
Taylor & Francis
Taylor & Francis Group

IISE Transactions

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/uiie21

# Interdiction of wildlife trafficking supply chains: An analytical approach

**Emily C. Griffin, Aaron Ferber, Lucas Lafferty, Burcu B. Keskin, Bistra Dilkina & Meredith Gore**

**To cite this article:** Emily C. Griffin, Aaron Ferber, Lucas Lafferty, Burcu B. Keskin, Bistra Dilkina & Meredith Gore (2024) Interdiction of wildlife trafficking supply chains: An analytical approach, IISE Transactions, 56:3, 355-373, DOI: 10.1080/24725854.2023.2255643

**To link to this article:** https://doi.org/10.1080/24725854.2023.2255643

IISE TRANSACTIONS
2024, VOL. 56, NO. 3, 355–373
https://doi.org/10.1080/24725854.2023.2255643

Taylor & Francis
Taylor & Francis Group

OPEN ACCESS Check for updates

# Interdiction of wildlife trafficking supply chains: An analytical approach

Emily C. Griffin[a,b], Aaron Ferber[c], Lucas Lafferty[b], Burcu B. Keskin[b], Bistra Dilkina[c], and Meredith Gore[d]

[a]Babson College, Operations and Information Management Division, Babson Park, MA, USA; [b]Department of Information Systems, Statistics, and Management Science, The University of Alabama System, Tuscaloosa, AL, USA; [c]Department of Computer Science, University of Southern California, Los Angeles, CA, USA; [d]Department of Geographical Sciences, University of Maryland at College Park, College Park, MD, USA

**ABSTRACT**
Illicit Wildlife Trade (IWT) is a serious global crime that negatively impacts biodiversity, human health, national security, and economic development. Many flora and fauna are trafficked in different product forms. We investigate a network interdiction problem for wildlife trafficking and introduce a new model to tackle key challenges associated with IWT. Our model captures the interdiction problem faced by law enforcement impeding IWT on flight networks, though it can be extended to other types of transportation networks. We incorporate vital issues unique to IWT, including the need for training and difficulty recognizing illicit wildlife products, the impact of charismatic species and geopolitical differences, and the varying amounts of information and objectives traffickers may use when choosing transit routes. Additionally, we incorporate different detection probabilities at nodes and along arcs depending on law enforcement's interdiction and training actions. We present solutions for several key IWT supply chains using realistic data from conservation research, seizure databases, and international reports. We compare our model to two benchmark models and highlight key features of the interdiction strategy. We discuss the implications of our models for combating IWT in practice and highlight critical areas of concern for stakeholders.

**ARTICLE HISTORY**
Received 16 February 2022
Accepted 21 July 2023

**KEYWORDS**
Wildlife trafficking; network interdiction; illicit supply chains; analytics

## 1. Introduction

Illicit Wildlife Trade (IWT) is a form of transnational organized crime that creates a wide array of issues for society and the environment (Gore *et al.*, 2019). Although the actual number is contested, one estimate places the economic value of IWT between US$5 billion and $23 billion annually (UNODC, 2017). IWT causes harm in various ways, including introducing zoonotic diseases to human populations, biodiversity loss, the proliferation of invasive species, land degradation, and threats to national security and legitimate economic enterprises (Avis, 2017; UNODC, 2020; Hubschle and Shearing, 2021). The COVID-19 pandemic and the vast subsequent harms to human and financial well-being have starkly illustrated the potential global impact of zoonotic diseases, for which wildlife trade – both legal and illegal – is a potential vector (UNODC, 2020). Despite its prevalence and social and economic impact, IWT has received relatively less attention and enforcement effort from authorities. This makes it both less risky and more profitable for traffickers than many other illicit trades (Nuwer, 2018; Utermohlen and Baine, 2018). Similar to other illicit trades, IWT activities are managed through complex supply chains with extensive geographical reach from harvest to end-users, a wide variety of species, various product types (perishable, live, processed, packaged, etc.), and elusive, opportunistic, agile criminals. Some of the impacted industries are furniture (e.g., rosewood), decor/jewelry (e.g., ivory), fashion (e.g., reptile skins, big cat skins), cosmetics (e.g., agarwood, wild orchids), food and medicine (e.g., pangolin, rhino horn, bear bile), pets and breeding (e.g., parrots, freshwater turtles, and great apes), and seafood (e.g., caviar, marine turtles) (UNODC, 2020).

Although the majority of poached wildlife comes from developing countries, both developed and developing countries are responsible for the demand (UNODC, 2017). Hence, nearly every country in the world plays a role in wildlife crime as a source, transit hub, or destination for illegal wildlife products. International trafficking being a broad issue (many species and countries) and traffickers being adaptable (species and country displacement) makes network interdiction a powerful approach for combating IWT. The international transit stage, be it by air, sea, or land, is one of the most vulnerable points of the illicit supply chain (UNODC, 2020). For high-value products such as ivory and rhino horn, the main international transportation mode is air transit. Between 2014 and 2019, 62% of all rhino horn was seized in air transit (UNODC, 2020). Seizures occurred at either transit nodes (e.g., Turkey (Awel, 2019)) or at destinations (e.g., Vietnam, Hong Kong, etc. (Leung,

**CONTACT** Burcu B. Keskin bkeskin@ua.edu.
Supplemental data for this article is available online at https://doi.org/10.1080/24725854.2023.2255643

2019; Linh and Thuy, 2019)). Hence, in this work, we utilize data from air transit networks to test our models.

Customs agents play an important role in enforcing international wildlife trade statutes; hence, they need to be enabled and motivated to detect and prevent wildlife trafficking. One difficulty for law enforcement is the identification of species. Most controls are specific to certain species, and it may be possible to evade controls by claiming a protected species is a non-protected look-alike or has a different country of origin. Although species that are commonly the focus for conservation groups, such as elephants and rhinos, also referred to as *charismatic* species, dominate headlines with demand for their ivory and keratin horns, IWT involves a much larger group of species. In February 2022, a European eel trafficker was given a 15-month prison sentence and a fine of 7,200,000 GBP. Media reports noted that the eel trade was as lucrative as the cocaine trade, but it received less media attention (Sharrock, 2022). The sophistication of concealment methods used is increasingly on par with those normally associated with drug smuggling. For example, in June 2018, Sri Lankan customs officials in Colombo Airport discovered 32 likely endangered geckos and lizards in a DHL shipment of computer towers. Furthermore, officials may be unfamiliar with the appearance and protected status of non-native species. These difficulties are further compounded by the variety of potential product forms (live, processed meat, fur, bones, jewelry, fashion items, powders, etc.). Further training for customs officials to profile suspect shipments and identify the species within can enhance the likelihood of successful interdiction. Investments in training can take the form of educational seminars on species identification, relevant laws, common methods of concealment, and proper procedures for successful interdiction. Training can also include investment in technology to improve communication on shipments or detection and sniffer dogs to quickly screen a large number of passengers (Utermohlen and Baine, 2018). Unfortunately, training investments are dampened by the typically smaller amount of resources allocated to the detection and investigation of wildlife trafficking in comparison with other illicit trades (UNODC, 2020). In this study, we directly incorporate the decision to train at a specific interdiction location into the optimization model to capture this issue while considering limited resources.

Another key issue that differentiates IWT from other forms of illicit trade is the lack of enforcement resources and inconsistent enforcement efforts between countries and across species. The Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) has 184 member parties and affords some form of protection to over 37,000 species of wild fauna and flora ((cites.org). CITES is not intended to replace national laws, and they state that the convention "provides a framework to be respected by each Party, which has to adopt its own domestic legislation to ensure that CITES is implemented at the national level." National laws and penalties for wildlife trafficking vary greatly and can strongly impact the success of interdiction efforts. Providing a global assessment of wildlife crime is challenging, because every country protects and acknowledges its animals, fish, timber, and other plant life in different ways (UNODC, 2020). Many countries focus on laws relating to domestic species, and monetary fines can be extremely inconsistent, with maximum punishments being as low as 50 USD in some countries but reaching 800,000 USD in others (Broussard, 2017). In addition, even if a country has laws in place, a case will still need to successfully move through the judicial system before penalties can be levied. There are substantial differences between countries in regard to their judicial system and law enforcement capabilities (The Global Organized Crime Index, 2021).

These differences and difficulties highlight a distinctive feature of IWT; specifically, for some non-charismatic species, the risk of getting caught or the associated penalties for traffickers may be so low that they have no impact on trafficking routes or only impact certain countries. Many papers in the network interdiction literature study traffickers that seek only to minimize their probability of detection. Other works look at models where interdiction efforts lengthen individual arcs to increase the total cost of a path. Both of these approaches are insufficient to capture the spectrum of utility functions that wildlife traffickers may have because they fail to capture the interplay between increased detection risk and variation in penalties due to the country of detection. To close this gap, we model three different types of utility functions for the trafficker and discuss their impact on the optimal interdiction actions.

We introduce a novel model and two benchmark models. The first benchmark we introduce is the naive traffickers model. It represents the current state for many products in IWT that are not charismatic and do not attract substantial enforcement attention. In this model, traffickers only seek to minimize their flight/transit costs across the network without regard for interdiction efforts. This is a realistic model when traffickers have no information about enforcement efforts, the probabilities of detection are low, or penalties for IWT are small. This model provides a good benchmark for the many species that are not the focus of international enforcement attention. The second benchmark model focuses on minimizing the probability of detection and represents the heavily protected and publicized products such as trafficking rhino horns, ivory, or cheetah cubs. This model is appropriate for products where getting caught is "game over" for the involved traffickers, and those risks outweigh any costs for transit or variations in penalties between countries. The issue with these benchmarks is that they represent two extremes that are only valid for limited cases, and they fail to capture the variation in penalties for traffickers across countries. The third model, our novel model, focuses on traffickers who minimize their total penalty when traveling across the network. The objective considers (i) the cost of traveling a specified route, (ii) the likelihood of getting caught at various locations along the route, and (iii) the penalties associated with being caught in various countries. This new objective allows us to investigate a much broader set of scenarios, and the model captures both of the previous models' insights at the extreme ends of the parameter values.

Our work makes several contributions to the literature. First, we introduce a new model that captures IWT characteristics, specifically the need for training customs agents in various locations. Second, we utilize a combination of real seizure data and scientific reports on IWT to form a comprehensive set of origin and destination countries for trafficking. Third, we use real data on flight routes, flight prices, and countries' resilience with respect to organized crime to create realistic instances for testing our models. Lastly, we compare the results with two other benchmark models and derive practical insights into strategies for combating IWT through customs inspection. The combination of these contributions makes a strong first step into determining an effective systematic approach for combating IWT.

The remainder of this article is organized as follows. In Section 2, we discuss the existing literature on network interdiction and wildlife trafficking and highlight the contributions of this study. Section 3 introduces the models and their assumptions. In Section 4, we discuss solution approaches for the models. In Section 5, we discuss the data sources and experimental design. In Section 6, we analyze the results of the models and derive key insights for combating IWT. Finally, Section 7 summarizes our contributions and insights.

## 2. Literature review

Our work focuses on applying and adapting techniques from the network interdiction literature to IWT Networks. Existing models have several deficiencies that limit their ability to handle the unique challenges of disrupting IWT. However, when properly adapted, these methods have the potential to drastically improve efforts to curb IWT activity. Our literature review considers relevant works in the network interdiction literature and wildlife crime literature to highlight opportunities for further study and new applications of existing methods.

### 2.1. Interdiction of illicit networks

Network interdiction is an important class of problems in the family of bi-level optimization, where the leader takes interdiction actions that block or inhibit the follower's operations by impacting the follower's objective, feasible region, or both. There is a large body of literature on network interdiction and most interdiction models fall into one of two classes: maximum flow or minimum cost formulations. Wood (1993) and Cormican *et al.* (1998) both present early models where the focus of interdiction actions is to minimize the maximum flow of goods through a network. Golden (1978) and Israeli and Wood (2002) provide examples of shortest-path network interdiction formulations where the goal is to maximize the length of the shortest path through the network using the available interdiction actions. We focus on shortest-path network interdiction in this work but the literature review by Smith and Song (2020) provides a comprehensive survey on network interdiction and the solution approaches. The vast literature on network interdiction has yielded many effective techniques for quickly solving these problems, including the dualize-and-combine technique utilized by Golden (1978) and Israeli and Wood (2002). This technique, which we employ in our models, enables the conversion of the bi-level optimization problems into an equivalent single-level optimization under certain conditions.

