traffickers and the anti-trafficking stakeholder learning the trafficker's disabilities over time. A relevant paper with this approach that focuses on discovering hidden parts of the network with the help of interdictions in an evader-interdictor setting is Borrero et al. (2016). However, incorporation of such a dynamic would require a large and granular dataset for a realistic representation of the network learning dynamics and the current human trafficking research lacks such kind of databases.

Another feature of our model is how an interdiction attempt's success gets updated over stages based on the decisions taken previously. We assume initial arc interdiction successes probabilities are given parameters, and when the interdictor is successful at an interdiction, the success probability for that arc gets updated for the next stage. These updates denote either gaining more experience on a certain arc and operating more effectively as a direct result, or revealing previous tactics and losing some of the previous success probability. We give a more detailed explanation and motivate these cases in the human trafficking context in the upcoming sections. However, one important assumption we make in this model is that a successful interdiction will only affect the success probability of that same arc in future time periods. Future extensions to the model could consider interdiction decisions that have a broader effect on the network by changing the success probabilities of neighboring arcs or all other arcs in the network to capture more of the dynamics of trafficker and interdictor behaviors. However, such extensions are outside of the scope of the present study as the current formulation is already challenging to solve without adding these additional network dynamics.

We first describe a single-stage model which incorporates stochastic interdiction success probabilities. We then use this single-stage model to create a base for building the multi-stage extension in Section 3.3, which incorporates dynamic, decision-dependent stochastic interdiction success probabilities.

3.2 Single-Stage Model

Let $G = (N, A)$ be a network which has source and sink nodes s and t, respectively. This network of physical locations as nodes and arcs with flow capacities represents how the trafficker and the interdictor are perceiving the trafficking flows for a geographical region. Therefore, the interdictor desires to minimize the maximum flow between the source and the sink, where we consider the flow as the trafficker's perception of operation ease (or desire to operate) while trafficking from the source to sink nodes. In other words arc capacities denote the operation level the trafficker considers possible without getting caught on that arc before any interdiction decision has been made. To minimize the trafficker's flow, the interdictor can attempt to disrupt arcs in the network.

Mathematically, these interdiction decision variables are represented with a vector $\mathbf{y}$, where y_{ij} takes value 1 if arc (i, j) is attempted to be interdicted and 0 if not. We let I_{ij} be the auxiliary interdiction effectiveness variable identifying whether arc (i, j) is successfully interdicted ($I_{ij} = 1$) or not ($I_{ij} = 0$). We will impose constraints such that when no interdiction attempt is made on arc (i, j) (i.e., when $y_{ij} = 0$), I_{ij} is equal to 0. On the other hand, if an interdiction attempt is made (i.e., when $y_{ij} = 1$), I_{ij} becomes 1 with probability p_{ij}; otherwise it is 0. Attempted interdiction either fully reduces the arc capacity to 0 or it does not affect the arc at all. We let Ω be the space of all possible scenarios with $\omega \in \Omega$ representing an outcome scenario. Parameter c_{ij} is the required cost for attempting an interdiction on the arc (i, j) and R is the budget of the interdictor. The optimal value of the trafficker's maximum-flow problem based on the interdictor's decisions ($\mathbf{y}$) and their realizations ($\mathbf{I}$) under scenario ω is denoted by $Q(\mathbf{y}, \mathbf{I}^{\omega})$. With this notation, the interdictor's problem is:

$$\underset{\mathbf{y}}{\text{minimize}}\ E[Q(\mathbf{y}, \mathbf{I}^{\omega})] \tag{1}$$

$$\text{subject to} \sum_{(i,j)\in A} c_{ij} y_{ij} \leq R \tag{2}$$

$$y_{ij} \in \{0,1\} \quad \forall (i,j) \in A \tag{3}$$

Objective function (1) minimizes the expected value of the maximum-flow through the network from source node s to sink node t. Therefore, $E[Q(\mathbf{y}, \mathbf{I}^{\omega})]$ can be represented as $\sum_{\omega\in\Omega} P_{\mathbf{y}}(\omega)Q(\mathbf{y}, \mathbf{I}^{\omega})$, where $P_{\mathbf{y}}(\mathbf{I}^{\omega})$ is the probability that realization $\mathbf{I}^{\omega}$ will occur under the probability space created by the decision $\mathbf{y}$, which we will discuss in detail shortly. Constraint (2) is the resource limitation constraint for the interdictor and constraint (3) is the domain of the decision variables.

Without loss of generality, we can order each arc in the network from 1 to $|A|$.Then, combining all arc interdiction decisions, realizations for a network under an interdiction decision can be represented with, $\mathbf{I} = \{I_1, I_2, ..., I_{|A|}\}$. This allows the probability of a realization on the network under interdiction decision $\mathbf{y}$ to be represented as a multiplication of arc realizations since we assume independence between arcs (Laumanns et al., 2014). We define the binary arc realization probabilities under interdiction decision $\mathbf{y}$ for all $(i,j) \in A$ as:

$$P_{\mathbf{y}}\{I_{ij} = I_{ij}^{\omega}\} = \begin{cases} y_{ij}p_{ij} & I_{ij}^{\omega} = 1 \\ (1 - y_{ij}) + y_{ij}(1 - p_{ij}) & I_{ij}^{\omega} = 0 \end{cases}$$

If an arc interdiction decision is given, (i.e., $y_{ij} = 1$) the arc realization corresponding to the successful interdiction (i.e., $I_{ij} = 1$) has a probability of p_{ij}. On the other hand, a failed attempt will have a probability of $(1 - p_{ij})$ for the arc. However, if no interdiction attempt for the arc is present, the realization must be zero as well, which is satisfied with the given definition.

Now using the arc realizations we can define a full network realization, or in other words, a scenario. The probability of scenario ω happening under decision $\mathbf{y}$ can be defined as;

$$P_{\mathbf{y}}\{\mathbf{I} = \mathbf{I}^{\omega}\} = \prod_{(i,j)\in A} P_{\mathbf{y}}\{I_{ij} = I_{ij}^{\omega}\}$$

This definition of the decision-dependent scenario probabilities creates a probability space when we consider all of the possible realizations under a given interdiction decision. To see why, think of a set of $|A|$ coins where the probability of flipping a head on a single coin is p_{ij}. Then the interdiction decision becomes which coins we are selecting to flip. Therefore, the size of the scenario space is changing with the interdiction decision. However, with the above given definitions, we can still find scenario probabilities as a joint distribution of arc realizations.

As the effect of anti-human trafficking efforts varies with respect to where the intervention occurs, we choose to allow the model to incorporate different interdiction success probabilities for each arc. We will use these probabilities and update their values based on our previous interdiction actions to estimate how our previous encounters with trafficking operations can impact future attempts' success. We will elaborate more on how these probabilities can be estimated in Section 5 when we discuss a case study.

The trafficker's subproblem for scenario $\omega \in \Omega$ can be seen below where $\overline{A}$ is the modified version of arc set A with the arc (t, s) included, i.e $\overline{A} := A \cup (t, s)$. This inclusion of the artificial return arc (t, s) with an infinite (or very large) capacity allows us to reformulate the maximum flow problem as a network flow problem (Bertsimas & Tsitsiklis, 1997):

$$Q(\mathbf{y}, \mathbf{I}^{\omega}) = \underset{\mathbf{x}}{\text{maximize}}\ x_{ts} \tag{4}$$

$$\text{subject to} \quad 0 \leq x_{ij} \leq u_{ij}(1 - I^{\omega}_{ij} y_{ij}) \quad \forall (i,j) \in \overline{A} \tag{5}$$

$$\sum_{j \in FS(i)} x_{ij} - \sum_{j \in RS(i)} x_{ji} = 0 \quad \forall n \in N \tag{6}$$

In this optimization problem, objective (4) represents a trafficker's desire to maximize the flow through the network. The trafficker does this by maximizing the flow on arc x_{ts} after the interdictor decides which flows to attempt to interdict ($\mathbf{y}$) and the extent to which the attempts are successful ($\mathbf{I}^{\omega}$) are observed. Constraints (5) are the set of equations for the stochastic arc capacities. If arc (i, j) isn't successfully interdicted, the capacity remains at u_{ij}. However, if an interdiction is successful, the capacity of the arc is reduced to 0. Constraints (6) are flow balance constraints for each node on the network, where the forward star of i, $FS(i)$, denotes the set of arcs directed out of node i and the reverse star of i, $RS(i)$, denotes the set of arcs directed into i.

Note that the same $\mathbf{I}^{\omega}$ can be observed under different interdiction decisions as the scenario spaces that interdiction decisions create are not necessarily disjoint and share common scenarios (i.e., successfully interdicted network instances). Therefore, maximum-flow values for these realizations should be identical as well. However, their probability coefficient in the expectation calculation can be different for every probability space that the interdiction decision $\mathbf{y}$ creates. So, if we calculate maximum flows under all possible scenarios (interdicted networks), the single level problem becomes finding the minimum flow expectation yielding a probability space with a feasible set of binary arc interdictions.

As previously mentioned, in our model the capacity parameter can be regarded as a proxy for the traffickers' desire to use certain arcs. Human trafficking literature has identified the push and pull factors that increase an area's vulnerability to trafficking, but the marginal effect of these factors remain difficult to quantify. With the flow capacity serving as a 'trafficking desirability' proxy, we provide an initial attempt to create such a parameter. This proxy is one of the main reasons why we choose to model the human trafficking network interdiction problem as a maximum flow problem; we use the arc capacities to have a bottleneck effect on the the trafficker's operations rather then an additive effect like in the shortest path problem.

3.3 Multi-Stage Network Interdiction Model

In the single-stage model, the interdictor attempts to disrupt some of the arcs in order to minimize the max-flow of the trafficker. However, in reality, trafficking interventions occur over time and the impact they have varies due to traffickers adapting to previous interventions or anti-trafficking stakeholders becoming more effective as more information is gained about the network. We incorporate this dynamic by extending the single-stage model to a multi-stage framework in which we consider updates to the probability of successfully interdicting an arc in future stages if the arc was successfully interdicted in the previous stage. An interdiction does not change the network structure for the next stage; rather, it updates the interdiction success parameters for future stages.

3.3.1 Interdiction Success Parameter Update

Let K represent the set of stages. Similar to the single-stage model, the probability of interdiction success for an arc (i, j) during stage $k \in K$ is denoted p_{ij}^k. In the multi-stage model, a successful interdiction has two effects: one short-term and one long-term.

The short term effect eliminates the trafficker's desire to use arc (i, j) in their trafficking operation in stage k by reducing the capacity of the arc to 0 for the current stage. Consistent with the human trafficking literature, we assume that the capacity of a successfully interdicted arc is only reduced for the current stage. That is, if interdiction efforts aren't implemented on arc (i,j) in future stages, traffickers may once again find arc (i,j) desirable.

The long term effect of a successful interdiction affects future interdiction success probabilities; we assume that every successful interdiction on an arc (i,j) will update the probability of the next stage's interdiction success on the same arc (i,j). We model this update in success probability with the rate parameter Δ. Specifically, we let $-1 \leq \Delta \leq 1$ denote a measure of the percent change in the interdiction success probability. Its scalar value represents how much new information is worth to the system, and its sign represents who favors from this update.