Network interdiction can be effectively used to model and solve problems related to disrupting illicit networks by respective law enforcement or other defense actors, such as supply chain or transportation networks supporting guns, drugs (Malaviya *et al.*, 2012; Baycik *et al.*, 2020; Jabarzare *et al.*, 2020), nuclear weapons (Morton *et al.*, 2007) or human trafficking (Keskin *et al.*, 2021), among others. The recent study of Anzoom *et al.* (2022) provides a comprehensive overview of the literature on illicit networks and how to disrupt them. Their review indicates the gap for more problem domains and related solutions for illicit networks, especially for human trafficking and IWT. Law enforcement interdiction in wildlife trafficking and seizures of illicit goods are important tools in the fight against illegal wildlife trafficking. Currently, it is believed that seizures only capture a small portion of IWT, and increased interdiction efforts are needed to curb IWT activity (UNODC, 2020). However, IWT brings several new challenges to network interdiction, such as the need for training and high variation in penalties between countries, which is not included in previous research (Smith and Song, 2020).

### 2.2. Illicit wildlife poaching and trafficking

There are currently two major streams of research at the intersection of operations research and IWT: illicit network identification and patrol routing. Although drug network interdiction has been studied widely, South and Wyatt (2011) and Magliocca *et al.* (2021) demonstrate the differences between illicit network structure and *modus operandi*. Noting the differences, both studies recommend alternative approaches to interdict these networks. Siriwat and Nijman (2023) study the illegal rosewood trade in Thailand and generate regional maps of trafficking networks throughout the country using seizure data.

Although the application of network interdiction approaches to large-scale wildlife trafficking networks has been limited, game-theoretic and bi-level optimization approaches have been used more widely in the context of interdiction at the source of the illicit wildlife supply chain. These works focus on the illegal poaching (trapping and/or killing) of animals in the areas where they naturally occur, particularly in protected wildlife conservation areas. Poaching is one of the primary sources of illicit wildlife products and is a major challenge for the protection of wildlife species globally (Nijman *et al.*, 2019). Increased poaching rates are unsustainable for wildlife populations and threaten conservation efforts. Due to these reasons, there have been several studies on optimizing patrol planning for conservation area protection, preventing poaching at the source. In many protected areas, there are limited rangers and other resources (e.g., budget) to patrol a vast area. The main goal of these studies is to recommend patrol routes to protect endangered animals against poachers (Haas and Ferreira, 2018; Xu *et al.*, 2020; Moore *et al.*, 2021). In most studies, the optimal interdiction strategies are planned in a Stackelberg security game (e.g., green security games) framework (Nguyen *et al.*, 2013; Nguyen *et al.*, 2016). Haas and Ferreira (2018) present two data-based, analytical software tools to plan more effective interdiction patrols for rhino poaching in wildlife reserves. Xu *et al.* (2020) presents a general patrol routing framework against a black-box poaching prediction model. More specifically, their framework optimizes directly over the space of feasible patrol routes and guarantees the implementability of any generated patrol strategy. Moore *et al.* (2021) utilize spatial optimization algorithms to allocate efforts of ranger patrols throughout Nyungwe National Park, Rwanda, and construct a Pareto efficiency frontier.

Patrol routing and illicit network identification are both important steps in reducing the prevalence of IWT. However, the majority of this work is regional in focus, and the existing sources of international seizure data are limited and biased in terms of the geographies and species represented (UNODC, 2020). Given the prevalence of species and geographic displacement in IWT supply chains (UNODC, 2020), it is critical that interdiction and detection efforts are expanded to *an international scale*. Our work offers an important step in this direction. Specifically, we contribute to the literature with domain-specific modifications of existing interdiction models, including the need for training. In addition, we incorporate the trade-off between node interdiction, which can be used to target multiple wildlife trafficking networks simultaneously at central transit hubs, and arc interdiction, which can be used to target specific routes with greater precision and reduced cost. We also introduce a new objective that captures the uneven enforcement landscape that is characteristic of wildlife trafficking. These adaptations are key to leveraging the powerful tools available in the network interdiction literature to tackle IWT on an international scale without omitting the key characteristics that make the trade difficult to disrupt. In the next section, we present our interdiction models and their formulations.

## 3. Mathematical model

We study three network interdiction games, two of them modifications of existing models in the literature and a third that introduces a new objective that captures unique characteristics of the wildlife trafficking domain. The new model introduces a multi-objective approach that is far more realistic for wildlife trafficking than other models available in the literature. It also presents several new challenges with solution speed, which we discuss and resolve in subsequent sections. In these models, the interdictor represents law enforcement authorities, which can invest limited resources to increase the probability that the evader is detected. The evader represents a wildlife trafficker, who attempts to smuggle wildlife illegally from an origin $s$ to a destination node $t$ in the directed network $G = (V, E)$. We assume that the transportation network structure is known, which is reasonable for international trafficking as points of entry into countries are limited and often heavily patrolled by law enforcement. We also assume a full information game, where the interdictor (leader) fully understands the response dynamics of the evader, and the evader (follower) has full knowledge of the interdictor's actions. Note that in future works, both of these assumptions may be relaxed. Both the interdictor and evader act rationally (optimize their utility) and use a pure strategy. Detection is probabilistic, as authorities can not screen everyone and, even if they do screen a trafficker, they may fail to identify illicit products (UNODC, 2020). Specifically, we incorporate a set of probabilities of detection at nodes and along arcs depending on the interdiction actions taken. We model the interdiction problem as a shortest-path interdiction problem because, in a wildlife trafficking context, it is the most intuitive formulation based on the available data for estimating parameters, the likely impact of interdiction actions, and the observed shipment sizes. With a maximum flow formulation, there is no clear path to estimate arc capacities from available data, in contrast with estimating increased costs along arcs. It is not realistic to assume that authorities can limit the total flow of illicit wildlife products through a network with existing interdiction resources. In addition, shipment volumes are often relatively consistent within a particular transit mode (i.e., passenger air, ocean freight, mail), as is common in licit supply chains. High-value products, such as rhino horn and pangolin scales, are often transported in smaller quantities by air and in larger mixed shipments via ocean freight. Perishable items such as live birds and reptiles are often transported in relatively small quantities by passenger air. Given that these shipments are similar in size for a specific transit mode, the shortest-path formulation is the most appropriate in these models.

We first introduce the two benchmark models as modifications (via the inclusion of training decisions and interdiction on both arcs and nodes) of classic models in the literature. These models are relevant to wildlife trafficking, but they lack the flexibility to capture the decisions that traffickers and law enforcement face when enforcement is uneven across countries or limited in effectiveness, due to the lesser importance often placed on IWT by authorities (Keskin *et al.*, 2022). The first model, called the Naive Traffickers Model (NTM), represents the case where the interdictor minimizes the probability of escape and the trafficker, naively, minimizes their travel cost. This is a simple model, but is a useful benchmark that provides insight into scenarios where chances of detection are low, and penalties for trafficking are small. Many non-charismatic species are not easily recognized and receive less attention from law enforcement. In these cases, the interdictor can still benefit from the increased information that comes from successful detection and preventing the goods from reaching markets via seizures. The second benchmark model, the Detection Maximization Model (DMM), captures scenarios where the interdictor seeks to maximize the probability of detecting the trafficker and the trafficker seeks to minimize the probability of detection. This combination is appropriate when the threat of capture is strong, and penalties, when caught, are high. This case is representative of charismatic species that are heavily threatened by poaching, such as rhinos, elephants, and tigers (UNODC, 2020).

Our new model, the Penalty Maximization Model (PMM), generalizes these benchmark models and captures scenarios that fall outside the scope of the previous study. It captures a more complex variant of the trafficker's utility function that considers (i) their transportation cost, (ii) their likelihood of getting caught, and (iii) the severity of consequences they will endure if caught. The objective of this formulation for the interdictor is to maximize the total expected reward (trafficker penalty), where the reward is the sum of travel cost and expected interdiction penalty (i.e., seizures, fines, imprisonment, etc.). This objective is especially relevant for wildlife trafficking where detection ability, corruption level, and legal penalties vary substantially between countries (Broussard, 2017). In some countries, there may be no legal action taken against traffickers aside from the seizure of illicit goods. In others, depending on the product seized, traffickers could face steep fines or even jail time. Existing models do not adequately capture this interplay and its potential impact on traffickers' decisions. This change allows authorities to concentrate interdiction efforts in countries where legal systems are best equipped to penalize traffickers. It also incorporates the trade-off between travel costs and legal repercussions and allows interdictors to target the most economically advantageous routes first. In this way, it acts as a bridge between the two benchmark models. The model presented below is a general representation of the traffickers' decision problem that encompasses the objectives of the previous two models, as well as differences between countries not captured previously in the literature.

We focus our study on trafficking across flight networks, although it can easily be extended/modified to other transit networks with fixed inspection points, where actions improve the detection probability for IWT screening efforts at nodes and on arcs. For flight networks, we assume that interdiction takes place at customs in the destination country of a flight. There are two types of interdiction with the corresponding purposes: (i) *flight (arc) interdiction:* detain a higher percentage of people from that flight for inspection, and (ii) *airport (node) interdiction:* increase the frequency of random detailed inspections of all arriving passengers for wildlife products.

When no actions are taken to prevent wildlife trafficking, there is a small chance that traffickers will still be detected through inspection for other purposes. We denote this probability with $p^0_{ij}$. Our model incorporates a fixed cost, $b^T_j$, for interdiction on node $j$ that represents the money needed for initial training and equipment. Training at a specific node $j$ is a binary decision represented by the decision variable $x^T_j$. Once the training is complete at a given node, there is a probability that law enforcement will detect traffickers without further interdiction effort, $p_j$. For interdiction on a node (airport), the interdiction decision is captured by the binary decision variable $x^N_j$. If law enforcement chooses to interdict a given airport, then they will increase the frequency of inspections for all travelers through that airport. This will result in an increased probability of detection for all flights arriving at that airport, denoted $q^N_j$. For example, the probability of detection at node $j$ with node interdiction and node training is $q^N_j$, because $q^N_j$ already includes the probability $p_j$ and the additional benefit from interdiction. We assume that detection occurs upon arrival at a node, so any trafficker that travels along an edge, $e_{ij}$, will be detected at node $j$ with the appropriate probability. The second interdiction decision is interdiction on the edges (flights), where the decision is represented by the binary variable $x_{ij}$. If law enforcement chooses to interdict a flight, then inspections of passengers arriving from that flight to node $j$ will increase, resulting in an increased detection probability $q_{ij}$. To achieve their objective, the interdictor may train on nodes, interdict on nodes, and/or interdict on arcs subject to their budget constraint. The interdictor selects a set of nodes to train ($x^T_j$), and interdict ($x^N_j$), as well as edges to interdict ($x_{ij}$) subject to a total budget constraint $\beta$. Additional constraints encode the setting where both interdiction types occur. A complete summary of the notation is in Table 3, available in the Appendix.

Let $p_{ij}$ represent the overall probability of detection on edge $e_{ij}$. We demonstrate how to compute the value of $p_{ij}$ for different interdiction decisions using Equation (1) and Table 1. To simplify the notation for the various probabilities of detection used in the formulations, we introduce the auxiliary variables $z^a_{ij}$. Where $z^a_{ij}$ is a binary variable that represents the scenario where action combination $a \in A = \{0$ - do nothing, T - train only, N - node interdiction and training, E - edge interdiction and training, B - node and edge interdiction and training $\}$ is taken on edge $e_{ij}$. The correspondence between the interdiction decisions, the $z^a_{ij}$ variables, and the values of $p_{ij}$ are shown in Table 1. We use the relationship $P(A \cup B) = P(A) + P(B) - P(A \cap B)$ to define the probability for $z^B_{ij}$, assuming that the probabilities of detection on the node and on arc are independent given the action choice. Using this table and that, for each edge, only one $z^a_{ij}$ variable can be non-zero, we can write a simplified equation to compute the value of $p_{ij}$.

$$p_{ij} = \sum_{a \in A} p^a_{ij} z^a_{ij}. \quad (1)$$

The general constraint set faced by the interdictor is denoted as *IC*, where,

**Table 1.** Detection probability on arc.

| Variable | $x^T_j$ | $x_{ij}$ | $x^N_j$ | $p^a_{ij}$ |
|---|---|---|---|---|
| $z^0_{ij}$ | 0 | 0 | 0 | $p^0_{ij}$ |
| $z^T_{ij}$ | 1 | 0 | 0 | $p_j$ |
| $z^E_{ij}$ | 1 | 1 | 0 | $q_{ij}$ |
| $z^N_{ij}$ | 1 | 0 | 1 | $q^N_j$ |
| $z^B_{ij}$ | 1 | 1 | 1 | $q_{ij} + q^N_j - q^N_j q_{ij}$ |

$$
IC = \left\{ \begin{array}{lll}
\sum_{j\in V} b_j^T x_j^T + \sum_{j\in V} b_j^N x_j^N + \sum_{(i,j)\in E} b_{ij} x_{ij} \le \beta, & & \\
x_{ij} \le x_j^T, & (i,j)\in E, j\in V, & z_{ij}^0 \le 1 - x_j^T, (i,j)\in E, j\in V, \\
z_{ij}^0 \ge 1 - x_j^T - x_j^N - x_{ij}, & (i,j)\in E, j\in V, & z_{ij}^T \le x_j^T, (i,j)\in E, j\in V, \\
z_{ij}^T \le 1 - x_j^N, & (i,j)\in E, j\in V, & z_{ij}^T \le 1 - x_{ij}, (i,j)\in E, j\in V, \\
z_{ij}^T \ge x_j^T - x_{ij} - x_j^N, & (i,j)\in E, j\in V, & z_{ij}^N \le x_j^N, (i,j)\in E, j\in V, \\
z_{ij}^N \le 1 - x_{ij}, & (i,j)\in E, j\in V, & z_{ij}^N \ge x_j^N - x_{ij}, (i,j)\in E, j\in V, \\
z_{ij}^B \le x_{ij}, & (i,j)\in E, & z_{ij}^B \le x_j^N, (i,j)\in E, j\in V, \\
x_{ij} + x_j^N \le z_{ij}^B + 1, & (i,j)\in E, j\in V, & z_{ij}^0 + z_{ij}^T + z_{ij}^N + z_{ij}^E + z_{ij}^B = 1, (i,j)\in E, j\in V, \\
x_j^T, x_j^N, x_{ij}, z_{ij}^0, z_{ij}^T, z_{ij}^N, z_{ij}^E, z_{ij}^B \in \{0,1\}, & j\in V, (i,j)\in E & x_j^N \le x_j^T, j\in V.
\end{array} \right.
$$

The first equation represents the budget constraint, where the first sum captures the training cost, the second sum captures the node interdiction cost, and the last sum captures the arc interdiction cost. The second and third equations enforce the constraint that we must train at the location where the flight arrives before the airport or flight interdiction can occur. The remaining constraints enforce the relationships between the $x$ and the auxiliary $z$ variables and ensure that the $z$ variables are mutually exclusive. In the following sections, we provide the complete formulation for the interdictor's decision problem, subject to the trafficker's optimal actions $y^*$.

In DMM and PMM, the interdiction and the trafficker's decisions are binary variables, denoted by $\mathbf{x}, \mathbf{z}, \mathbf{y}$. Hence, as shortest-path network interdiction problems, they are NP-hard (Ball *et al.*, 1989; Smith and Song, 2020). In NTM and DMM benchmarks, the binary variables are $y_{ij}$, which denote whether the trafficker chooses to travel along edge $e_{ij}$ or not. In PMM, the binary variables are $y_k$, which denote whether the trafficker chooses to travel along path $k \in \kappa$ or not. For all formulations, $\mathbf{y}$ denotes the vector of $y$ variables. Following Smith and Song (2020), let $T$ be the node-arc incidence matrix, where each row corresponds to a node in $N$ and each column to an arc in $E$. For each arc $e_{ij} \in E$, the corresponding column in $T$ will have a one in row $i$, a −1 in row $j$, and zeros everywhere else. Let $\mathbf{l} \in \mathbb{Z}^{|V|}$ be a vector, where $l_j = 0$ for all $j \in V \setminus \{s,t\}$, $l_s = 1$, and $l_t = -1$.

### 3.1. Benchmark models

#### 3.1.1. NTM

The first benchmark model minimizes the probability of the trafficker escaping, subject to the traffickers' optimal decisions $y_{ij}^*$, to the lower-level problem, and a budget constraint. We study the bi-level optimization problem where the trafficker naively minimizes travel costs, with no consideration for detection. Note that naive cost minimization is equivalent to the case where the trafficker has no information about the interdiction actions. This is a reasonable approach when enforcement is infrequent or ineffective. Unfortunately, this is often the case for wildlife trafficking, which makes this a useful benchmark model. To model the interdictor's objective, we define the probability of escape using the log transformation (Taha, 2019). Using our notation, the described objective is $\sum_{(i,j)\in E} \log(1-p_{ij})y_{ij}$. Using the definition of $p_{ij}$ from Equation (1), we can rewrite this objective in terms of the interdictor's decisions as shown below. This approach is successful because $\sum_{a\in A} z_{ij}^a = 1$, i.e., the $z$ variables are mutually exclusive. The constraint set for the interdictor is captured in $IC$, described above.

$$\min \sum_{(i,j)\in E} \left[ \sum_{a\in A} \log(1-p_{ij}^a) z_{ij}^a \right] y_{ij}^*, \text{ s.t. } IC.$$

The traffickers' problem is a classic shortest-path problem. It is well documented in the literature that a shortest-path problem formulated with a node-arc incidence matrix and the assumption of no negative cost cycles has an integer solution when formulated with the constraints shown below (Smith and Song, 2020):

$$\min \sum_{(i,j)\in E} c_{ij} y_{ij}, \text{st.} T\boldsymbol{y} = \boldsymbol{l}, \text{ and } \boldsymbol{y} \ge 0.$$

#### 3.1.2. DMM

The second benchmark model studies the bi-level optimization problem where the interdictor (trafficker) maximizes (minimizes) the probability of detection, subject to the traffickers' optimal decisions $y_{ij}^*$, to the lower-level problem, and a budget constraint. The probability of detection on each edge is dependent on the interdiction actions. This approach captures cases where interdiction efforts strongly impact traffickers' decisions and is more appropriate for heavily protected species such as rhinos and elephants. The formulation below shows the interdictors' problem, which is the same as for NTM:

$$\min \sum_{(i,j)\in E} \left[ \sum_{a\in A} \log(1-p_{ij}^a) z_{ij}^a \right] y_{ij}^*, \text{ s.t. } IC.$$

The traffickers' problem changes from NTM now to considering interdiction actions when selecting routes. This changes the objective to maximize their probability of escape instead of minimizing the transportation cost, as shown below.

$$\max \sum_{(i,j)\in E} \left[ \sum_{a\in A} \log(1-p_{ij}^a) z_{ij}^a \right] y_{ij} \text{ s.t. } T\boldsymbol{y} = \boldsymbol{l}, \text{ and } \boldsymbol{y} \ge 0.$$

### 3.2. PMM

Our new model maximizes the total expected reward (penalty) for the interdictor (trafficker). The expected penalty function captures the monetary penalty (cost) of traveling along a path, $c_k$, and the expected interdiction penalty the trafficker will incur on the path, $P_k$. For example, if a trafficker is traveling along the path $(1,5),(5,7),(7,9)$, then their expected interdiction penalty would be $P_k = R_5 p_{15} + R_7 p_{57}(1-p_{15}) + R_9 p_{79}(1-p_{57})(1-p_{15})$, where the $R_j$ values are the node-specific penalties (rewards) that traffickers (interdictors) will incur if detection is successful. $P_k$ is a function of the interdiction variables, $z_{ij}^a$, since $p_{ij} = \sum_{a\in A} p_{ij}^a z_{ij}^a$. This objective is nonlinear in the interdiction decision variables $z_{ij}^a$ since we need to account for the probability of escape at previous airports along the route to avoid a "double jeopardy" situation. It is unlikely that a trafficker would continue along their route after being detected at an earlier node since seizures are the most common interdiction action. We cannot utilize the log transformation in this formulation, due to the structure of $P_k$. This requires switching to a path-based formulation where the decision variables $y_k$ represent the trafficker's decision to travel on path $k \in \kappa^L$ and $\kappa^L$ is the set of all paths that contain $L$ or fewer edges. For our experimentation, we utilize a three-edge limit that is not restrictive given our context with flight paths and allows for substantial deviations from the shortest/quickest route, but various limits can be used depending on the context. The formulation requires the use of additional auxiliary variables, $Z_k$, to remove the non-linearity. The variables composing $Z_k$ have multiple indexes, the first is the path index $k$, the second is the action along the first edge $a_1 \in A_1$, the third is the action along the second edge $a_2 \in A_2$, and so on until the final edge $L$. Note that the action sets $(A_1, \ldots, A_L)$ are changing for each edge, this is because not all paths $k \in \kappa^L$ contain exactly $L$ edges. If a path has less than $L$ edges, then the action set for the missing edges will be limited to zero, do nothing. For convenience, we define $E_k$ as the ordered set of edges belonging to path $k$, where $e_1 = (i,j)$ is the first edge in path $k$. The individual variables in $Z_k$ take the form $z_{k,a_1,\ldots,a_L}$ and are tied to the $z_{ij}^a$ variables through an additional set of constraints that ensure that $z_{k,a_1,a_2,\ldots,a_L} = z_{e_1}^{a_1} \cdot z_{e_2}^{a_2} \ldots \cdot z_{e_L}^{a_L}$. This approach is known as the McCormick linearization in the literature (McCormick, 1976). The constraint set for the path-based formulation is denoted by $IC_P$ and is shown below:

$$IC_P = \begin{cases} IC, & \\ \sum_{a_1\in A_1}\sum_{a_2\in A_2}\cdots\sum_{a_L\in A_L} z_{k,a_1,a_2,\ldots,a_L} = 1, & k \in \kappa^L, \\ z_{k,a_1,a_2,\ldots,a_L} \le z_{e_1}^{a_1}, & e_1 \in E_k, k\in\kappa^L, a_1\in A_1,\ldots,a_L\in A_L, \\ z_{k,a_1,a_2,\ldots,a_L} \le z_{e_2}^{a_2}, & e_2 \in E_k, k\in\kappa^L, a_1\in A_1,\ldots,a_L\in A_L, \\ \ldots & \\ z_{k,a_1,a_2,\ldots,a_L} \le z_{e_L}^{a_L}, & e_L \in E_k, k\in\kappa^L, a_1\in A_1,\ldots,a_L\in A_L, \\ z_{k,a_1,a_2,\ldots,a_L} \ge z_{e_1}^{a_1} + z_{e_2}^{a_2} + \ldots + z_{e_L}^{a_L} - L + 1, & e_1, e_2, \ldots, e_L \in E_k, k\in\kappa^L, a_1\in A_1,\ldots,a_L\in A_L, \\ z_{k,a_1,a_2,\ldots,a_L} \in \{0,1\}, & k\in\kappa^L, a_1\in A_1,\ldots,a_L\in A_L. \end{cases}$$

We define $\Theta_k(Z_k) = c_k + P_k$ as the expected penalty function for path $k$. Then, using the McCormick linearization (McCormick, 1976), we can compute the expected penalty function as follows:

$$\Theta_k(Z_k) = c_k + \sum_{a_1\in A_1}\cdots\sum_{a_L\in A_L}\left(R_{e_1}p_{e_1}^{a_1} + R_{e_2}p_{e_2}^{a_2}(1-p_{e_1}^{a_1}) + \ldots + R_{e_L}p_{e_L}^{a_L}(1-p_{e_{L-1}}^{a_{L-1}})\ldots(1-p_{e_1}^{a_1})\right) z_{k,a_1,a_2,\ldots,a_L}.$$

We can then model the interdictor's problem using the constraint set $IC_P$ and the expected penalty function $\Theta_k(Z_k)$ described above.

$$\max \sum_{k\in\kappa^L} \Theta_k(Z_k) y_k^*, \text{ s.t. } IC_P.$$

The traffickers' problem is again a shortest-path problem, but it is reformulated to incorporate the path-based decision variable $y_k$. The constraint that the trafficker selects exactly one path through the network results in a totally unimodular matrix with an integer right-hand side which, along with the constraint $\mathbf{y} \ge 0$, guarantees an integer optimal solution.

$$\min \sum_{k\in\kappa^L} \Theta_k(Z_k) y_k \text{ s.t. } \sum_{k\in\kappa^L} y_k = 1, \text{ and } \boldsymbol{y} \ge 0.$$

## 4. Solution procedures

In this section, we highlight the different approaches we utilize to solve the three interdiction model types. We incorporate a combination of approaches prior to using commercial solvers, including dualize-and-combine, warm start, and bounds to reduce the network size. The combination of these procedures led to more efficient computational performance for the models discussed. We also introduce an approximation to the objective of PMM that allows us to reformulate the problem and substantially decrease solution times across all instances. We provide data on the solution times in Section 6.