Positive update rates, $0 < \Delta \leq 1$, indicate that the interdictor is becoming more successful at reducing trafficking in an area with each successful interdiction. This can happen under the case where law enforcement is discovering the modus operandi of the trafficking operation on an arc and then using this information to obtain a higher likelihood of success in further interdictions. For example, a rate of 0.5 means that with each new successful interdiction on arc (i,j), the probability of successful interdiction on arc (i,j) increases by fifty percent of the remaining amount (i.e., 50% of $1 - p_{ij}^k$). That is, an arc that had a $p_{ij}^k = 0.8$ probability of successful interdiction in stage k would increase to the probability $p_{ij}^{k+1} = 0.9$ in stage $k+1$ if the interdiction in stage k was successful.

On the other hand, successful interdictions can create updates in the favor of the trafficker as well. This corresponds to update rates $-1 \leq \Delta < 0$ and represents the percent reduction in interdiction success in future stages. If a trafficker is interdicted on a specific arc, other traffickers may gain knowledge about the interdiction tactics of law enforcement in a manner that allows them to continue operating on the arc with a lower chance of being detected. Therefore, successful interdictions may reduce the likelihood of future successful attempts on an arc. For example, a rate of -0.5 means that with each new successful interdiction on arc (i,j), the probability of successful interdiction on arc (i,j) decreases by the fifty percent (i.e., 50% of p_{ij}^k). That is, an arc that had a $p_{ij}^k = 0.8$ probability of successful interdiction in stage k would decrease to a $p_{ij}^{k+1} = 0.4$ likelihood of successful interdiction in stage $k+1$ if the interdiction in stage k was successful.

However, as this is a stochastic model with the outcome of interdictions represented by scenarios, the probability updates for the arcs are also represented in expectation terms. We introduce the following equations to update interdiction probabilities for the arcs at each stage. (Note that $\mathbf{y}$ and $\mathbf{I}$ have also been indexed by stage for the multi-stage model.)

$$p_{ij}^{k+1} = \begin{cases} \mathrm{p}_{ij}^{k} + (1 - p_{ij}^{k}) y_{ij}^{k} E[I_{ij}^{k}]\Delta & 0 \leq \Delta \leq 1 \\ \mathrm{p}_{ij}^{k} + p_{ij}^{k} y_{ij}^{k} E[I_{ij}^{k}]\Delta & -1 \leq \Delta < 0 \end{cases} \tag{7}$$

We also use the notation $P_{\mathbf{y}}^{k}(\mathbf{I}^{\omega})$ to denote the scenario probability for scenario ω, which is generated by the interdiction decision $\mathbf{y} = (\mathbf{y^1}, \mathbf{y^2}, ..., \mathbf{y^K})$. Each vector $\mathbf{y^k}$ denotes the corresponding stage's interdiction decision. It is important to note that the future stages' decisions do not effect previous stages' probability spaces. We use the full interdiction vector $\mathbf{y}$ to be consistent. Calculation for the scenario probabilities under interdiction are done similar to the single-stage case, with one major difference. For the first stage, interdiction probabilities are parameters and they become active or not depending on the first stage's interdiction decision. Starting from the second stage, arc interdiction probabilities become variables and change values depending on the previous stage's interdiction decision.

Example with Positive Rate Parameter: To illustrate how the update equation works, consider a network with just two nodes, node A and node B, and a single arc connecting them (AB). Suppose the probability that the interdictor successfully interdicts this arc if she attempts to is 80% initially ($p_{AB}^{1} = 0.8$) and the update rate is 50% ($\Delta = 0.5$). When the interdictor attempts to interdict arc (AB), there are two possible scenarios: the interdiction is successful with probability $P^{k=1}(I^{\omega} = 1) = p_{ij}^{1} = 0.8$ (as there is only one arc on the network), which results in $I_{AB}^{1} = 1$; or the interdiction is unsuccessful with probability $P^{1}(\omega = 2) = 1 - p_{ij}^{1} = 0.2$, which results in $I_{AB}^{2} = 0$. Under scenario 1, where the arc is successfully interdicted, the probability of successful interdiction in the next stage becomes $p_{AB}^{k=2,\omega=1} = 0.8 + (1 - 0.8) * 1 * 1 * 0.5 = 0.9$. Under scenario 2, where the interdiction attempt fails, there is no increase in probability ($p_{AB}^{k=2,\omega=2} = 0.8$). Therefore, the expected updated probability under the decision of attempting to interdict arc (AB) becomes $p_{AB}^{2} = 0.8 * 0.9 + 0.2 * 0.8 = 0.88$.

Example with Negative Rate Parameter: If the update rate was instead $\Delta = -0.5$, then the successful interdiction in scenario 1 would result in a probability of successful interdiction of $p_{AB}^{k=2,\omega=1} = 0.8 + 0.8 * 1 * 1 * (-0.5) = 0.4$ in the next stage. If the interdiction attempt was unsuccessful (i.e., scenario 2), there is no change in the success probability ($p_{AB}^{k=2,\omega=2} = 0.8$). Therefore, the expected updated probability under the decision of attempting to interdict arc (AB) becomes $p_{AB}^{2} = 0.8*0.4+0.2*0.8 = 0.48$.

We use the percentages for the rate variable, Δ, first and foremost to model the changing incremental effect of the information gained (i.e., successful interdictions provide information). Since this is a normalized parameter, the magnitude of its effect depends on the initial success probabilities, p_{ij}^1. For example, when $0 < \Delta$, if the initial probabilities (p_{ij}^1) are very low, the interdictor will gain a greater marginal increase in future interdiction success probabilities than compared to a p_{ij}^1 value near 1. The motivation for this is that a low probability of success may correspond to the interdictor not having much information about the trafficking network. Any successful interdictions when the interdictor doesn't have much information about the network could have a drastic difference as it provides insights into the ongoing human trafficking network in the area. On the other hand, if law enforcement is already effective against the traffickers, successful interdictions will only have a fine-tuning effect, i.e. they will still increase the success probability but in a relatively slight margin.

Symmetrically, if the initial probabilities (p_{ij}^1) are very low and $\Delta < 0$, the trafficker is able to fine tune their evasion tactics to avoid interdiction. If the initial probabilities (p_{ij}^1) were much higher, the trafficker has more opportunity to reduce their likelihood of interdiction in future stages.

With the multi-stage nature of the model, the budget parameter R and the cost parameter c can become stage dependent as well. Recourse variables and decision variables also depend on the stage of the problem from now on. For the multi-stage version of the model, scenario probabilities can be found using the multiplication of arc realization probabilities given below. As previously mentioned, the p_{ij}^k's can be found using the probability update formula given the interdiction vector $\mathbf{y}$:

$$P_{\mathbf{y}}^k\{I_{ij} = I_{ij}^{\omega}\} = \begin{cases} \mathrm{y}_{ij}^k p_{ij}^k & I_{ij}^{\omega} = 1 \\ (1\text{-}\mathrm{y}_{ij}^k) + y_{ij}^k(1 - p_{ij}^k) & I_{ij}^{\omega} = 0 \end{cases}$$

3.3.2 Model Formulation

The formulation for the multi-stage stochastic network interdiction with probability updates can be seen below for the case of $0 \leq \Delta \leq 1$. The only change required for model formulation to account for the case of $-1 \leq \Delta \leq 0$ is replacing constraint (11) with the associated $-1 \leq \Delta \leq 0$ equation from (7).

$$\underset{\mathbf{y},\mathbf{p}}{\text{minimize}} \sum_{k \in K} E^k[\ Q^k(\mathbf{y}, \mathbf{I}^{\omega})] = \sum_{k \in K} \sum_{\omega \in \Omega} P^k(\omega) Q^k(\mathbf{y}, \mathbf{I}^{\omega}) \tag{8}$$

$$\text{subject to} \sum_{(i,j)\in A} c_{ij}^k y_{ij}^k \leq R^k \quad \forall k \in K \tag{9}$$

$$y_{ij}^k \in \{0,1\} \quad \forall (i,j) \in A, \forall k \in K \tag{10}$$

$$p_{ij}^{k+1} = p_{ij}^k + (1 - p_{ij}^k) y_{ij}^k E[I_{ij}^k]\Delta \quad \forall (i,j) \in A, \forall k \in \{0, ..., K-1\} \tag{11}$$

In the above formulation, objective function (8) seeks to minimize the summation of the expected maximum flows over every stage. Constraints (9) are the set of resource constraints for every stage, where each stage has its own budget that does not roll over into future stages. Constraint set (11) ensures that for each arc the probability of the next stage is updated based on the current decision, its expected realization, probability of success, and the update rate. This constraint connects consecutive stages according to the hitherto mentioned probability updates. Finally, constraint set (10) is the domain of the interdiction decision variables $\mathbf{y}$.

At each stage, the trafficker solves the following max-flow problem based on the interdiction decisions $\mathbf{y}$ and their outcomes $\mathbf{I}^\omega$.

$$Q^k(\mathbf{y}, \mathbf{I}^\omega) = \underset{\mathbf{x}}{\text{maximize}}\ x_{ts}^k \tag{12}$$

$$\text{subject to} \sum_{j\in FS(i)} x_{ij}^k - \sum_{j\in RS(i)} x_{ji}^k = 0 \quad \forall i,j \in N \tag{13}$$

$$0 \leq x_{ij}^k \leq u_{ij}(1 - I_{ij}^\omega y_{ij}^k) \quad \forall (i,j) \in A \tag{14}$$

4 Solution Approach

One common approach to solve network interdiction models is to take the dual of the inner maximization problem and combinine it with the outer minimization problem (Smith et al., 2013; Cormican et al., 1998). This allows the bi-level min-max problem with different objective functions to be transformed into a single minimization problem. The dual of the follower's max flow problem is given below with dual variables α_n and β_{ij} corresponding to (13) and (14).