### 4.1. Benchmark models

NTM is easy to solve sequentially using commercially available solvers. Since the traffickers do not respond to interdiction actions and simply minimize their travel cost, we can first solve their shortest-path problem without any interdiction decisions and then use the optimal $y^*_{ij}$ values in the formulation of the interdictor's problem. The interdictor's problem can then be solved quickly using commercial solvers.

To solve DMM, we utilize the dualize-and-combine approach that is popular in the literature (Israeli and Wood, 2002; Smith and Song, 2020). This approach converts the bi-level optimization problem into a single-level optimization problem that can be solved with commercial solvers. This approach works for our model because the follower's problem is a shortest-path problem, i.e., a convex optimization problem (Smith and Song, 2020). When combined with the strategic use of auxiliary variables and the log transformation to remove any non-linearity, this approach is capable of solving realistic instances in reasonable time frames. Following the convention in the literature, we use $\pi \in \mathbb{R}^{|V|}$ to represent the dual variables associated with the shortest-path constraints.

The single-level formulation of the detection maximization model with intelligent trafficker response is shown below. Recall that $l$ is the vector that forms the right-hand side of the shortest-path constraints and $T$ is the node-arc incidence matrix. Define $u$ as the vector of length $|E|$, where for edge $e \in E$, we have $u_e = \sum_{a \in A} \log(1 - p^a_e) z^a_e$. Then we can rewrite the bi-level formulation as follows.

$$\max \boldsymbol{l}'\boldsymbol{\pi}, \text{s.t } T'\boldsymbol{\pi} \le u, \text{ and } IC.$$

### 4.2. Solution approaches for PMM

PMM can also be solved using a dualize-and-combine approach. However, the computation times are much longer for this model, due to the large number of variables introduced by the path-based formulation. The dual of the path-based shortest-path problem has a single dual variable $\pi$ to match the single constraint, that only one path can be selected. The dual constraints require that the value of $\pi$ be less than the value of the primal objective, $\Theta_k(Z_k)$, for all paths $k \in \kappa^L$. As in DMM, we also include the interdiction constraints $IC_P$. The combined single-level formulation is:

$$\max \pi, \text{ s.t. } \boldsymbol{\pi} \le \Theta_k(Z_k), \qquad \forall k \in \kappa^L, \text{ and } IC_P.$$

This formulation can be solved using a commercial solver, but it is time-consuming for realistic network sizes. To improve the solution time for this model, we use two different approaches: warm starting the optimization process and removing certain unused paths from $\kappa^L$ prior to the optimization process.

There are many potential approaches for deciding on the initial solution used in the warm start. The nature of the interdiction model makes it easy to generate many feasible interdiction solutions and then solve the shortest-path problem that arises. Our approach was to first solve the model with a small budget and then use that solution to warm start instances with larger budgets. In addition to the warm start, we used a bound to remove unused paths from the network to reduce its size. The bound is determined by calculating the largest possible penalty $\Theta_k(Z^B_k)$ for all paths $k \in \kappa^L$, where $Z^B_k$ indicates that both arcs and nodes are interdicted on all legs of path $k$. Then, the bound can be represented by $\gamma$, where $\gamma = \min_{k \in \kappa^L} \Theta_k(Z^B_k)$. This bound represents the worst possible case for the trafficker, they will always be able to travel on a path with a penalty at least this low, even if the interdiction budget is unlimited. We can then use $\gamma$ to remove any path $k \in \kappa^L$ such that $\gamma < \Theta_k(Z^0_k)$, which is the base penalty from traveling the path when no interdiction actions are taken.

#### 4.2.1. Double jeopardy objective approximation

Solving the PMM, even after removing unnecessary paths with the bound, is very time-consuming. Results presented in Section 6 show that the average solution time is extremely high for certain origin–destination pairs and that some instances could not be solved using commercial software within our time frame of 86,400 seconds. To improve the solution speed for PMM, we introduce an approximation to the objective function that allows us to take advantage of the structure of DMM and its much faster solve time. Specifically, we relax the assumption that traffickers can only be caught once along their route and calculate the objective as though they can be caught in each country and face the respective penalties according to the probability of detection along the specific node and arc. We call this the "Double Jeopardy" Approximation (DJA) after the procedural defense that prevents a person from being prosecuted twice for the same offense. This approximation always returns a feasible solution, because it uses the constraint set from DMM, but the solution it returns often has an optimality gap. Since it always returns a feasible solution, we evaluate the performance of the DJA solution as a warm start for PMM. The DJA can be solved using an arc-based formulation instead of a path-based formulation, which yields substantial improvements in solution speed. The revised expected penalty function for the DJA is shown below.

$$\begin{aligned}\Theta_k(Z_k) = {} & c_k \\ & + \sum_{a_1 \in A_1} \sum_{a_2 \in A_2} \cdots \sum_{a_L \in A_L} (R_{e_1} p^{a_1}_{e_1} z^{a_1}_{e_1} + R_{e_2} p^{a_2}_{e_2} z^{a_2}_{e_2} + \ldots \\ & + R_{e_L} p^{a_L}_{e_L} z^{a_L}_{e_L}).\end{aligned}$$

We can convert the expected penalty function to an arc-based formulation now that we no longer account for the probability of escape on previous arcs along the path. The single-level formulation of the DJA is shown below using a similar notation to DMM. We define $u$ as the vector of length $|E|$, where for edge $e \in E$ we have $u_e = c_e + \sum_{a \in A} R_e p^a_e z^a_e$. Then, we can rewrite the bi-level formulation as follows using IC as the constraint set because it is an arc-based formulation.

$$\max \boldsymbol{l}'\boldsymbol{\pi}, \text{ s.t } T'\boldsymbol{\pi} \le u, \text{ and } IC.$$

## 5. Data sources and experiments

In this section, we discuss the data used in our models and any data pre-processing that we performed. To capture a varied and realistic set of instances, we sourced data from several conservation groups and other entities and combined seizure records with flight infrastructure and pricing data.

### 5.1. External data sources

Seizure data is an important source of information about IWT networks and provides a limited understanding of trafficking routes and the species involved. It is important to recognize that seizure data is incomplete and often not representative of the true state of IWT because it is heavily biased by variations in enforcement. In this study, we use seizure data from the Wildlife Trade Portal (WTP: wildlifetradeportal.org). The WTP states that

> while wildlife incident data is a vital source of information, it should not be inferred that there is a direct correlation between incidents and the overall IWT or that information across locations, species or time is consistent.

The data we accessed includes records of global seizures for all wildlife species that occurred on air transit networks between October 1, 2017, and January 1, 2021. With 1067 records for a variety of species and trafficking routes, we identify candidate networks with the origin and destination airports for each seizure record for model testing. The airport and flight network was created from data gathered from the open-source database, OpenFlights.org. The files contain information on 8267 airports located around the world and the corresponding commercial flights. It must be noted that the routes were last updated in June 2014. All new airports and flights which were represented in the seizure data have been added to the data set. We used the combination of both data sources to form a base global flight network, then we narrowed the network to focus on potential paths between origin and destination airports. Flight prices were collected using the Skyscanner API (https://skyscanner.github.io/slate/). For each pair of airports, we used the API to request flight quotes for November 2021 (all API requests were executed on October 14, 2021). In total, we amassed a data set containing 44,462 price quotes. We then used the lowest price in that time window as the price between the source and destination airport. The API did not return valid responses for several airport pairs without existing flight plans. Additionally, we note that data was collected during the coronavirus pandemic, as historical data was not available, and some flight data was not present.

We used reports from UNODC to supplement the seizure data (UNODC, 2020). The report draws from a variety of sources and provides a more holistic view of wildlife trafficking with relevant data for several product groups, not just those most commonly represented in seizure data. To fully capture the utility of PMM, we need information about countries' abilities to enforce legal penalties for wildlife trafficking. Unfortunately, to the best of our knowledge, there is no database or ranking of countries' wildlife trafficking enforcement efforts. However, The Global Organized Crime Index (2021) contains information on the prevalence of different forms of organized crime in a country and the country's resilience. Though this is not a perfect proxy for a country's ability to penalize IWT activities, we use this data to test the capabilities and responses of the penalty maximization model when faced with varying penalties.

### 5.2. Experimental design

When designing our experimentation, we first determined the Origin–Destination (OD) pairs that should be used in the analysis. The choice of OD pairs is important because it determines the flight network structure and size. To properly represent real-life trafficking and interdiction networks, we utilized two approaches for selecting OD pairs: (i) analyzing the most prevalent OD pairs from air trafficking seizure data, and (ii) finding the key origin and destination countries for specific product groups using data from the UNODC (2020) report. Figure 6 (in the Appendix) shows the OD pairs that were most prevalent in the seizure data, and Figure 7 (in the Appendix) shows the pairs obtained by the product group analysis. These figures illustrate why using seizure data alone is not sufficient. Current interdiction efforts are heavily focused on certain species and regions. As a result, seizure data mostly document trafficking between African countries and Southeast Asian countries. By specifically seeking out countries of interest for a wide variety of illicit wildlife products, we can diversify the networks studied and take a more global approach to battle wildlife crime. For each selected OD pair, we formed the flight network for the interdiction model using the OpenFlights data by identifying all airports and flights that were part of a path of length three or less between the origin and destination. All edge costs for the flight network were assigned using the flight pricing results from the Skyscanner API.

In our experiments, the interdiction and training costs are constant across all locations. The model and solution procedures will work for varying costs, but identifying critical areas of interest was more straightforward without the added dimension of variability. We set the training cost at an airport to \$200 and the airport and flight interdiction costs to \$100 and \$40, respectively. These values represent the traditional intuition that upfront training costs are more expensive to start and that interdiction of a broader population, such as all passengers traveling through an airport, is more costly than interdicting a targeted group, such as all passengers on a specific flight. To complement these costs, we test our models using a variety of budgets for each network. The budgets are adjusted depending on the model and the specific flight network. In particular, NTM requires a smaller budget because traffickers never stray from the most cost-efficient path. To generate the budgets for these networks, we identify a maximum budget value that corresponds to the cost of interdicting the entire flight network, where the flight network is problem-specific. We also identify a minimum budget, which is the smallest amount needed to execute any interdiction action. We then generate budget levels at even increments between the identified minimum and maximum budgets. We report most of the interdiction results as a proportion of the maximum budget for ease of comparison.

When determining the detection probability values, we employed a similar strategy to that used for specifying the

Table 2. Summary of instances, including network size and interdiction model solution time averages over all budget values for an OD pair.

| O-D pair | $\|E\|$ | $\|V\|$ | $\|\kappa\|$ | Average Solve Time by Model (seconds) | | | | | DJA Gap (%) |
|---|---|---|---|---|---|---|---|---|---|
| | | | | NTM | DMM | PMM | DJA | PMDJ | |
| BCN-HKG | 1877 | 201 | 1678 | 1.92 | 6098.43 | 38,379.95 | 4913.01 | 24,272.51 | 0.65 |
| MEX-MIA | 2059 | 164 | 1897 | 2.17 | 1121.47 | 35,325.86 | 2.41 | 35,633.43 | 25.22 |
| BKK-LAX | 1522 | 137 | 1387 | 1.62 | 5636.00 | 31,063.47 | 1911.75 | 13,432.00 | 0.75 |
| LIM-ORD | 1508 | 181 | 1329 | 1.03 | 3408.28 | 29,023.93 | 414.60 | 10,889.37 | 0.68 |
| MNL-VIE | 757 | 118 | 641 | 0.50 | 2257.38 | 15,645.49 | 559.94 | 4488.07 | 1.87 |
| BKK-MAA | 968 | 111 | 859 | 0.70 | 1.55 | 15,075.47 | 0.63 | 16,594.78 | 29.84 |
| JNB-HKG | 926 | 108 | 820 | 0.76 | 420.52 | 13,706.69 | 33.75 | 3081.99 | 0.61 |
| ADD-PVG | 658 | 98 | 562 | 0.38 | 330.28 | 13,034.64 | 20.09 | 2839.48 | 1.47 |
| JNB-KUL | 740 | 95 | 647 | 0.47 | 115.78 | 12,425.53 | 28.91 | 2794.82 | 0.65 |
| MAA-SIN | 862 | 100 | 764 | 0.72 | 18.77 | 12,310.18 | 0.48 | 9954.78 | 19.89 |
| CDG-HND | 1271 | 203 | 1070 | 1.05 | 8.04 | 11,379.10 | 0.84 | 22,243.19 | 20.37 |
| ADD-HKG | 690 | 88 | 604 | 0.39 | 83.68 | 11,029.41 | 0.28 | 10,131.47 | 19.74 |
| ADD-CAN | 552 | 88 | 466 | 0.39 | 357.71 | 9954.11 | 25.93 | 1554.50 | 0.64 |
| DXB-SGN | 1028 | 140 | 890 | 0.69 | 3.20 | 9577.17 | 0.55 | 11,851.10 | 17.56 |
| CGK-SIN | 936 | 95 | 843 | 0.96 | 15.09 | 5066.70 | 0.40 | 5840.60 | 27.76 |
| DPS-ICN | 720 | 96 | 626 | 0.44 | 367.76 | 4727.92 | 0.31 | 3832.11 | 21.18 |
| LOS-CAN | 432 | 60 | 374 | 0.27 | 57.75 | 4188.91 | 5.26 | 1073.41 | 1.64 |
| ADD-CTU | 280 | 62 | 220 | 0.18 | 208.78 | 1454.67 | 11.89 | 416.06 | 1.40 |
| DAR-HKG | 304 | 73 | 233 | 0.21 | 118.36 | 887.65 | 0.79 | 307.34 | 2.18 |
| RGN-CSX | 225 | 45 | 182 | 0.17 | 2.41 | 706.30 | 0.79 | 292.49 | 3.34 |
| TIJ-PVG | 82 | 32 | 52 | 0.06 | 0.52 | 159.91 | 0.63 | 54.54 | 0.89 |
| MXL-SEA | 83 | 39 | 46 | 0.06 | 0.49 | 61.26 | 0.32 | 29.14 | 1.02 |
| CNX-MFM | 96 | 21 | 77 | 0.07 | 0.28 | 50.07 | 0.15 | 23.38 | 0.31 |
| FIH-SGN | 80 | 29 | 53 | 0.06 | 0.33 | 49.75 | 0.22 | 18.56 | 1.16 |
| MPM-HAN | 31 | 15 | 18 | 0.03 | 0.06 | 12.02 | 0.07 | 3.54 | 0.26 |