$$Q_k^\omega(\mathbf{y}, \mathbf{I}^\omega) = \underset{\alpha,\beta}{\text{minimize}} \sum_{(i,j)\in A} (u_{ij}(1 - I_{ijk}^\omega y_{ijk}))\beta_{ijk}^\omega \tag{15}$$

$$\text{subject to } \alpha_{ik}^\omega - \alpha_{jk}^\omega + \beta_{ijk}^\omega \geq 0 \quad \forall (i,j) \in A, \quad \forall i,j \in N \tag{16}$$

$$\alpha_{tk}^\omega - \alpha_{sk}^\omega \geq 1 \tag{17}$$

$$\beta_{ijk}^\omega \geq 0 \quad \forall (i,j) \in \overline{A} \tag{18}$$

Combining this problem with the leader's problem we can obtain the equivalent problem:

$$\underset{\mathbf{y},\alpha,\beta}{\text{minimize}} \sum_{k \in K} E[\, Q_k(\mathbf{y}, \mathbf{I}^\omega)] = \sum_{\substack{k \in K \\ \omega \in \Omega}} \mathbb{P}_k(\omega) \sum_{(i,j) \in A} (u_{ij}(1 - I^\omega_{ijk} y_{ijk}))\beta^\omega_{ijk} \tag{19}$$

$$\text{subject to} \sum_{(i,j) \in A} c_{ijk} y_{ijk} \leq R_k \quad \forall k \in K \tag{20}$$

$$y_{ijk} \in \{0, 1\} \quad \forall (i,j) \in A, \forall k \in K \tag{21}$$

$$p_{ij,k+1} = p_{ijk} + (1 - p_{ijk}) y_{ijk} E[I_{ijk}]\Delta \quad \forall (i,j) \in A, \forall k \in \{0, ..., |K| - 1\} \tag{22}$$

$$\alpha^\omega_{tk} - \alpha^\omega_{sk} \geq 1 \omega \in \Omega \quad k \in K \tag{23}$$

$$\alpha^\omega_{ik} - \alpha^\omega_{jk} + \beta^\omega_{ijk} \geq 0 \quad \forall (i,j) \in A \tag{24}$$

$$\beta^\omega_{ijk} \geq 0 \quad \forall (i,j) \in \overline{A}, \omega \in \Omega, k \in K \tag{25}$$

We note that it is not possible to solve the above problem directly with traditional linear programming methods due to the the nonlinearity introduced by the scenario probability term in the objective. Specifically, the $P^k_{\mathbf{y}}(\omega)$ terms contain the multiplication of the binary arc interdiction decisions and interdiction probabilities (which are themselves decision variables after the initial stage due to constraints (11)). We also multiply this with the corresponding value of the minimum cut which creates a nonlinear term. Therefore, we cannot use standard integer programming solution approaches. Instead, we use a genetic algorithm (GA) to solve the model with nonlinearities.

4.1 Genetic Algorithm for the Maximum Flow Network Interdiction Model

Briefly, GAs are methods for searching a solution space for solutions with the highest (or lowest, depending on the type of the objective) objective values (Mitchell, 1998; Haupt & Haupt, 2004). Motivated by biological evolution, GA terminology usually refers to solutions as *individuals* and objective functions as *fitness functions*. Each individual is composed of multiple *bits* representing specific decision variable values. To be consistent with the nomenclature we will use the same terminology as well.

GAs and evolutionary algorithms are a common method of solving network interdiction problems (Ramirez-Marquez et al., 2010; Dai & Poh, 2002; Ramirez-Marquez et al., 2009). Dai & Poh (2002) uses a GA to solve the deterministic maximum flow network interdiction model on a directed graph where each individual represents a cut in the network. Inspired by this approach, we developed a GA for our problem. However, one major difference is in how we define the individuals. Since Dai & Poh (2002) only considers a single-stage deterministic model, each bit in an individual represents which side the corresponding node belongs to after the network is partitioned by a cut. However, since we consider a multi-stage model and we have also coded the interdiction decisions over the arcs, the individuals we consider consist of bits that represent an interdiction decision at stage k for the corresponding arc. Therefore, the individuals in our solution effectively consist of $|K|$ copies of the individuals that are present in a single-stage version, one for each stage.

The operations of our GA are described below and a summary of all related GA parameters is given in Table 2. Pseudo-code for the GA is provided in the Appendix.

4.1.1 Representation and Fitness Function

Each individual is a binary string of length of $|A| * |K|$ where A is the set of arcs and K is the set of stages. If an arc a is attempted to be interdicted at stage k the corresponding bit (a, k) takes the value 1; otherwise it is 0. Therefore an individual includes interdiction decisions for all of the stages.

To evaluate the fitness of an individual, we first generate the possible interdicted networks for each stage with their corresponding probabilities by using $P_{\mathbf{y}}(\omega)$. Then, we solve the deterministic maximum flow problem for each scenario w and take the expectation over all scenarios by using the hitherto calculated probabilities for each stage. While we are moving on from the first stage, we also update the interdiction probabilities according to the probability update functions we introduced in the multi-stage problem. Therefore, depending on the rate, each stage yields different flow amounts and we determine these values iteratively for an individual. Finally, we sum the expected maximum flows over the stages to calculate the fitness of an individual.

4.1.2 Creating the Initial Population

Due to our knapsack constraint (9), we use the primitive primal heuristic from Chu & Beasley (1998) to generate an initial population. This algorithm ensures all individuals in the initial population are feasible by starting with all variables as zeros and then randomly picking a variable and making it one unless it makes the individual infeasible. A population size of 100 individuals was used and was determined through initial experiments that were shown to quickly converge to near-optimal values.

4.1.3 Parent Selection

Parent selection is the operation of selecting individuals from the current population in order to conduct reproduction operations, namely crossover and mutation. We have used the tournament selection method with a tournament size of 4 individuals and fitness scaling to ensure that we favor better performing individuals more than their raw fitness score (see Shukla et al. (2015) for tournament selection and other selection techniques in GAs).

4.1.4 Crossover and Mutation

Crossover and mutation are reproductive operations to iterate the GA. After the parent selection operation, we have a set of individuals from the current population to generate the new population. We implemented a uniform crossover function which takes the input as two parents from the parent selection and a random string of zeros and one. It then assigns the values from the first parent to the new individual where the random string has values equaling one and assigns values from the second parent where the random string has values equaling zero. Therefore the output becomes a new individual from two parents.

The mutation operation essentially changes the bits of the individual following a probability distribution with an aim of reducing the chance of getting stuck at local optimums. We have used the bit flip mutation as we have binary values. This operation flips (changes the ones to zeros and the zeros to ones) the value if the bit is selected to be mutated. In other words, for an individual that will go through the mutation operation, we first select which bits to mutate and then flip them. We have mutated 10% of selected individuals.

We also let 90% of the population be generated from the crossover operation, 5% from the mutation and the rest from the elites. Elite individuals are the best fitness function yielding individuals that carry-on through the iterations.

4.1.5 Repair Operation

As can be seen from above reproduction operations, we do not consider the budget constraint while conducting crossover and mutation, which might generate infeasible individuals for the new generation. Searching through infeasible solutions is not an efficient use of solution time.

To handle individuals that exceed the budget constraint and to restrict the random search to the feasibility set, we implemented an approach that uses pseudo-utility ratios tailored to our network interdiction model with dynamic interdiction success probabilities. In their 1998 paper, Chu & Beasley showed that these types of operations perform well for a search with knapsack constraints. Our pseudo-utility ratio considers the expected capacity of an interdicted arc (i, j) and the cost required to attempt the interdiction: $\frac{E[capacity]}{cost} = \frac{p_{ijk} * u_{ij}}{c_{ijk}}$. This value is an estimate of the interdictor's utility of interdicting each arc on the network.

The repair operator uses the ratio as follows. If the individual is infeasible, the operator starts removing interdiction decisions from the individual for the given stage, starting from the lowest pseudo-utility yielding arcs. It is important to note that these values are pre-processed before the algorithm starts iterating. The operator removes arcs in this manner until it becomes feasible. After the individual becomes feasible, the operator starts adding interdiction decisions, now, starting from the highest ratio yielding ones, while considering the budget. The operation terminates when we can not add any more interdiction decisions while staying feasible.

4.2 Termination Criteria

The GA terminates when negligible or no improvement is observed between the last 10 generations' best (i.e., lowest fitness function yielding) individuals. We have accepted improvements over 0.0001% of the current fitness function as significant and selected the number of stalling generations to be 10 to avoid getting stuck at local optimums. A termination guarantee condition that stops the algorithm after 100 iterations/generations is also specified, although this condition never became active in our experiments.

Table 2: Genetic Algorithm Parameters

Parameter	Description	Value
PopSize	Population size	100
TournSize	Tournament size	4
ElitePop	Percentage of population generated by keeping elite individuals	5
CrossoverPop	Percentage of population generated by crossover	90
MutatePop	Percentage of population generated by mutation	5
MutateProb	Fraction of individual mutated	0.1
MaxIter	Maximum number of iterations	100
MaxIterNoImprove	Maximum number of iterations with no improvement	10

4.3 Grid Networks

We test our GA on grid-like networks in the spirit of papers like Atamturk et al. (2018) and Janjarassuk & Linderoth (2008). We generate an $a \times b$ rectangular grid network with a horizontal layers of b nodes each. In these networks horizontal arcs are directed in the orientation of the source and the sink. Vertical arcs are oriented randomly.

With these numerical experiments, we aim to illustrate how our GA works and how our problem's solution space differs from other stochastic network interdiction problems due to decision-dependent success probabilities.

We have selected two grid networks for our experiments. The first is a 3×3 grid network, which we will denote as the small network. The second is a 5×5 grid network and we will denote this network as the large network. In the small network we allow all of the arcs to be interdicted and in the large network we allow half of the arcs in the grid to be interdicted. These interdictable arcs are shown in the Figure 1 with dashes and in red for the large network; the small network can be seen in the Appendix. For each network we denote the source and sink nodes with square shapes. The source node is indicated by node 1 in both networks, and node 11 and 27 in the small and large networks, respectively. Horizontal arcs are arcs that are directed in the immediate direction from the source to the sink, such as arc (1,4) in the large network. An example for a vertical arc from the large network is arc (3,4). Our network sizes are comparable to the smaller networks Janjarassuk & Linderoth (2008) consider, yet is computationally difficult due to the probability updates; each stage's decision changes the other stage's success probabilities and therefore the scenario probabilities became decision variables rather than parameters, adding to the complexity.

We have generated random arc capacities and the initial interdiction probabilities for the arcs are from uniform distributions with ranges from 1 to 10 and from 0 to 1, respectively. Arc capacities and the initial interdiction probabilities can be seen on the arcs with the corresponding pseuodo-utility in the format of (cost, interdiction probability, psuedo-utility). We use unit costs of interdiction for each arc.

We benchmark the performance of the GA with the optimal solutions we obtained from complete enumeration. In this section we will discuss how well the GA converged in our experiments and the effect of the budget on the solutions. As these networks and their parameters are not generated specifically for the trafficking context, we will conduct our policy related discussion in the case study section.