costs of interdiction. Specifically, we set the base probability of detection with no interdiction as the smallest value and incremented this base probability to arrive at the detection probabilities associated with airport training, airport interdiction, and flight interdiction. This process led to the set of detection probabilities $p_{ij}^0, p_j, q_j^N, q_{ij} = \{0.05, 0.1, 0.15, 0.2\}$, which we feel is reasonable since authorities can inspect a larger proportion of items on a single flight than they can in an entire airport.

The final piece of the experimental design is the penalty values for PMM. We investigated three different types of penalties: low, high, and varied. The low and high penalty cases are comparisons to NTM and DMM, respectively. These low and high penalties were set at \$1000 and \$5000 for all countries in each experiment, respectively. For the varied penalty case, we set the penalty for each country based on its resilience scores (The Global Organized Crime Index, 2021). The resilience scores for the countries are shown in Figure 9, in the Appendix. We assigned the penalties such that countries with a resilience score of 10 had the maximum penalty of \$2000 and countries with a score of zero have a penalty of \$0. Note, these settings are solely for the purpose of testing the model and are not necessarily an accurate representation of the countries' abilities to combat IWT. More research and cooperation are needed to truly estimate the variations between countries' ability to successfully indict and convict traffickers.

## 6. Computational results

In this section, we will discuss and interpret the performance of the proposed solution approaches and the results for the three interdiction models. We provide insight into the structure of the optimal interdiction decisions, how those decisions change as the budget increases, and the differences between the models and their specific uses. We use several representative trafficking networks to give insight into what these strategies look like in practice and highlight any implementation concerns for the various models. Our computational experiments are run with Gurobi (9.1) (Gurobi Optimization, 2021) on five 32-core machines with Intel 2.1 GHz CPUs and 264 GB of memory.

### 6.1. Solution times and performance

Table 2 shows the solution times for all three models for each OD pair and the key network characteristics of the pair. Relative to the other models, solution times for the NTM are fast and primarily determined by the number of paths through the network, which is labeled with $|\kappa|$ in the table. The instance with the longest solution time for this model had an average duration of only 2.17 seconds with a standard deviation of 1.51 seconds. This highlights the usefulness of this model as a first step for practitioners who are unlikely to have extensive computational resources.

The solution times for DMM are larger than those of NTM. However, the average solution time was 825 seconds (0.23 hours) per instance, and the largest network took 1.7 hours to solve on average, which is reasonable for a strategic problem. In general, across all the models, the networks generated from the OD pairs from the UNODC data (shown in Figure 7 in the Appendix) took longer to solve than those generated from the WTP data (shown in Figure 6 in the Appendix). This is likely due to the increased distance between the OD pairs obtained from UNODC. In total, 37 instances out of the 500 across the OD pairs were not solved in the time limit for DMM, 31 UNODC (3 hour limit) and six WTP (1 hour limit). Table 4,

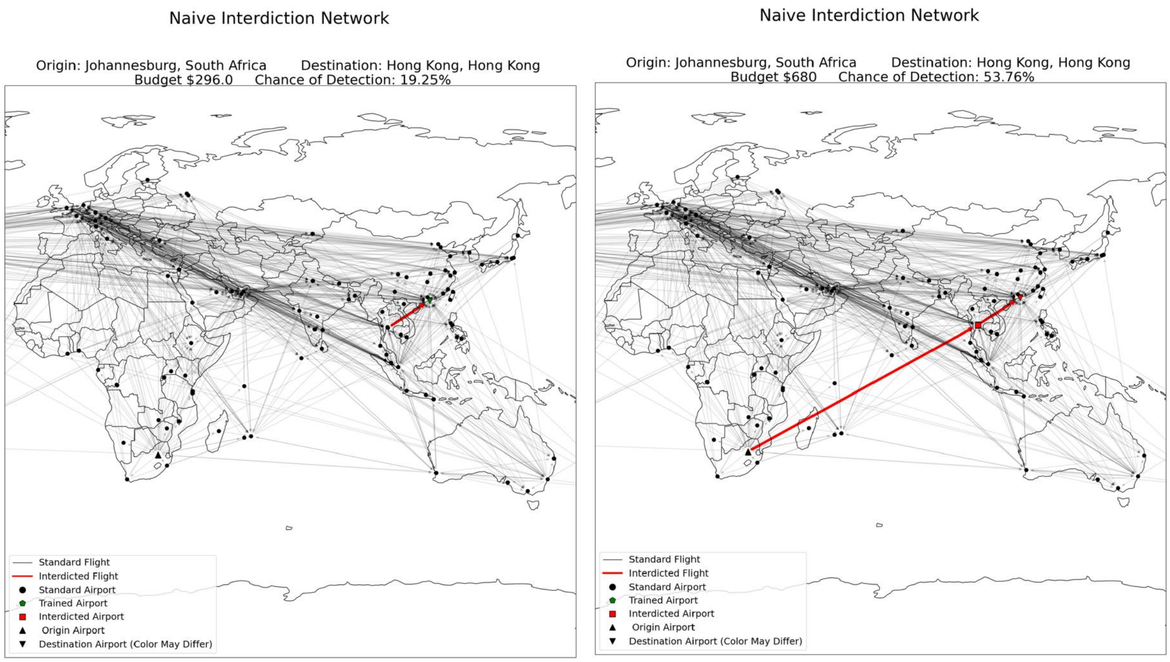


**Figure 1.** Naive traffickers model interdiction decisions for trafficking between Johannesburg and Hong Kong with different budgets.

in the Appendix, shows that the change in the length of the traffickers' paths post-interdiction is a key factor that impacts the solution time. In particular, instances, where the budget increase from the previous instance leads to a change in the trafficking path length, are difficult to solve because the lack of strong bounds delays the convergence.

PMM is the slowest of the three models, with the largest network taking an average of 10.66 hours to solve when using the path-based formulation with the path fathoming and basic warm start approaches. The path-fathoming approach was most successful in instances with lower penalties because a larger number of paths can be pruned. The warm start improved solution times for a larger set of instances but the largest instances were still time-consuming to solve. In addition, 74 instances in the high penalty group, out of a total of 1500 instances across all penalty groups, hit the 24-hour time limit. DJA has a similar formulation to DMM and was much faster to solve than the path-based formulation for PMM, with an average solve time of 317.36 seconds, compared with 11,011.85 seconds for the path-based formulation. Due to the similarity to DMM and reduced solution times, we used a 6-hour time limit for DJA and only 17 instances out of 1500 hit the time limit. DJA always returns a feasible solution, but the optimality gap varied between 0.27 and 29.85% with an average gap of 8.05% across all OD pairs, for instances that did not hit the time limit. The best results were achieved by using the DJA as a warm start for PMM, which we refer to using the acronym PMDJ. This approach provided PMM with a good, at times extremely good, initial feasible solution, which reduced the solution times by an average of 31.13%, including the time to solve DJA and PMDJ, and solved the model to optimality. The number of instances hitting the 24-hour time limit was also reduced to 32 for PMDJ in comparison with 74 instances for PMM. The time to solve both the DJA and the PMDJ was 7583.47 seconds, on average, compared with 11,011.85 seconds for the initial solution approach. The complete set of solution times for all models is shown in Table 2. The solution times for the DJA mirror the solution time for DMM, which is intuitive given the structure of the formulation. The largest optimality gaps for the DJA were correlated with the slowest solving instances of PMDJ, which demonstrates the value of higher quality starting solutions.

### 6.2. NTM insights

For NTM, Figure 1 shows the interdiction strategy for two different budget levels on trafficking between Johannesburg and Hong Kong. This figure is an example of how the solution changes as the budget increases. The solutions require relatively few interdiction actions and are easy to describe in a simple policy. Interdiction only takes place along the lowest-cost flight path, because traffickers do not adapt in this model. A simple strategy that can be used by practitioners is to start at the destination and work back through the network. First, training the node, then interdicting the preceding arc, then interdicting nodes in a greedy fashion. The model is capable of handling varied probabilities and interdiction costs at different airports, but this was not part of our experimentation. The probabilities of detection after interdiction in NTM are high, and the relative budgets required to achieve high probabilities of detection are much less than other models. Although NTM is simple, it represents a reasonable first step for interdiction of less "charismatic" species where political will and funds for enforcement are scarce as mentioned earlier.

### 6.3. DMM insights

DMM yields more complex solutions than NTM. Figure 2 shows how the probability of detection and optimal path

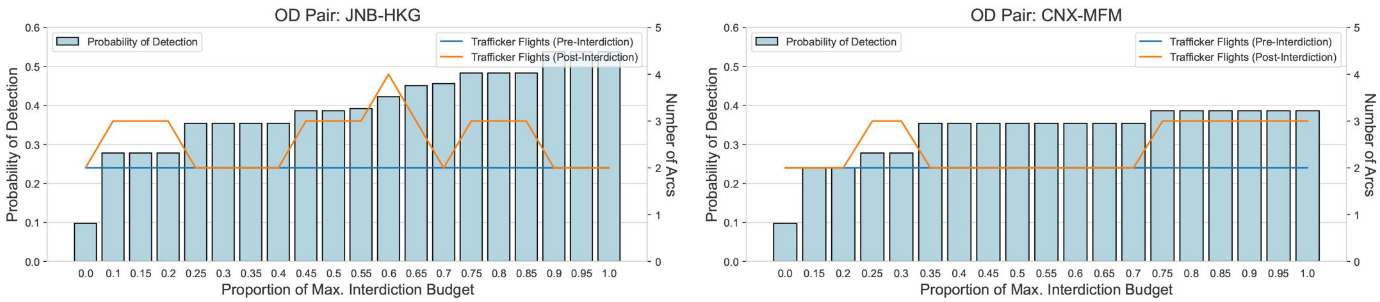


**Figure 2.** Detection probability and optimal path length by budget (Johannesburg to Hong Kong and Chiang Mai to Macau).

length change as the interdiction budget changes for two networks, Johannesburg to Hong Kong and Chiang Mai to Macau. The figure shows several plateaus in the probability of detection and cycles in the optimal path length. One key aspect of this model is the inclusion of traffickers' risk of detection on every flight, so if all flights have an equal probability of detection, then they take as few flights as possible. If the interdiction decisions make it impossible to travel a path of the shortest length without using an interdicted arc or node, then the trafficker will switch to a longer path that avoids interdiction if it exists. As interdiction actions target longer paths, traffickers will switch between those paths to avoid interdicted flights and airports until there are no remaining paths of the same length that have no interdiction. At this point, if there is a longer path, traffickers may switch to that one, or they may switch back to their original path of shorter length and accept the penalty if traveling through a single trained/interdicted flight. This cycle repeats as the level of interdiction increases from just training, to training and flight interdiction, and eventually to training, flight interdiction, and airport interdiction. Figure 3 shows how the interdiction decisions and trafficker response vary at two different plateaus in detection probability for Johannesburg to Hong Kong. In the first network, top left, the budget is $1058, and the flight interdiction actions ensure that there are no paths of length two that can avoid traveling on an interdicted flight. In the bottom left of Figure 3, with a budget of $3632, there are additional interdiction actions that ensure all paths of length two or three are impacted by an interdiction action. The graphs on the right show the impact of these interdictions on the optimal path for the traffickers at the same budget levels. We can see that the top right map shows that the traffickers had an original path of length two and have shifted to a path of length three to avoid interdiction. In the bottom right map, all the paths of length three face at least one interdiction effort, so the traffickers have returned to their original path of length two. The difference is that in the bottom right map, they now face a probability of detection of 35.4%, up from 27.8% in the top right map.

This cyclic interdiction strategy is intuitive and also follows the same idea of starting from the destination and working back through the network toward the origin. The main issue with this strategy is that it requires cooperation among all countries that are part of the set of flights and airports interdicted at that stage. This might be easy at lower budgets if the focus is on flights that all land in the destination airport, so only one country needs to enforce. However, in later stages, if any one country fails to enforce, then it becomes much harder to increase the detection probability. It may still be possible, for some products, to garner this amount of political will to prevent trafficking in a large number of countries. However, this model also does not take flight cost or time into account, which leads to interdiction in countries that are unlikely to have ever experienced the trafficking of a certain product. This highlights some of the issues with this model and its limited applicability to products that receive little international attention or resources.

Another limitation of DMM is that it assumes traffickers focus solely on avoiding interdiction and are willing to fly wildly expensive or time-consuming routes in order to do so. In Figure 3, the model interdicts flights between Los Angeles and Hong Kong when the traffickers origin is in South Africa. This is a highly convoluted route that is unlikely to be used in practice, due to its cost and duration. This calls into question this model's ability to accurately predict the traffickers' behavior. For the interdiction model to yield practical insights, it has to consider all factors traffickers weigh when making transit decisions. Traffickers may exhibit this behavior when avoiding strong punishments for detection, but are unlikely to do so to avoid smaller fines. It is possible to remove some very expensive paths from the network before solving the interdiction problem. However, it may not be clear where to stop. PMM resolves all of these issues by directly comparing the flight cost to the penalties faced by traffickers.

### 6.4. PMM insights

PMM combines the best aspects of the previous models to represent the traffickers' incentives more accurately. This model is much more flexible, and the data requirements are intuitive for practitioners and easy to estimate, though there are still difficulties in gathering global data sets. By using real penalties that traffickers incur when caught, authorities can better understand the costs and risks that traffickers face. The objective of this model is highly practical and represents the total expected cost to traffickers traveling on a certain route from both penalties and flights. This information can complement existing data about profit margins and selling prices for wildlife products and, hopefully, lead to increased costs pushing many traffickers out of business entirely. With this information, authorities can understand what levels of enforcement and penalties, and their

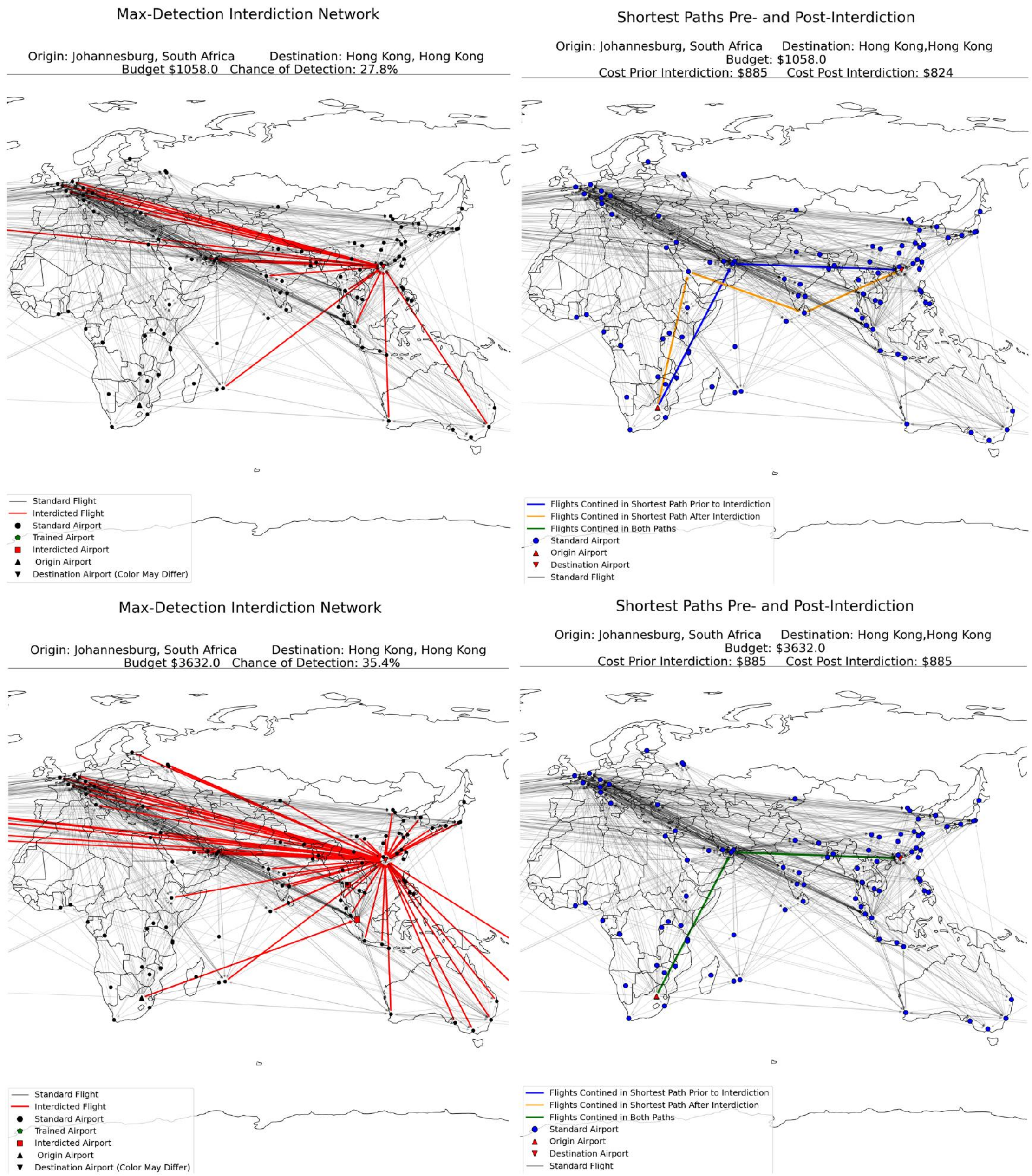


**Figure 3.** DMM interdiction decisions and trafficker paths for routes between Johannesburg and Hong Kong with budgets of $1058 and $3632 on the top and bottom line, respectively.

corresponding budgets, are needed to eradicate profits from trafficking specific products.

Figure 4 shows the optimal path lengths and objective values for PMM at various budget proportions. We further break out the objective into the flight cost and detection penalty components, and we show the impact of low, high, and varied penalty values. When the penalty values are high, the figure shows similar behavior to the DMM, where there are cycles of longer and shorter trafficking paths. When penalty values are low, the behavior is more reminiscent of NTM, but the trafficker paths do still shift as they react. With low penalty values, the shifts occur between a smaller array of potential paths that have less deviation from the cheapest path. In this example, the varied penalty behaves like the low penalty. This is because the average penalty among countries is the same in both cases. We purposefully chose to use a lower penalty for the varied case to accurately represent the situation faced with many wildlife products. Variations in penalties between countries will have less impact on the values shown in Figure 4 but a strong impact on the geographies of the airports and flights chosen for interdiction at each budget level.

Figure 5 shows the interdiction decisions for the varied and high penalty models. This figure captures the shift from eliminating any potential path without interdiction (high penalty) to interdicting more heavily along key paths that are likely to have a high volume of trafficking (varied penalty). With the varied penalty, we see more interdiction at earlier stages in the transit route and heavy interdiction at the airports that are most central to the route. This centralization of interdiction efforts highlights the key role that hub airports play in successful interdiction strategies. The

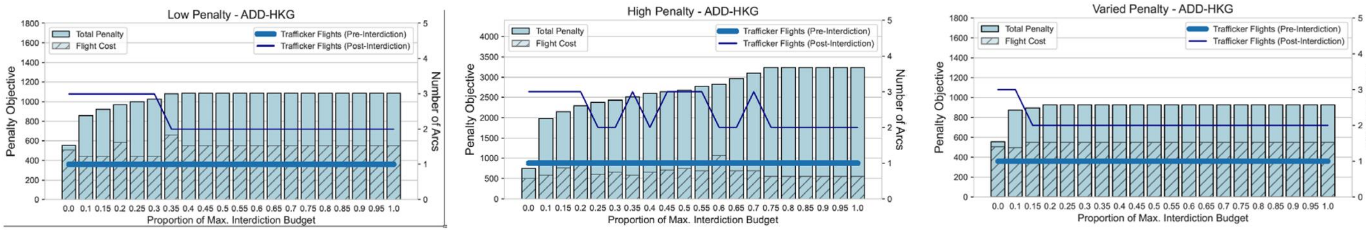


**Figure 4.** Detection probability and optimal path length by budget (Addis Ababa to Hong Kong).

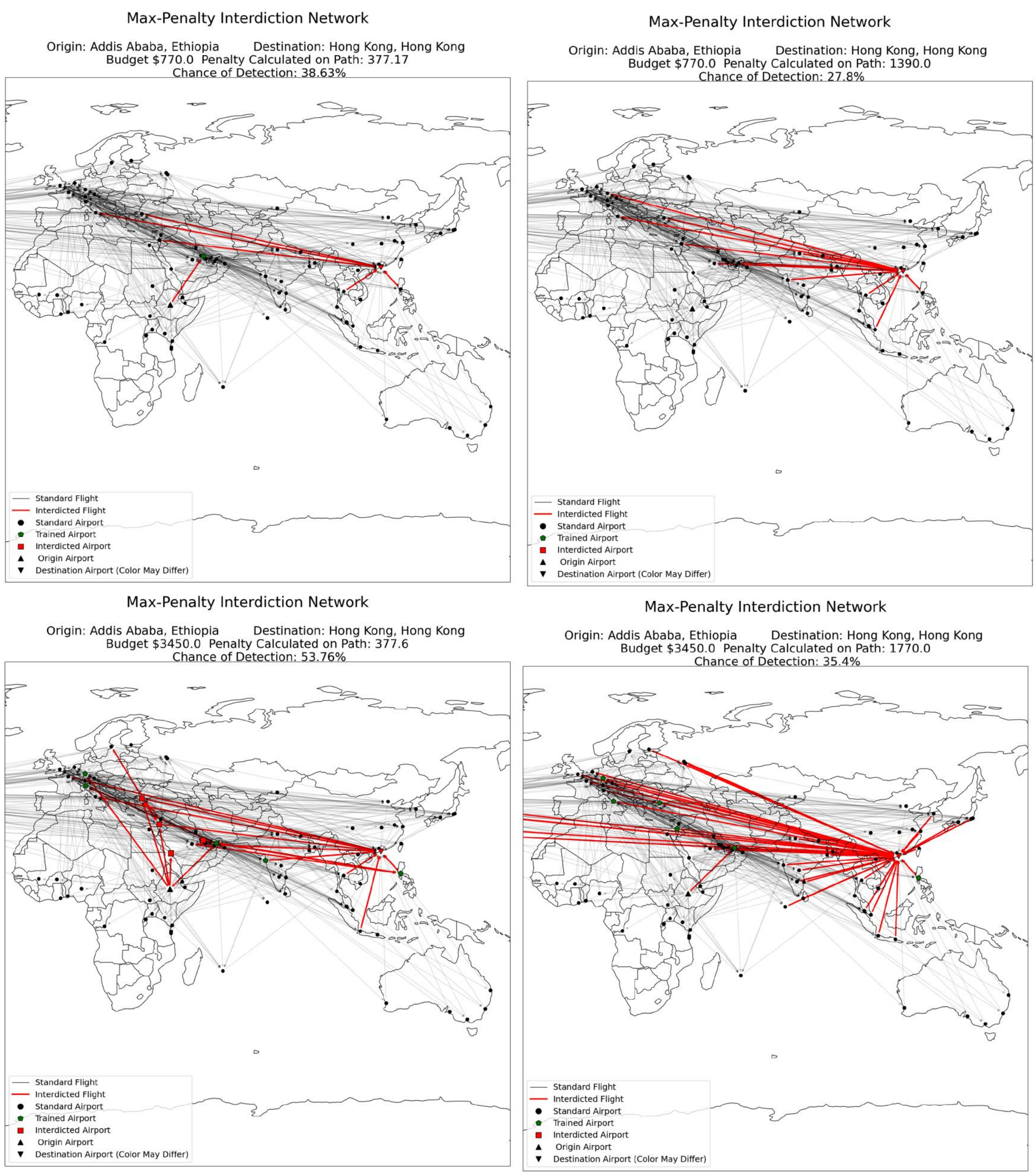


**Figure 5.** Interdiction networks for varied penalty (left side) and high penalty (right side) for budgets of $770 (top) and $3450 (bottom).

variations between the low and varied penalty cases are more subtle and focus on switching out individual flights that are interdicted for flights that arrive in countries with higher penalties. PMM is flexible enough to be applied in a variety of different enforcement landscapes, containing the best features of NTM and DMM, and it yields realistic solutions that have appealing characteristics for practitioners.