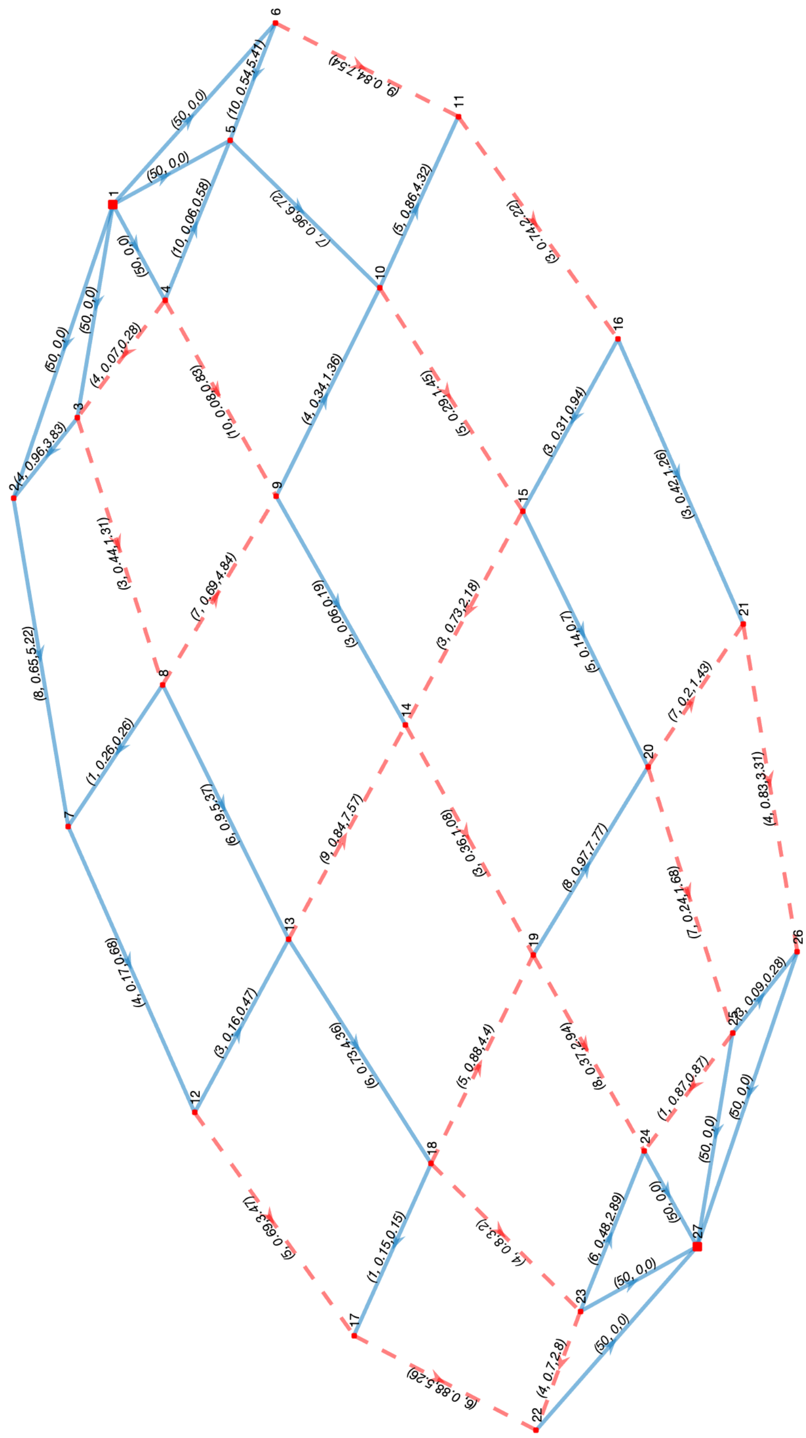

Figure 1: Large Networks

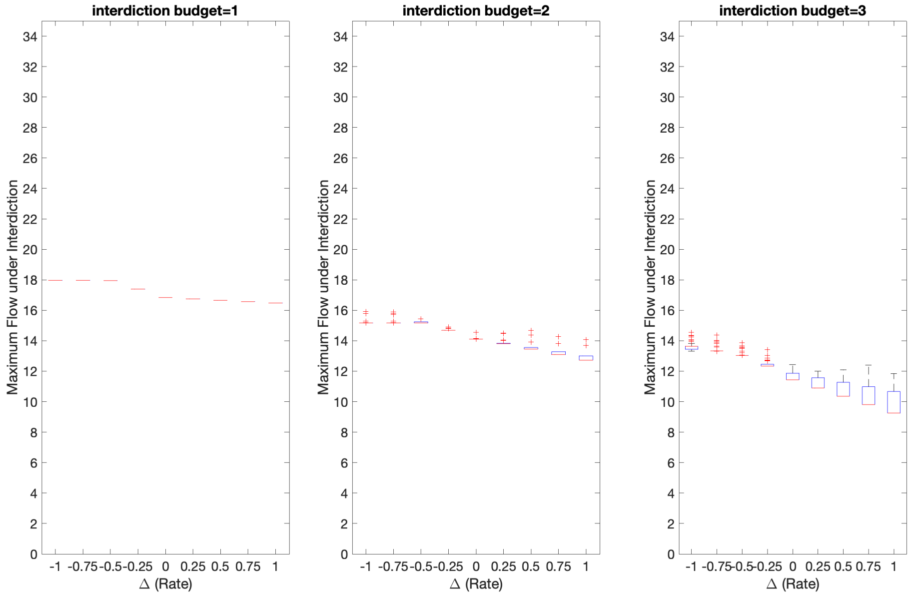

Figure 2: GA Performance on 3x3 Grid Network

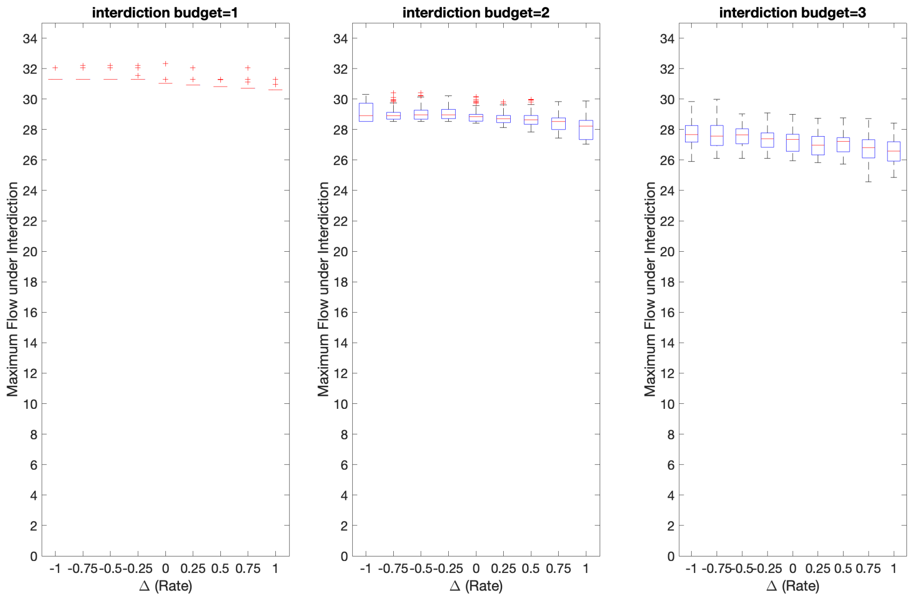

Figure 3: GA Performance on 5x5 Grid Network

Figure 2 and Figure 3 show how well the GA performed for both networks. We present the results of the GA with box plots to present the results of 100 experiments for each setting and the optimal solutions. Our first observation is the increase in the spread of the solutions that GA converged to as the budget increases for each network. This is an expected observation as the solution space gets larger when the interdiction budget increases. We also observe an increase in the spread as the rate parameter increases within the same budgets for both networks.

We also observed that when the rate is positive the optimal solutions always consist of having the same set of interdictions in the first and the second stages. Therefore, we have created a modified GA (MGA) that forces the first and the second stage interdictions to be identical. We discuss the reasoning behind this in greater detail in Section 5.2.1.

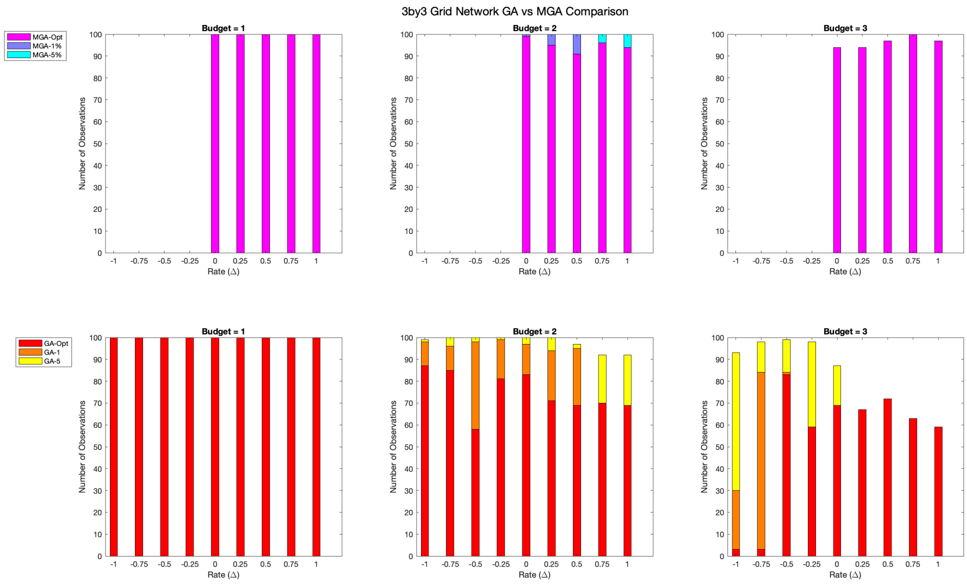

Figure 4: GA and Modified GA Performance on 3x3 Grid Network

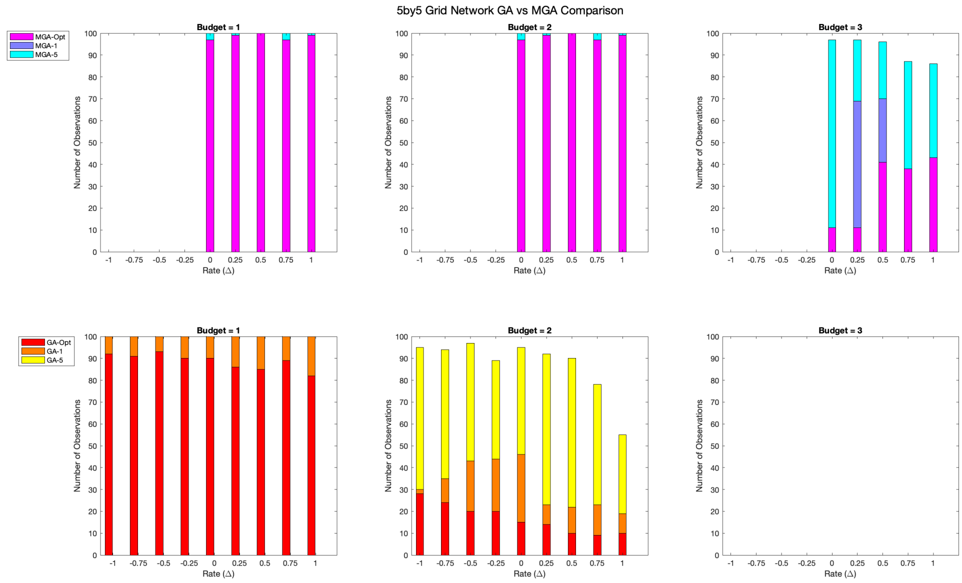

Figure 5: GA and Modified GA Performance on 5x5 Grid Network

We can see this in more detail in Figure 4, as well which shows how the best GA solutions in the 100 runs found the optimal solution, or a solution within 1% or 5% of the optimal solution. We observe that most of the GA runs converged to the optimal solution which we have found by enumeration. MGA provided better results for positive rate values as we illustrate in Figure 4 and Figure 5. On the first row of Figure 4 we observe the MGA converging to optimal solutions more frequently compared to the GA. As GAs iterate in a stochastic fashion we present the cases where the algorithm converges to sub-optimal solutions as well. From these experiments we observe that the convergence to sub-optimal solutions became more frequent when the interdiction budget increases. To give an example, the worst performing set of experiments are from interdiction budget is equal to 3. In this setting, when the rate is 1, the GA found the optimal solution in 59% of the experiments for the small network, and 88% of the solutions were within 15% of the the optimal solution. For the large network, the GA's performance dropped and it wasn't able to converge to any solution within 5% of the optimal solution. However for this instance, we observe MGA converging to optimal or near-optimal solutions frequently.

As expected, the GA's performance on the 5x5 grid decreased compared to the 3x3 grid. We also observe that MGA's performance is better as enforcing the same solution for the both stages reduces the search space. To promote consistency in comparing the results of the GA and MGA across different networks, we keep the termination criteria the same for all network instances. Thus, we didn't conduct our experiments with dynamic termination criteria based on problem instance's size so this reduction in performance is expected as the search space got larger with the larger network. Tailoring the termination criteria for each network instance may provide better, but less comparable, results.

From these grid-networks we illustrate how the GA can be used for the model from a computational perspective. Although it is difficult to provide optimality bounds on the performance of a GA, we have illustrated the ability of the GA and MGA to provide an optimal or near-optimal solution obtained through enumeration for two grid networks. This provides an initial understanding of how well the GA and MGA may do for larger networks that are not enumerable. Furthermore, as our model is nonlinear and multi-stage (two-stage in the experiments), a GA is a practical way to solve the problem.

In the next section we also illustrate how the utility measure we built for the GA can be useful for the policy analysis by itself as it gives a measure of arc desirability and the cost over the network.

5 Case Study: Nepal

We illustrate the network interdiction model using a case study of traffickers operating on a road network in the Eastern Development Region of Nepal. This is motivated by the efforts of non-governmental organizations, such as Love Justice International, who monitor human trafficking transit activity along the Nepal-India border (Hudlow, 2015). The Nepal network, which we will discuss in more detail in this section, will have 34 nodes, 38 arcs and 33 of these arcs are interdictable.

5.1 Parameter and Network Generation

Through analyzing six years of Love Justice International's human trafficking transit activity data, El Khalkhali et al. (2020) identified that people crossing the Nepal-India border at Kakarbhitta, Bhadrapur, and Biratnagar who exhibit signs of being potential human trafficking victims are commonly from the Taplejung and Khadbari districts. Using this knowledge, our case study focuses on disrupting human trafficking along the road network in the Eastern Development Region of Nepal, with Taplejung and Khadbari as source nodes and Kakarbhitta, Bhadrapur, and Biratnagar as sink nodes. We convert this multi-source, multi-sink network into a single source, single sink node network for the network interdiciton model by introducing artificial source s' and sink nodes t' connected to the Taplejung and Khadbari; and Kakarbhitta, Bhadrapur, and Biratnagar nodes, respecively. In the remainder of the manuscript, we refer to Taplejung and Khadbari as source nodes s; Kakarbhitta, Bhadrapur, and Biratnagar as sink nodes t; the singular artificial source node as s'; and the singular artificial sink node as t'.

As previously mentioned, the prevalence of human trafficking and the nature of how traffickers operate on a physical network are largely outstanding research questions due to not having a universally agreed definition of the crime, the illicit nature of human trafficking, and a victim's propensity to not self-identify as victims (Farrell & de Vries, 2020). In the absence of this data, a common approach is to estimate possible trafficking flows using the number of human trafficking cases investigated, hypothetical trafficking indicators and related demographic metrics from high level datasets. Danailova-Trainor et al. (2006) and Hernandez & Rudolph (2015) are two studies that identify factors related to trafficking between two countries, including the country's' income differentials, border policies, migrant populations, and population size.

These studies and identifiers are useful for our model, as we use them to generate the desirability parameter for each arc. This parameter limits the maximum flow that can go through an arc and is traditionally referred to as the arc capacity. Therefore, since the trafficker wants to maximize the overall expected flow on the network, arcs with a higher desirability (i.e., higher capacity) will be more appealing for the trafficker.

To obtain the desirability parameters, we first begin by calculating a measure of the trafficking flow (u_{st}) between every source sink pair (s, t) using census data and the Danailova-Trainor et al. (2006) and Hernandez & Rudolph (2015) indicators: income ratio ($IncDiff_{st}$), total population ($PopSum_{st}$), and total foreign population ($Fpop_{st}$) (Government of Nepal Central Bureau of Statistics, 2012). Distances ($Dist_{st}$) were obtained from UN RCHC in Nepal (2011). Each of these four parameters is weighted by a respective value from $\mathbf{w}$, where $\mathbf{w} = \{w_{IncDiff}, w_{PopSum}, w_{Dist}, w_{Fpop}\} = \{1.208, 0.783, -0.974, 0.393\}$. These values are originally from Hernandez & Rudolph's (2015) regression analysis and used in this case study with illustrative purposes to show how the different trafficking indicators may be weighted differently. For a more realistic study, future research is needed to obtain better estimators that are tailored to the context being modeled. The arc capacities representing desirability of trafficking between two locations (u_{st}) is calculated as:

$$u_{st} = w_{IncDiff} * IncDiff_{st} + w_{PopSum} * PopSum_{st} + w_{Dist} * Dist_{st} + w_{Fpop} * Fpop_{st}$$

Table 3 provides the resulting baseline flow estimates.

Table 3: Flow Between each Source-Sink Pair

Source\Sink	*Biratnagar*	*Bhadrapur*	*Kakarbhitta*
Khadbari	3	2	1
Taplejung	3	2	2

The above function generates a normalized estimation of the trafficking flow between every source and every sink. However, it is also important to know the various paths traffickers can take between source and sink nodes. We obtain this information from the Nepal road network as shown in Figure 6 (UN RCHC in Nepal, 2011), where triangles denote source nodes, stars denote the sink nodes, and squares denote transit nodes. Each node represents a district in the Eastern Development Region of Neapl.

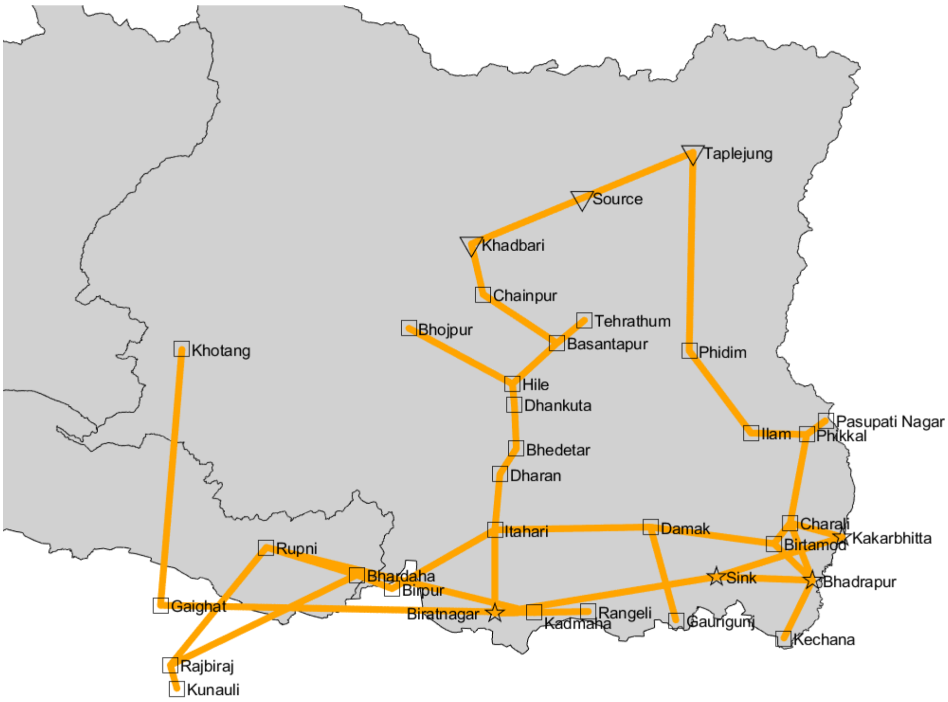

Figure 6: Road Network for the Eastern Developmental Region of Nepal

To calculate the arc desirability (i.e., capacity) parameters for the arcs in the network, we used the network topology of Figure 6 and found every possible path from each source to sink. Then for each arc, we identified every path that included the arc and added the corresponding path's estimated flow to the arc's desirability parameter.

Arc desirabilities for each node in the network are given in Table 4. To illustrate how we use all possible source-sink paths to calculate the arc desirabilites, consider arc (1,6) in Table 4 connecting nodes Damak and Itahari (locations can be seen in Figure 6). This arc is present in six paths between source and sink nodes: it is in two paths between Taplejung - Bhedetar, two paths between Khadbari - Bhadrapur, and two paths between Khadbari - Kakarbhitta. When we multiply these numbers with the corresponding flow values from Table 3, we obtain the arc desirability. In this case, arc 16 has a desirability of: $2(3)+2(2)+2(1) = 12$. Without any interdiction, the network with arc desirabilities as capacities is a proxy for the amount of trafficking that occurs between districts.

Table 4: Arc Desirabilities and Pseudo-Utility Ratios

Node i	Node j	Arc #	Arc Desirability	Interdiction Cost	Initial Interdiction Probability	Pseudo-Utility Ratio
Taplejung	Phidim	1	12	2	0.271	1.626
Taplejung	Source	2	Uncapacitated	N/A	0	0
Phidim	Ilam	3	12	2	0.651	3.906
Ilam	Phikkal	4	12	2	0.651	3.906
Phikkal	Pasupati Nagar	5	0	1	0.374	0
Phikkal	Charali	6	12	4	0.651	1.953
Charali	Kakarbhitta	7	4	2	0.651	1.302
Charali	Birtamod	8	8	1	0.651	5.208
Charali	Bhadrapur	9	8	2	0.651	2.604
Kakarbhitta	Sink	10	Uncapacitated	N/A	0	0
Birtamod	Bhadrapur	11	8	1	0.271	2.168
Birtamod	Damak	12	12	1	0.271	3.252
Bhadrapur	Kechana	13	0	1	0.171	0
Bhadrapur	Sink	14	Uncapacitated	N/A	0	0
Damak	Gaurigunj	15	0	1	0.271	0
Damak	Itahari	16	12	2	0.271	1.626
Itahari	Biratnagar	17	9	2	0.651	2.9295
Itahari	Dharan	18	9	1	0.651	5.859
Itahari	Birpur	19	0	1	0.271	0
Biratnagar	Rangeli	20	0	1	0.651	0
Biratnagar	Sink	21	Uncapacitated	N/A	0	0
Dharan	Bhedetar	22	9	1	0.271	2.439
Bhedetar	Dhankuta	23	9	1	0.198	1.782
Dhankuta	Hile	24	9	1	0.198	1.782
Hile	Bhojpur	25	0	20	0.651	0
Hile	Basantapur	26	9	1	0.171	1.539
Basantapur	Tehrathum	27	0	1	0.271	0
Basantapur	Chainpur	28	9	1	0.198	1.782
Chainpur	Khadbari	29	9	1	0.171	1.539
Khadbari	Source	30	Uncapacitated	N/A	0	0
Birpur	Bhardaha	31	0	1	0.195	0
Bhardaha	Rajbiraj	32	0	1	0.271	0
Bhardaha	Rupni	33	0	1	0.198	0
Rajbiraj	Kunauli	34	0	1	0.271	0
Rajbiraj	Rupni	35	0	1	0.271	0
Rupni	Kadmaha	36	0	1	0.198	0
Kadmaha	Gaighat	37	0	1	0.195	0
Gaighat	Khotang	38	0	3	0.271	0

The cost, c_{ijk}, of attempting an interdiction along arc (i, j) was assumed to be directly proportional to the sum of the node populations ($PopSum_{ij}$) and to the distance between the nodes ($Dist_{ij}$) given that covering long distances and monitoring activities involving large populations could be more costly. In this case study, we assume that the cost of interdiciton does not vary over time (i.e., $c_{ijk} = c_{ij} \forall k$) and equals

$$c_{ij} = PopSum_{ij} * Dist_{ij}.$$

After calculating the cost for attempted interdicitons along each arc, the cost values were scaled to be between 1 and 20 (Table 4).