Figure 8 in the Appendix shows how the average flight cost, across all OD pairs, from the traffickers' optimal response varies with different interdiction budgets for both models. The size of the bubbles indicates the probability of detection. The graph shows that, for DMM, the flight cost varies wildly as the budget changes. When the budget and detection probability are both very small the traffickers shift to taking a very expensive route. The variation in flight costs is much lower in PMM. Although this is not necessarily a "good" thing, since it represents lower travel costs for traffickers, it does indicate that the model is potentially a more realistic representation of trafficker behavior. Also, if legal penalties are high enough that traffickers take extremely expensive flight routes to avoid detection, PMM will capture this and the solution will approach the solution of DMM. In fact, we see evidence of this behavior in Figure 4.

## 7. Conclusions

In this article, we highlight several key challenges for authorities working to interdict IWT activities and solve three variants of an interdiction model to address those challenges. Wildlife products are illegally traded in very complex supply chains with many possible source and demand locations. Air transit is a common trafficking mode for high value or perishable products and there is ample opportunity to inspect for illicit products. However, customs and security officials may be unfamiliar with the wide array of trafficked wildlife and the numerous processed forms of illicit products. Training is key for proper identification and seizure of illicit products and our models incorporate that requirement into the interdiction formulation. Policies, capacities, and regulatory frameworks differ between countries, prompting criminals to turn to places where they can operate efficiently with a low risk of punishment. Traditional models often assume that traffickers solely focus on avoiding detection, without considering flight cost, duration, or varying legal penalties between countries. We present a new network interdiction model (PMM) that can handle varied penalties across countries and capture the trade-off between flight costs and detection risks that traffickers face. PMM is versatile in its ability to capture a variety of cases with differing levels of enforcement resources and attention. PMM necessitates the switch to a path-based formulation which is time-consuming to solve. To handle this, we introduce an objective approximation that leverages the structure and faster solution times of DMM. We utilize the solutions from this approximation to provide an excellent starting solution for PMM which substantially reduces the solution times for many of the networks we investigate. We provide an in-depth discussion of the underlying structure of the network interdiction strategies generated by the three models and their impact on traffickers and enforcement authorities with varying interdiction budgets.

To ensure our analysis captures practical issues, we use real flight networks and pricing data with origin and destination cities obtained from seizure data and technical reports. The variety of OD pairs provides realistic test cases for a variety of product types, including pangolin scales, rhino horn, ivory, live reptiles, European glass eels, tigers, sea cucumbers, and live birds. Using these test cases, we highlight areas where solutions to traditional interdiction models may result in unrealistic decisions, with enforcement occurring on distant or expensive flight routes before the cheapest route has been fully interdicted. These contributions highlight how traditional models can be best adapted to solve practical problems in IWT applications.

Although this work is a strong first step in combating IWT using operations research methods, there are still many opportunities for future research. Regarding methods, there are opportunities to incorporate multi-period and multi-product decisions. Regarding data, seizure data currently presents many challenges because it is often biased towards countries with stronger enforcement and products with strong law enforcement attention. Future work can investigate innovative ways to utilize available data and develop strategies for interdiction that improve our understanding of IWT networks, which in turn will help us combat them more effectively. Some previous research considers the impact of imperfect information on network interdiction models. Future work might also look to expand to cases with incomplete or asymmetric information about interdiction actions or trafficker preferences (Bayrak and Bailey, 2008). A better understanding of how traffickers incorporate learned or revealed information about interdiction activities would enable researchers to devise methods that generate increasingly practical solutions. Finally, network interdiction is an important step in reducing the exploitation of endangered or threatened species, but it is unlikely to be sufficient by itself (UNODC, 2020). Elimination of IWT requires a focus on both demand and supply reduction. Regardless of efforts to reduce supply, if high levels of demand exist, illicit markets will evolve towards less-regulated locations or substitute species. Many opportunities exist for research into demand reduction, poaching protections, and generating alternative streams of income to draw labor away from IWT.

## Acknowledgments

The authors thank the editor, associate editor, and the three anonymous reviewers for their helpful comments that have improved the earlier presentations of the manuscript. The authors are also grateful for the support, helpful insights, and critical feedback of Dr. Nickolas K. Freeman on an earlier version of the manuscript. Finally, the authors also thank Mr. J. Oakley Prell for his help in preparing some of the charts and graphs.

## Notes on contributors

*Emily C. Griffin* is an assistant professor of operations management in the Operations and Information Management Division at Babson College. Her research focuses on supply chain and inventory optimization with applications in sustainability and retailing. Dr. Griffin utilizes techniques from nonlinear and integer optimization and data science in her research.

*Aaron Ferber* is a PhD student at the University of Southern California, working in the Center for AI in Society (CAIS). He works at the intersection of machine learning (ML) and combinatorial optimization (CO) and is passionate about applying ML and CO to social good settings.

*Lucas Lafferty* is a data scientist at PNC Bank. At the time of the research, he was a Business Analytics MS student.

*Burcu B. Keskin* is a professor of operations management (OM) and the Reese Phifer Fellow in Operations/Manufacturing Management in the Department of Information Systems, Statistics, and Management Science at The University of Alabama. She has conducted research in different areas of supply chain management, including inventory theory, facility location, network design, vehicle routing, and recently illicit supply chains. She has obtained funding for her research through

government agencies and several companies. She has over 40 publications that appeared in prestigious Operations Research journals. Dr. Keskin serves on the editorial boards of OMEGA: The International Journal of Management Science, Computers and Operations Research, and INFORMS Journal on Applied Analytics. She is also an ad-hoc reviewer for numerous journals.

***Bistra Dilkina*** is an associate professor of computer science at the University of Southern California. She is also the co-Director of the USC Center for AI in Society (CAIS). Her work spans discrete optimization, network design, stochastic optimization, and machine learning. Dr. Dilkina is one of the faculty leaders in the young field of computational sustainability, and has co-organized workshops, tutorials, special tracks at major conferences on computational sustainability and related subareas.

***Meredith L. Gore*** is an associate professor of human dimensions of global environmental change in the Department of Geographical Sciences at University of Maryland, College Park. She works to advance understanding about the human dimensions of global environmental change such as biodiversity loss and climate change. Dr. Gore's research uses risk concepts to explore human-environment interactions and to build evidence for action. She brings an interdisciplinary perspective to a range of conservation issues such as wildlife trafficking, illegal fishing and illegal logging.

## ORCID

Burcu B. Keskin http://orcid.org/0000-0002-2273-1002

## References

Anzoom, R., Nagi, R. and Vogiatzis, C. (2022) A review of research in illicit supply-chain networks and new directions to thwart them. *IISE Transactions*, **54**(2), 134–158.

Avis, W. (2017) Criminal networks and illicit wildlife. Technical report, K4D. https://www.ids.ac.uk/projects/k4d-research-helpdesk/

Awel, M.A. (2019) Turkey: 21 rhino horns seized at Istanbul airport. https://www.aa.com.tr/en/life/turkey-21-rhino-horns-seized-at-istanbul-airport/1387405. Accessed: January 20, 2022.

Ball, M.O., Golden, B.L. and Vohra, R.V. (1989) Finding the most vital arcs in a network. *Operations Research Letters*, **8**(2), 73–76.

Baycik, N.O., Sharkey, T.C. and Rainwater, C.E. (2020) A Markov decision process approach for balancing intelligence and interdiction operations in city-level drug trafficking enforcement. Socio-Economic Planning Sciences, **69**, 1–16.

Bayrak, H. and Bailey, M.D. (2008) Shortest path network interdiction with asymmetric information. *Networks: An International Journal*, **52**(3), 133–140.

Broussard, G. (2017) Building an effective criminal justice response to wildlife trafficking: Experiences from the ASEAN Region. *Review of European, Comparative and International Environmental Law*, **26**(2), 118–127.

Cormican, K.J., Morton, D.P. and Wood, R.K. (1998) Stochastic network interdiction. *Operations Research*, **46**(2), 184–197.

Golden, B. (1978) A problem in network interdiction. *Naval Research Logistics Quarterly*, **25**(4), 711–713.

Gore, M.L., Braszak, P., Brown, J., Cassey, P., Duffy, R., Fisher, J., Graham, J., Justo-Hanani, R., Kirkwood, A.E., Lunstrum, E., *et al.* (2019) Transnational environmental crime threatens sustainable development. *Nature Sustainability*, **2**, (784–786.

Gurobi Optimization. (2021) Gurobi optimizer reference manual. Gurobi Optimization. https://www.gurobi.com/

Haas, T.C. and Ferreira, S.M. (2018) Optimal patrol routes: Interdicting and pursuing rhino poachers. *Police Practice and Research*, **19**(1), 61–82.

Hubschle, A. and Shearing, C. (2021) *Conservation, the Illegal Wildlife Trade and Local Communities*. Routledge.

Israeli, E. and Wood, R.K. (2002) Shortest-path network interdiction. *Networks: An International Journal*, **40**(2), 97–111.

Jabarzare, Z., Zolfagharinia, H. and Najafi, M. (2020) Dynamic interdiction networks with applications in illicit supply chains. *Omega: The International Journal of Management Science*, **96**.

Keskin, B.B., Bott, G.J. and Freeman, N.K. (2021) Cracking sex trafficking: Data analysis, pattern recognition, and path prediction. *Production & Operations Management* To Appear, **30**(4), 1110–1135.

Keskin, B.B., Griffin, E.C., Prell, J.O., Dilkina, B., Ferber, A., MacDonald, J., Hilend, R., Griffis, S. and Gore, M.L. (2022) Quantitative investigation of wildlife trafficking supply chains: A review. *Omega*, **115**, 102780.

Leung, C. (2019) Customs seizes HK $16.5 million record haul of rhino horns in Hong Kong. https://www.scmp.com/news/hong-kong/law-and-crime/article/3004956/customs-seizes-hk165-million-record-haul-rhino-horns. Accessed January 20, 2022.

Linh, N. and Thuy, T. (2019) Holding in custody 125.15kg of rhino horn transported to Noi Bai International Airport. https://english.haiquanonline.com.vn/holding-in-custody-12515kg-of-rhino-horn-transported-to-noi-bai-international-airport-11467.html. Accessed January 20, 2022.

Magliocca, N., Torres, A., Margulies, J., McSweeney, K., Arroyo-Quiroz, I., Carter, N., Curtin, K., Easter, T., Gore, M., Hübschle, A., *et al* (2021) Comparative analysis of illicit supply network structure and operations: Cocaine, wildlife, and sand. *Journal of Illicit Economies and Development (3)* 1, 50–73.

Malaviya, A., Rainwater, C. and Sharkey, T. (2012) Multi-period network interdiction problems with applications to city-level drug enforcement. *IIE Transactions*, **44**(5), 368–380.

McCormick, G. (1976) Computability of global solutions to factorable nonconvex programs: Part I-convex underestimating problems. *Mathematical Programming*, **10**, 147–175.

Moore, J.F., Udell, B.J., Martin, J., Turikunkiko, E. and Masozera M.K. (2021) Optimal allocation of law enforcement patrol effort to mitigate poaching activities. *Ecological Applications, (31)* 5, 23–37.

Morton, D.P., Pan, F. and Saeger, K.J. (2007) Models for nuclear smuggling interdiction. *IIE Transactions*, **39** (1), 3–14.

Nguyen, T., Yang, R., Azaria, A., Kraus, S., and Tambe, M. (2013). Analyzing the effectiveness of adversary modeling in security games. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Volume 27, AAAI Press, Palo Alto, California, USA, pp. 718–724.