Finally, each arc also has an associated probability of being successfully interdicted. While robust data to inform these parameter values does not exist, we estimate the initial interdiction success probabilities, p_0, as a function of node population. This is based on Farrell et al. (2010), which surveyed law enforcement's perception of human trafficking in their local area and concluded that agencies with human trafficking training were more prepared to address human trafficking. Their findings also indicate that, in general, the percentage of law enforcement personnel that have human trafficking training is positively correlated with the population of the jurisdiction (Table 5). As such, we have assigned arc (i, j) an interdiction probability equal to the training percentage corresponding to the sum of the node i and j populations (see Table 4).

Table 5: Population Probability Matrix

Population Size	Training as Probability Proxy
4,999 and below	12.4%
5,000-9,999	17.1%
10,000-24,999	19.5%
25,000-49,999	19.8%
50,000-74,999	17.1%
75,000-99,999	37.4%
100,000-249,999	27.1%
250,000 and above	65.1%

See **?** *for the full table.*

For this network, a heatmap of the expected pseudo-utility ratios that are used in the repair operation is given in Figure 7. Darker edges denote the arcs with higher expected pseudo-utility ratios. They are calculated by using the respective arc's parameters; however, since the arc capacity parameter is estimated iteratively by considering all paths through the network, the network structure effects the arc's capacity and conse-

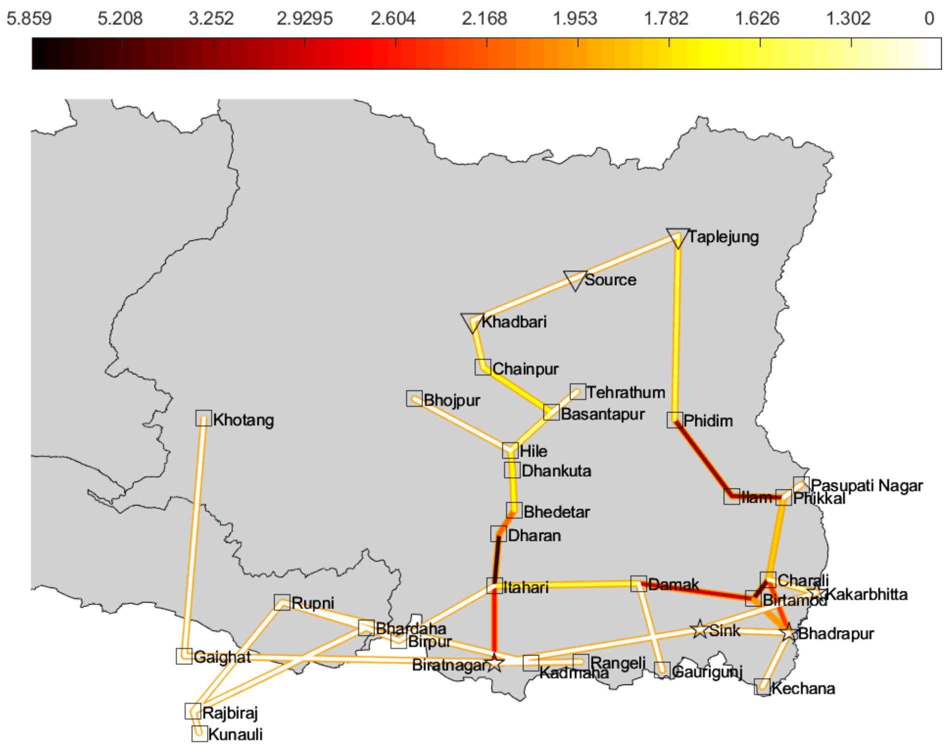

Figure 7: Heatmap for the expected pseudo-utility ratios

quently effects the pseudo-utility ratios as well. The corresponding pseudo-utility values are presented in Table 4.

We acknowledge that the parameter estimation methods described in this section are a simplistic way to calculate how a trafficker and an interdictor operate on the network, yet it serves the purpose of testing how the model behaves and algorithm works given that robust human trafficking data is scarce. If more sophisticated and accurate ways to quantitatively measure these parameters are found, our model can be used with the updated parameters without needing to make fundamental changes to the modelling formulation.

5.2 Findings

Since the parameters needed to implement this model remain an open research question in the human trafficking field, we solved instances with varying budgets and probability update rates for a two-stage model. We assume the budget remains the same in each stage.

As previously mentioned, GAs are not guaranteed to provide an optimal solution. Therefore, we assessed the GA's performance for low budget instances that we were able to solve to optimality through enumeration; we started with a budget of 3 and increased the budget by 1 until it was computationally infeasible for us to compute the optimal solution by enumeration. Table 6 shows the min-max flows at stage 1 (MMF1) and min-max flow at stage 2 (MMF2) under the optimal interdictions and the best results from 100 runs of the GA with budgets equalling 3, 4 and 5. The results indicate that the GA with a repair function is able to converge to optimal in 100 experiments for each setting regardless of the value of the update rate Δ, which can be observed in Figure 8. Figure 8 also shows that MGA was able to find the optimal solutions in most of the experiments. Budgets larger than 5 were prohibitively costly to calculate through enumeration. Although a provably optimal solution was not obtained for a budget of 10, we provide a population diversity graph in the Appendix to illustrate the diversity of the solutions when the algorithm terminated. We also present the performance of the GA and the MGA in the Nepal network just as we did for the grid networks in Figure 8 and notice a similar result: the MGA performs better than the GA and performance decreases with increasing budget.

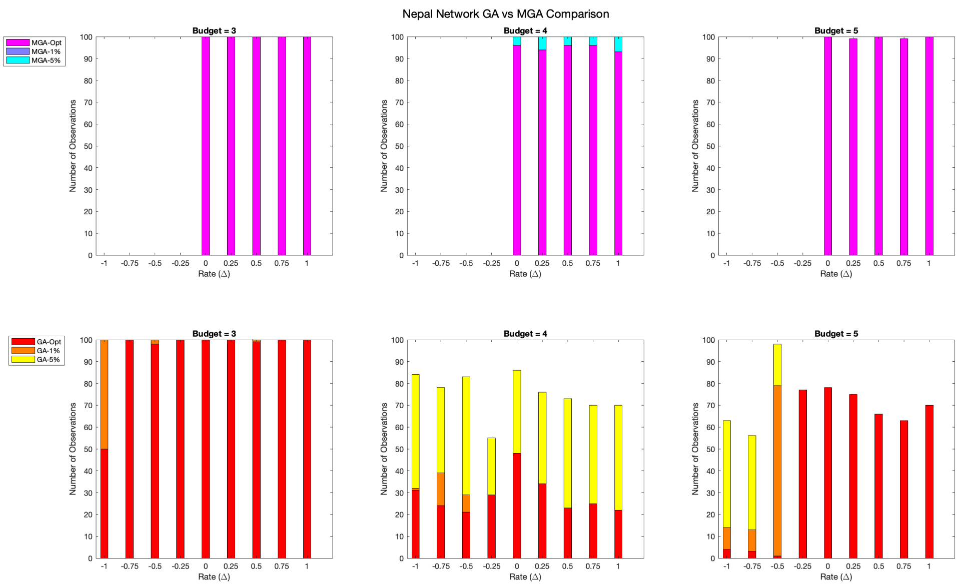

Figure 8: GA and Modified GA Performance on Nepal Network

5.2.1 Interdictors Becoming More Successful

From Table 6, we can observe that when the success update parameter $\Delta \geq 0$, it is best to follow the same interdiction strategy for both stages. Simply determine the best interdiction strategy for the initial stage and follow it for the second stage as well. This makes sense because the first stage problem is minimizing the trafficker's desirability

Table 6: Results under Optimal Policy and GA

	Optimal Solution					GA Solution					
Rate	1st Int.	MMF1	2nd Int.	MMF2	Total MMF	1st Int.	MMF1	2nd Int.	MMF2	Total MMF	MMF Difference
Budget = 3											
1.00	3 , 18	7.329	3, 18	2.558	9.887	3, 18	7.329	3, 18	2.558	9.887	0.000
0.75	3 , 18	7.329	3, 18	3.751	11.080	4, 18	7.329	4, 18	3.751	11.080	0.000
0.50	3 , 18	7.329	3, 18	4.943	12.272	3, 18	7.329	3, 18	4.943	12.272	0.000
0.25	3 ,18	7.329	3, 18	6.136	13.465	3, 18	7.329	3, 18	6.136	13.465	0.000
0.00	3 , 18	7.329	3, 18	7.329	14.658	4, 18	7.329	4, 18	7.329	14.658	0.000
-0.25	3 , 18	7.329	4, 18	8.283	15.612	3, 18	7.329	4, 18	8.283	15.612	0.000
-0.50	3 , 18	7.329	4, 18	9.236	16.565	4, 18	7.329	3, 18	9.236	16.565	0.000
-0.75	3 , 18	7.329	4, 18	10.190	17.519	3, 18	7.329	4, 18	10.190	17.519	0.000
-1.00	3 , 18	7.329	4, 22	10.749	18.078	4, 22	10.749	3, 18	7.329	18.078	0.000
Budget = 4											
Rate	1st Int.	MMF1	2nd Int.	MMF2	Total MMF	1st Int.	MMF1	2nd Int.	MMF2	Total MMF	MMF Difference
1.00	3 , 18 , 22	6.478	3, 18, 22	2.044	8.522	3, 18, 22	6.478	3, 18, 22	2.044	8.522	0.000
0.75	3 , 18 , 22	6.478	3, 18, 22	3.077	9.555	3, 18, 22	6.478	3, 18, 22	3.077	9.555	0.000
0.50	3 ,18 , 22	6.478	3, 18, 22	4.160	10.638	3, 18, 22	6.478	3, 18, 22	4.160	10.638	0.000
0.25	3 , 18 , 22	6.478	3, 18, 22	5.294	11.771	3, 18, 22	6.478	3, 18, 22	5.294	11.771	0.000
0.00	3 , 18 , 22	6.478	3, 18, 22	6.478	12.956	3, 18, 22	6.478	4, 18, 22	6.478	12.956	0.000
-0.25	3 , 18 , 22	6.478	4, 18, 22	7.248	13.726	4, 18, 22	6.478	3, 18, 22	7.248	13.726	0.000
-0.50	3 , 18 , 22	6.478	4, 18, 22	8.053	14.531	3, 18, 22	6.478	4, 18, 22	8.053	14.531	0.000
-0.75	3 , 18 , 23	6.707	4, 18, 22	8.563	15.270	3, 18, 24	6.707	4, 18, 22	8.563	15.270	0.000
-1.00	3 , 18, 23	6.707	4, 18, 22	9.258	15.965	3, 18, 23	6.707	4, 18, 22	9.258	15.965	0.000
Budget = 5											
Rate	1st Int.	MMF1	2nd Int.	MMF2	Total MMF	1st Int.	MMF1	2nd Int.	MMF2	Total MMF	MMF Difference
1.00	3, 4, 18	4.603	3, 4, 18	1.274	5.877	3,4,18	4.603	3,4,18	1.274	5.877	0.000
0.75	3, 4, 18	4.603	3, 4 ,18	1.990	6.593	3,4,18	4.603	3,4,18	1.990	6.593	0.000
0.50	3, 4, 18	4.603	3, 4, 18	2.784	7.386	3,4,18	4.603	3,4,18	2.784	7.386	0.000
0.25	3, 4, 18	4.603	3, 4, 18	3.654	8.257	3,4,18	4.603	3,4,18	3.654	8.257	0.000
0.00	3, 4 , 18	4.603	3, 4, 18	4.603	9.205	3,4,18	4.603	3,4,18	4.603	9.205	0.000
-0.25	3, 4, 18	4.603	3, 4, 18	6.578	11.181	3,4,18	4.603	3,4,18	6.578	11.181	0.000
-0.50	3, 18, 22, 23	6.024	4, 18, 22, 24	7.288	13.313	4,18,22,28	6.024	3,18,22,23	7.288	13.313	0.000
-0.75	1, 3, 18	6.194	4, 18 , 22, 23	7.697	13.891	1,3,18	6.194	4,18,22,24	7.697	13.891	0.000
-1.00	1, 3, 18	6.194	4, 18, 22, 23	8.254	14.449	1,3,18	6.194	4,18,22,24	8.254	14.449	0.000
Budget = 10											
Rate	1st Int.	MMF1	2nd Int.	MMF2	Total MMF	1st Int.	MMF1	2nd Int.	MMF2	Total MMF	MMF Difference
1.00	NA	NA	NA	NA	NA	3,4,8,18,22,23,26,28	2.683	3,4,8,12,18,22,23,28	0.419	3.102	NA
0.75	NA	NA	NA	NA	NA	3,4,8,18,22,23,26,28	2.683	3,4,8,12,18,22,23,26	0.844	3.526	NA
0.50	NA	NA	NA	NA	NA	3,4,8,18,22,23,24,28	2.643	3,4,8,12,18,22,23,28	1.362	4.005	NA
0.25	NA	NA	NA	NA	NA	3,4,6,18,22	2.800	3,4,8,12,18,22,23,24	2.174	4.974	NA
0.00	NA	NA	NA	NA	NA	3,4,8,18,22,23,24,28	2.643	3,4,8,18,22,23,24,28	2.643	5.577	NA
-0.25	NA	NA	NA	NA	NA	3,4,8,18,22,23,24,28	2.643	3,4,12,18,22,23,24,28	4.121	6.764	NA
-0.50	NA	NA	NA	NA	NA	3,6,18,22,23,24	2.934	3,4,18,22,23,24,26,28	4.084	7.018	NA
-0.75	NA	NA	NA	NA	NA	3,4,8,9,18,22,24	2.885	3,6,18,22,23,28	5.820	8.705	NA
-1.00	NA	NA	NA	NA	NA	3, 6, 8, 18, 22, 23	3.298	3, 4, 18, 22, 23, 24, 26, 28	5.740	9.038	NA

of operating on the network subject to a budget constraint that is consistent in both stages. Since the probability updates are positive (i.e., $\Delta \geq 0$), a successful interdiction will further increase the likelihood of successfully interdicting the same arc in future stages. Therefore, the optimal first stage policy becomes even more attractive in the second stage.

This is also observed in Figure 9, which illustrates how the first and second stage objective functions behave as the success rate parameter Δ varies. It illustrates that since successful interdictions become even more successful in future stages when $0 < \Delta$, the trafficker's desire to operate on the network decreases in the second stage.

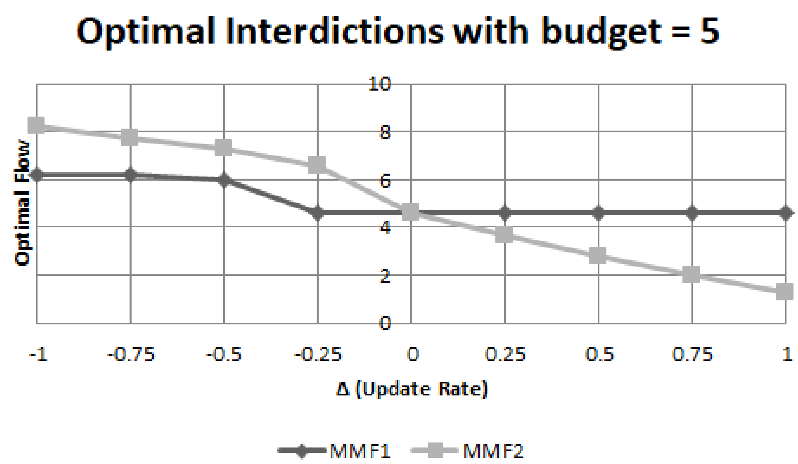

Figure 9: Optimally interdicted flow under budget = 5

5.2.2 Traffickers Adapting

However, in the case where the trafficker is learning from the interdictions and adapting accordingly (i.e., $\Delta < 0$), interdicting different arcs for each stage might yield a better total expected min-max flow over the planning horizon than following the same strategy for both stages since successfully interdicted arcs become less successful in future stages.

In the case of $\Delta < 0$, as the budget increases and the Δ gets closer to -1, the optimal strategy is to be less aggressive in the first stage, relative to the cases where Δ is higher. This results in the trade off of allowing more flow through the network in the first stage in order to preserve some effective interdictions for the next stage. We can observe this by noticing that the optimal first stage interdiction decision when $\Delta = -1$ allows more trafficking flow than when $\Delta = -0.5$ for budgets greater than or equal to 4. (This can be seen from both Table 6 and Figure 9.) This means that even though there exist interdiction decisions that would decrease the trafficking in Stage 1 more, these decisions would produce a worse outcome in the second stage and allow for a greater amount of trafficking to occur overall.

Since the optimal first and second stage interdiction decisions are the same when $0 < \Delta$ but may differ when $\Delta < 0$, we investigate how much of a difference not following the optimal interdiction strategy would make when $\Delta < 0$. We do this by assuming the interdictor is not changing strategies and continues to implement the initial stage's best interdiction policy assuming the success change rate is 0, when in actuality it is negative. Observations under this problem instance showed that acknowledging the ability of the trafficker to adapt and change the interdiction strategy accordingly can reduce the total expected maximum minimum flow by up to 40%, depending on the rate and the interdiction budget (see Table 7).

Figure 9 also illustrates that when $\Delta < 0$ and traffickers learn from successful interdictions, the network becomes more desirable for traffickers to operate on over time. However, it is important to note that while the network becomes more desirable to traffickers in the second stage as compared to the first, it is still less desirable than a network that was never interdicted. That is, even though interdictions become less successful over time, it is still beneficial to pursue interdictions rather than not doing anything. Similar patterns are observed for other budget values.

6 Conclusion and Future Work

This paper introduces a multi-stage stochastic network interdiction model with decision-dependent success probabilities to aid in anti-human trafficking disruption efforts. The trafficker's movement throughout a physical network is captured using a maximum flow problem where the traditional arc capacity parameters are redefined to be a proxy for the desirability of a trafficker to operate along the arc. An interdictor—which could include law enforcement, healthcare personnel, non-profit organizations, service providers, or policy makers—attempts to disrupt the trafficking network by interdicting arcs. To capture the uncertain nature of interdiction attempts, we assume there is a positive probability that an interdiction attempt may be unsuccessful. We also consider that the success probability is a function of prior interdiction decisions and may change over time as traffickers or interdictors learn more information about the network. In other words, the expertise and knowledge we aim to utilize in this model are trafficking estimations over a region, estimations about the probability of success

Table 7: Optimal Interdictions vs Fixed Interdictions

Budget = 3										
Rate	Optimal Solution 1st Int.	MMF1	2nd Int.	MMF2	Total MMF	Assume 1st Stage Solution = 2nd Stage Solution 2nd Int.	MMF2	Total MMF	MMF Difference	% MMF Difference
-0.25	3, 18	7.329	4 , 18	8.283	15.612	3 , 18	9.554	16.883	1.271	8.1
-0.50	3, 18	7.329	4 , 18	9.236	16.565	3 , 18	11.779	19.108	2.543	15.4
-0.75	3, 18	7.329	4 , 18	10.190	17.519	3 , 18	14.004	21.333	3.814	21.8
-1.00	3, 18	7.329	4 , 22	10.749	18.078	3 , 18	16.229	23.558	5.480	30.3

Budget = 4										
Rate	Optimal Solution 1st Int.	MMF1	2nd Int.	MMF2	Total MMF	Assume 1st Stage Solution = 2nd Stage Solution 2nd Int.	MMF2	Total MMF	MMF Difference	% MMF Difference
-0.25	3, 18, 22	6.4778	4, 18, 22	7.248	13.726	3, 18, 22	8.520	14.997	1.271	9.3
-0.50	3, 18, 22	6.4778	4, 18, 22	8.053	14.531	3, 18, 22	10.596	17.074	2.543	17.5
-0.75	3, 18, 22	6.7071	4, 18, 22	8.563	15.270	3, 18, 22	12.708	19.415	4.145	27.1
-1.00	3, 18, 22	6.7071	4, 18, 22	9.258	15.965	3, 18, 22	14.855	21.562	5.597	35.1

Budget = 5										
Rate	Optimal Solution 1st Int.	MMF1	2nd Int.	MMF2	Total MMF	Assume 1st Stage Solution = 2nd Stage Solution 2nd Int.	MMF2	Total MMF	MMF Difference	% MMF Difference
-0.25	3, 4, 18	4.6026	3 , 4 , 18	6.578	11.181	3, 4, 18	6.578	11.181	0.000	0.0
-0.50	3, 4, 18	6.0244	4 ,18, 22 , 24	7.288	13.313	3, 4, 18	8.823	14.848	1.535	11.5
-0.75	3, 4, 18	6.1941	4 , 18 , 22 , 23	7.697	13.891	3, 4, 18	11.338	17.532	3.641	26.2
-1.00	3, 4, 18	6.1941	4, 18, 22 , 23	8.254	14.449	3, 4, 18	14.122	20.316	5.867	40.6

for the trafficking interdiction, and how this probability will change based on previous actions in the same region. To solve the resulting nonlinear model, we developed a GA and Modified GA that uses expected pseudo-utility ratios in its repair operation.