Nguyen, T.H., Sinha, A., Gholami, S., Plumptre, A., Joppa, L., Tambe, M., Driciru, M., Wanyama, F., Rwetsiba, A., Critchlow, R., Beale, C.M. (2016) A new predictive anti-poaching tool for wildlife protection, in *AAMAS '16*: International Conference on Agents and Multiagent Systems Singapore, International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, pp. 767–775.

Nijman, V., Morcatty, T., Smith, J.H., Atoussi, S., Shepherd, C.R., Siriwat, P., Nekaris, K.A.-I. and Bergin, D. (2019) Illegal wildlife trade–surveying open animal markets and online platforms to understand the poaching of wild cats. *Biodiversity*, **20**(1), 58–61.

Nuwer, R. (2018) *Poached: Inside the Dark World of Wildlife Trafficking*, Da Capo Press, Boston, MA.

Sharrock, D. (2022, February) Eel smuggler hit with world record €7.2m fine. https://www.thetimes.co.uk/article/eel-smuggler-hit-with-world-record-7-2m-fine-dg5jlcmlj (accessed 23 March 2022).

Siriwat, P. and Nijman, V. (2023) Quantifying the illegal high-value rosewood trade and criminal trade networks in the greater Mekong region. *Biological Conservation*, **277**, 109826.

Smith, J.C. and Song, Y. (2020) A survey of network interdiction models and algorithms. *European Journal of Operational Research*, **283**(3), 797–811.

South, N. and Wyatt, T. (2011) Comparing illicit trades in wildlife and drugs: An exploratory study. *Deviant Behavior*, **32**(6), 538–561.

Taha, H.A. (2019) *Operations Research: An Introduction* (10th Edition ed.), Pearson.

The Global Organized Crime Index. (2021) Global initiative against transnational organized crime: The global organized crime index.

https://globalinitiative.net/analysis/ocindex-2021/ (accessed 14 October 2021).

UNODC. (2017) Enhancing the detection, investigation, and disruption of illicit financial flows from wildlife crime, UNODC: United Nations Office on Drugs and Crime, Vienna, pp. 1–136.

UNODC. (2020) World wildlife crime report, UNODC: United Nations Office on Drugs and Crime, Vienna, pp. 1–136.

Utermohlen, M. and Baine, P. (2018) Flying under the radar: Wildlife trafficking in the air transport sector. *Routes*, **114**, 1–114.

Wood, R.K. (1993) Deterministic network interdiction. *Mathematical and Computer Modelling*, **17**(2), 1–18.

Xu, L., Gholami, S., McCarthy, S., Dilkina, B., Plumptre, A., Tambe, M., Singh, R., Nsubuga, M., Mabonga, J., Driciru, M., *et al.* (2020) Stay ahead of poachers: Illegal wildlife poaching prediction and patrol planning under uncertainty with field test evaluations (short version), in *2020 IEEE 36th International Conference on Data Engineering (ICDE)*, IEEE Press, Piscataway, NJ, pp. 1898–1901.

## Appendix and Additional Resources

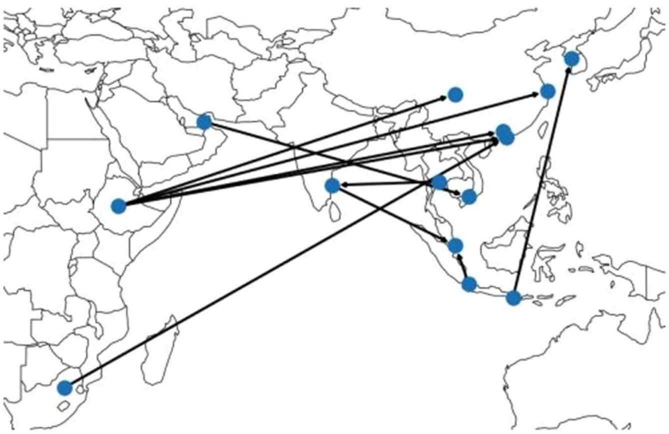

**Figure 6.** Most frequently occurring Origin-Destination Pairs from seizure data.

**Figure 7.** Origin-Destination Pairs for key product groups.

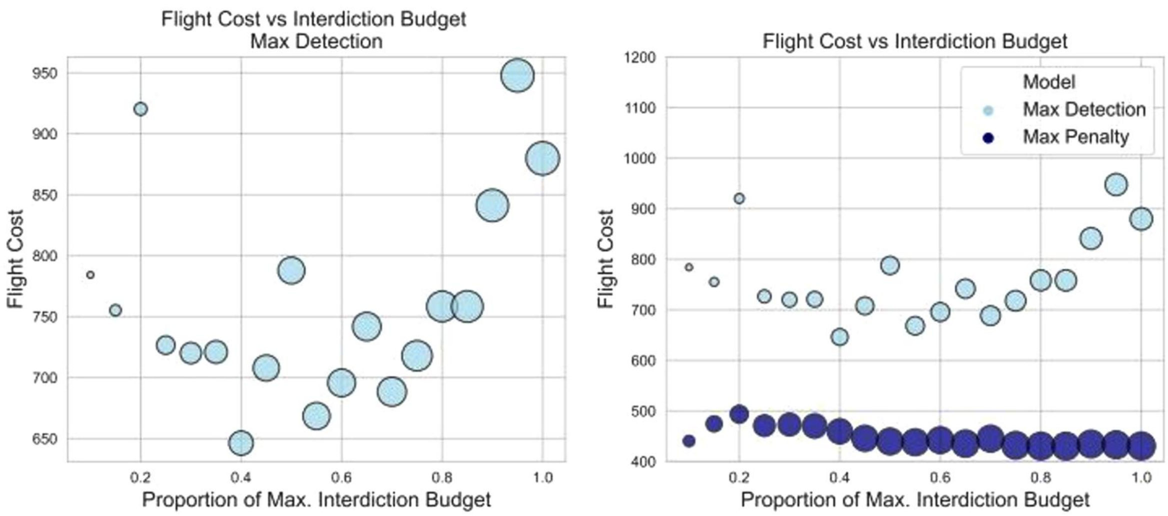


**Figure 8.** Average trafficker flight cost by model and by budget proportion.

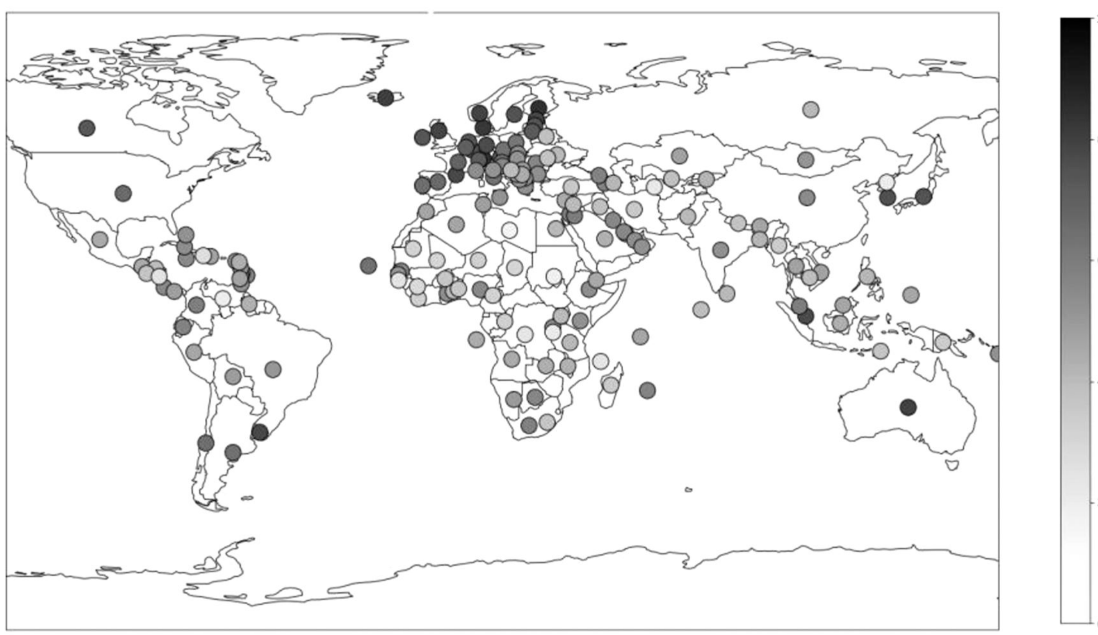

**Figure 9.** Resilience scores for penalty calculation.

**Table 3.** Summary of notation.

| | |
|---|---|
| Parameters | |
| $V$ | the set of nodes in the flight network, $\|V\| = n$ |
| $E$ | the set of edges in the flight network, $\|E\| = m$ |
| $\kappa$ | the set of all paths between the origin and destination, $k = 1, 2, \ldots$ |
| $E_k$ | the ordered set of edges in path $k \in \kappa, e_1, e_2 \ldots$ |
| $\mathbf{I}$ | a vector $\in \mathbb{Z}^{\|V\|}$ where $I_j = 0$ for all $j \in V \setminus \{s, t\}$, $I_s = 1$, and $I_t = -1$. |
| $T$ | a node-arc incidence matrix for the node set $V$ and arc set $E$. |
| $u$ | a vector of length $\|E\|$ with values $u_e = \sum_{a \in A} log(1 - p_e^a) z_e^a$ for edge $e \in E$. |
| $A$ | the set of combinations of actions $a$ that can be taken on an edge, {0 - do nothing, T- train only, N- node interdiction and training, E- edge interdiction and training, B- node and edge interdiction and training}. |
| $b_j^T$ | the fixed cost of training for detection at node $j$, $j = 1, \ldots, n$. |
| $b_j^N$ | the variable cost for general screening at node $j$, $j = 1, \ldots, n$. |
| $b_{ij}$ | the variable cost for enhanced screening on edge $e_{ij}$, $e_{ij} \in E$. |
| $c_{ij}$ | the cost for a trafficker to travel on edge $e_{ij}$, $i, j = 1, \ldots, n$. |
| $p_{ij}^0$ | the base probability of detection before training on edge $e_{ij}$, $e_{ij} \in E$. |
| $p_j$ | the base probability of detection after training, $j = 1, \ldots, n$. |
| $q_{ij}$ | the enhanced probability of detection on edge $e_{ij}$, $e_{ij} \in E$. |
| $q_j^N$ | the enhanced probability of detection at node $j$, $j = 1, \ldots, n$. |
| $\beta$ | the total interdiction budget. |
| $R_j$ | the reward (penalty) for the interdictor (trafficker) if the trafficker is detected at node $j$, $j = 1, \ldots, n$. |
| **Decision Variables - Interdictor** | |
| $x_j^T$ | 1, if node $j$ is given training, 0 otherwise. |
| $x_{ij}$ | 1, if edge $e_{ij}$ is interdicted, 0 otherwise. |
| $x_j^N$ | 1, if node $j$ is interdicted, 0 otherwise. |
| **Decision Variables - Trafficker** | |
| $y_{ij}$ | 1, if trafficker chooses to travel along edge $e_{ij}$, 0 otherwise. |
| $\pi$ | dual variable(s) associated with the shortest path constraint(s). |
| **Auxiliary Variables** | |
| $z_{ij}^a$ | 1, if action $a \in A$ is taken on edge $e_{ij}$ , 0 otherwise. |
| $Z_k$ | the set of path-based auxilliary variables associated with path $k \in \kappa^L$. |
| $z_{k,a_1,a_2,\ldots,a_L}$ | 1, if action sequence $a_1, a_2, \ldots, a_L \in (A_1, \ldots, A_L)$ is taken on path $k$, 0 otherwise. |

**Table 4.** Variations in time to solve the interdiction model by interdiction model type and differences in the number of arcs contained in the shortest path before and after interdiction.

| *Trafficker # of Flights* | | *Interdiction Average Solve Time (s)* | | |
|---|---|---|---|---|
| *Pre-Interdiction* | *Post-Interdiction* | *Naive Traffickers* | *Max. Detection* | *Max. Penalty* |
| 1 | 1 | 0.963 | 3.086 | |
| 1 | 2 | | 919.774 | 8940.133 |
| 1 | 3 | | 1609.793 | 34,474.014 |
| 2 | 2 | 0.87 | 169.381 | 8177.588 |
| 2 | 3 | | 1765.133 | 26,217.988 |
| 2 | 4 | | 2583.924 | |
| 3 | 2 | | | 196.313 |
| 3 | 3 | 0.348 | 0.359 | 163.08 |
| 4 | 4 | 1.615 | | |