The two-stage version of our model was tested on a case study of a trafficking network in the Eastern Development Region of Nepal. Results indicate that the trafficker's ability to adapt to previous interdictions is a driving factor in determining the optimal interdiction policy over time. If the trafficking operation is unable to adapt to disruptions such that the interdictor becomes more successful at interdicting as time progresses, the optimal interdiction strategy is to interdict the same arcs in the first and second stage. However, if the trafficker learns from successful interdictions, thereby reducing the effectiveness of future interdictions along the same arcs, it is often optimal to interdict different arcs in the first and second stages.

One valid concern regarding the applicability of the present model is the availability of data it requires, given the hidden/covert nature of human trafficking. In many communities, there is currently a lack of data and understanding about trafficking flows. However, more communities are starting to understand the value of collecting data related to human trafficking operations and operational knowledge of trafficking is increasing. Thus, this model highlights the benefit of collecting such data so that decision-makers can utilize this knowledge to develop effective interdiction plans in a cost restrained environment.

To the best of our knowledge, our model is the first network interdiction model tailored to disrupting physical human trafficking networks. As such, we acknowledge that there are multiple limitations of our model; human trafficking network structures and operating dynamics largely remain an open research question, which limits the input data available for network interdiction models. In light of this gap, we have generated estimates of model parameters based on the current human trafficking literature. It is our hope that this model serves as illustration of the types of practice and policy insights that can be obtained if more robust human trafficking data was available and provides motivation for interdisciplinary research to collect such data.

There are many nuances of human trafficking that motivate the need for further extensions of our model to capture the growing knowledge of human trafficking networks. As an example, we are currently working on extending the present model to incorporate collaboration and information sharing among multiple anti-trafficking stakeholders each seeking to disrupt a trafficker's operation.

Another extension can address the sequential nature of the interdictor and trafficker decisions. In the current problem, the interdictor makes a decision and only after observing the outcome of this decision does the trafficker determine how to maximize their flow through the network. This assumption is somewhat limiting as traffickers and interdictors often don't have full knowledge of each others actions and don't alternate making decisions. As such, network interdiction literature related to dynamic games in which players don't have static strategies could be incorporated into the current model (Lunday & Sherali, 2010; Fischetti et al., 2018; Zhang et al., 2018). Furthermore, loosening the assumption that a trafficker optimizes their use of the network should also be considered; in reality, the trafficker might take random or partially informed actions on the network.

In conclusion, network interdiction models are uniquely positioned to aid in disrupting human trafficking networks. To effectively use this methodology, additional research is needed to obtain robust data to serve as input into the network interdiction models and current network interdiction theory must continue to evolve to capture the nuances of human trafficking.

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A Genetic Algorithm (GA)

A.1 GA with Repair Operation for the Trafficking Interdiction Model with Probability Updates

1. Input: All model parameters: u_a, c_a where $a \in A$, where A is the set of arcs in the network G. K denotes the set of stages and indexed by k. Budget/resources of the leader is denoted by R_k for each stage $k \in K$. Pseudo-utility ratios for each arc in the network can be calculated a priori as well.

   Genetic Algorithm Parameters: *PopSize, TournSize, MutateProb, CrossoverPop, MutatePop, ElitePop, MaxIter* and *MaxIterNoImprove* (Descriptions given in Table 2).

2. Generate the initial population. Repeat (a) to (c) *PopSize* times.

   (a) Create an individual, say y in the length of $|A| * |K|$ with all bits are zero.

   (b) Randomly pick a bit from the individual and make it one (denotes arc interdiction attempt for the law enforcement/leader) unless it makes the individual infeasible. Repeat until individual becomes infeasible which can be checked with $\sum_{a \in A} y_{ak} c_a \leq R_k \; \forall k \in K$.

   (c) Evaluate the individual by finding the expected maximum flow under the selected interdicted arcs at (b). This value is the fitness function of the individual.

3. Set $k = 0$ and $h = 0$ where k is a counter on the number of iterations and h is a counter on the number of consecutive iterations without improving the population.

4. While $h <$ *MaxIterNoImprove* and $k <$ *MaxIter*

   (a) Elites: Set the best performing - lowest fitness function yielding - *ElitePop*PopSize* individuals to the set of elite individuals.

   (b) Parent Selection and Crossover: Randomly select *TournSize* individuals with a bias towards lower fitness function yielding individuals and use tournament selection for selecting 2 parents. Use these parents to conduct the uniform crossover operation to generate another individual. Repeat this step *CrossoverPop*PopSize* times.

   (c) Mutation: Select *ElitePop*PopSize* individuals and use the bit-flip mutation on each of them with the mutation probability *MutateProb* for each bit in the individual.

(d) Repair: Use the pseudo-utility ratios to repair the infeasible individuals generated by reproduction operations (c) and (d). To do so, if the individual is infeasible remove the bits with the lowest pseudo-utility ratio and after the individual becomes feasible, start adding bits that yield the highest pseudo-utility ratios until no more addition can be made.

(e) Increment k and evaluate the fitness values of the now repaired individuals and if the best fitness value is better than the previous best fitness value solution set $h = 0$; otherwise, increment h.

5. Report the best fitness value and the corresponding individual.

A.2 Small Network

B Case Study

B.1 Parameters

Table 8: Indicator parameters for the source and sink nodes

Node	*Location*	*Population*	*Income*	*Foreign Population*
Source 1	Khadbari	26301	738	0.00089453
Source 2	Taplejung	127461	813	0.00172602
Sink 1	Biratnagar	242548	774	0.00649595
Sink 2	Bhadrapur	50249	759	0.00751615
Sink 3	Kakarbhitta	21366	759	0.00751615

Table 9: Source-Sink Pair Desirabilities

Source (s)	*Sink (t)*	*Income Ratio*	*Total Population*	*Distance*	*Total Foreign Population*	*Desirability* (u_{st})
Source 1	Sink 1	0.953488	268849	114	0.00739049	3
Source 1	Sink 2	0.972332	76550	248	0.00841068	2
Source 1	Sink 3	0.972332	47667	243	0.00841068	1
Source 2	Sink 1	1.050388	370009	334	0.00822197	3
Source 2	Sink 2	1.071146	177710	242	0.00924217	2
Source 2	Sink 3	1.071146	148827	238	0.00924217	2

Distance data is from Google Maps and UN-Nepal Roadnetwork UN RCHC in Nepal (2011) and the rest is from Nepal Census Data Government of Nepal Central Bureau of Statistics (2012)

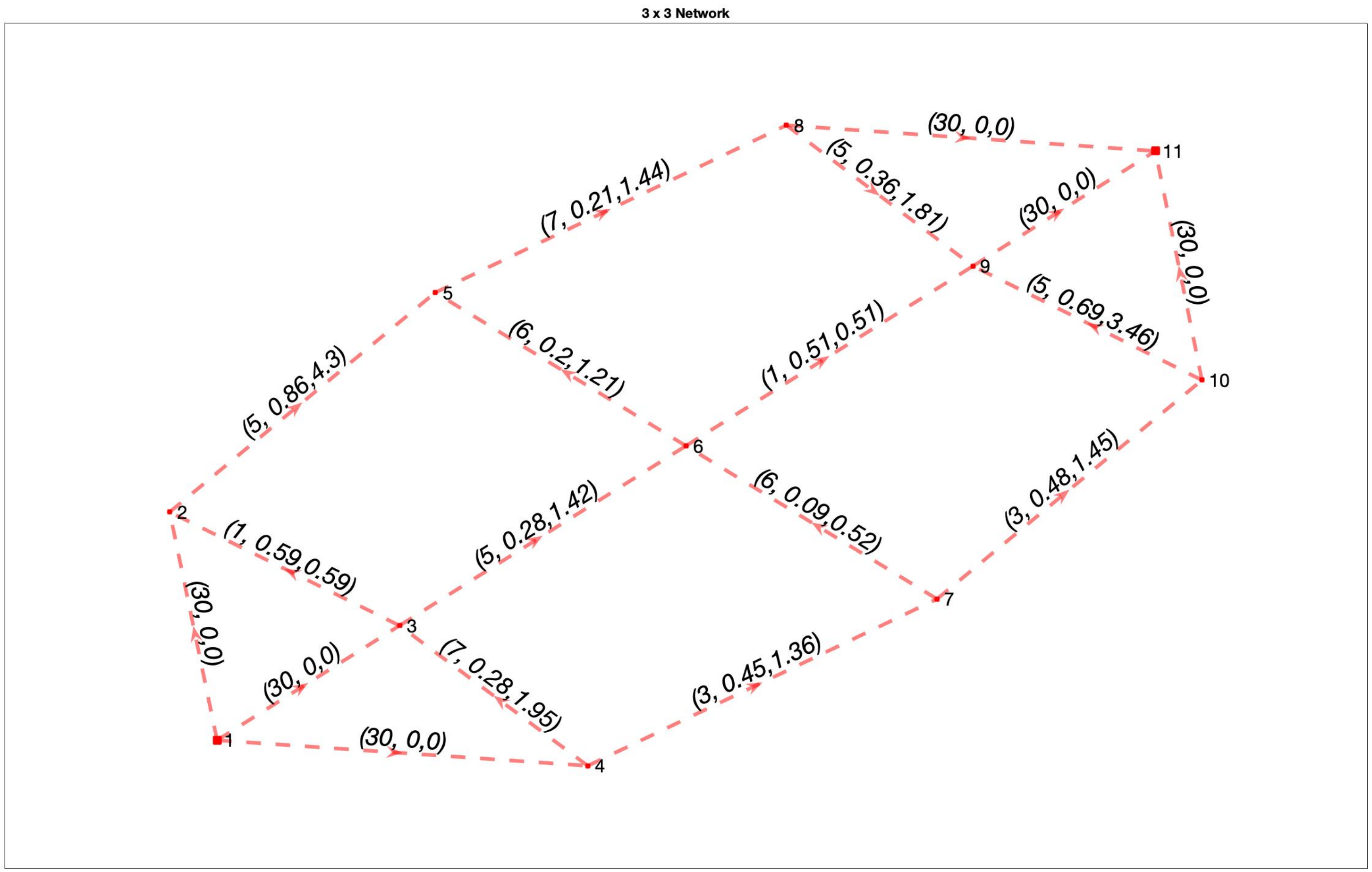

Figure 10: Small Network

B.2 Final Population Diversity Plot for budget = 10 and $\Delta = -1$

Figure 11: Final Population Diversity of GA converging to 9.038 (best observed)