Human Trafficking Interdiction Problem: A Data Driven Approach to Modeling and Analysis

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***Abstract*—Based on the human trafficking incidence data from the Las Vegas Metropolitan Police Department (LVMPD), we have built a model of movement patterns of traffickers within the contiguous US states. We utilized the model for developing interdiction strategies for the law enforcement authorities, with the goal of maximizing interdiction pay-off within the agency budget, where pay-off is measured in terms of the number of trafficking incidences disrupted. In addition, from the U.S. Interstate Highway Map, we have built a U.S. Interstate Network Graph (USING) to test our interdiction pay-off maximization algorithm. This is a realistic approximation of the U.S. highway system and will be made available to researchers engaged in trafficking interdiction research. Finally, we evaluate our techniques on the data from LVMPD on USING and present the results.**

I. Introduction

The U.S. Dept. of Justice in its "National Strategy to Combat Human Trafficking" (January 2022), declared its goal to "enhance its capacity to identify human trafficking victims and to detect human trafficking networks". One of the ways to detect and disrupt trafficking networks is through *interdiction*. Accordingly, interdiction problems of trafficking in illicit material have received considerable attention the research community in the last few years [1]–[6]. Different research groups have taken different approaches to modeling and analysis, depending on domain specific characteristics of the problem. In a paper published in the IEEE International Symposium on Technologies for Homeland Security (2018) [4], the authors studied transnational criminal organizations operating as interdependent contraband smuggling, and money laundering networks and proposed tools and techniques to disrupt such networks. Motivated by the need for countering proliferation of nuclear material, researchers at the Los Alamos National Laboratory studied the problem for stochastic evaders by introducing a model in which the evader follows a Markovian random walk, guided by the least-cost path to the target [1]. The authors in [5] modeled cocaine traffickers and counterdrug interdiction forces as a complex adaptive system. Game theoretic approaches to the interdiction problem were studied in [2] and [3], and are modeled as a *zero-sum game* and a *Stackelberg game* respectively. In this paper, we take a data driven approach to modeling and analysis, with the objective of maximizing interdiction payoff for law enforcement authorities.

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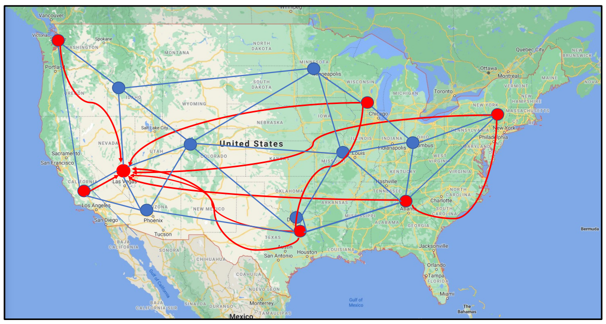
II. Data Driven Interdiction Model

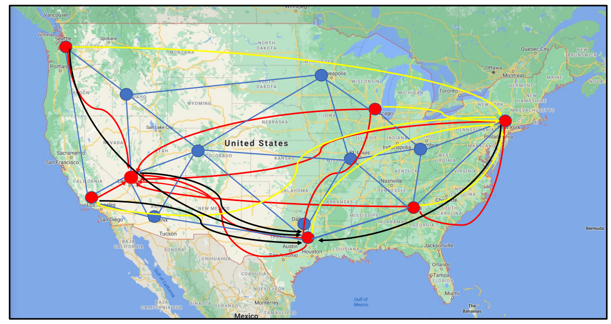
This research is made possible by a grant from the National Science Foundation to investigate human trafficking incidences in U.S. Southwest. We received significant amount of anonymized human trafficking incidence data from the Las Vegas Metropolitan Police Department (LVMPD). A summary of LVMPD data is shown in the Table I, where each row corresponds to a recorded incidence and the columns correspond to various factors related to the incidence. The LVMPD data was collected between 2011 and 2020 and had almost 1700 incidences. 99% of all reported incidence data involved

Incidence No.	Date, Time & Location	Victim Id.	Trafficker Id.	Trafficker Type	Destination City	Intermediate Cities	Originating City
I_1	$\cdots$	V_1	T_1	"Romeo"	C_1	C_2, C_3, C_4	C_5
I_2	$\cdots$	V_2	T_2	"Boss"	C_1	C_3, C_6	C_7
I_3	$\cdots$	V_3	T_3	"Boss"	C_1	$\emptyset$	C_8
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
I_n	$\cdots$	V_n	T_n	"Boss"	C_1	$C9$	C_{10}

TABLE I: Human Trafficking Incidence Data in Local Law Enforcement Records of City C_1

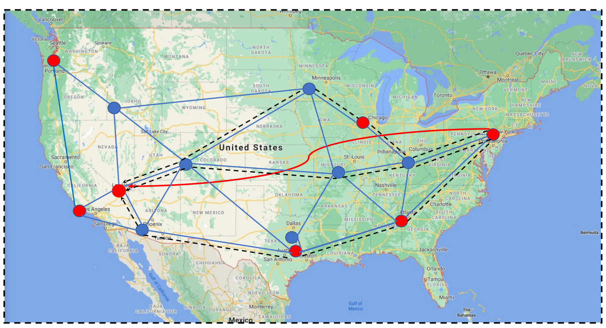


(a) Visualization of Human Traffic Movement: Multiple Cities to a Single City

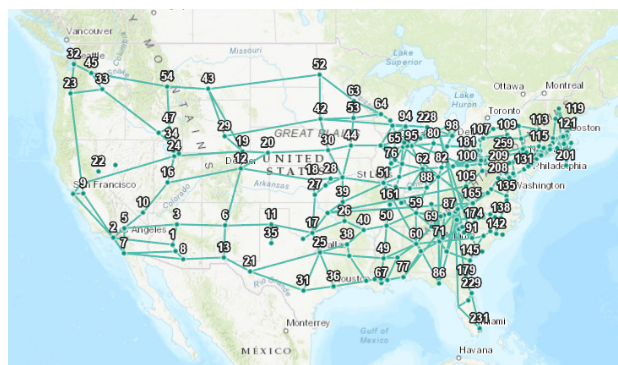


(b) Visualization of Human Traffic Movement: Multiple Cities to Multiple Cities

Fig. 1: Visualization of Trafficker Movement



(a) Logical to Physical Path Mapping



(b) U.S. Interstate Network Graph (USING)

Fig. 2: Logical and Physical Paths (Left) and the USING (Right)

road travel as the mode of transportation. Most of the records included the travel originating city/state, but only a few included the names of the intermediate cities visited on the way to Las Vegas.

For the purpose of interdiction, this high level information, that the victim traveled from the originating city, say Atlanta, to the destination city, say Las Vegas, isn't very helpful, because there are multiple paths that could have been taken using Interstate Highways, to travel from Atlanta to Las Vegas. Lower level information, such as various path segments that the trafficker might have taken (e.g., Atlanta to Birmingham to Memphis or Atlanta to Montgomery to Mobile etc.) will be crucial, as only then can the Law Enforcement authorities set up checkpoints to interdict the illicit traffic through those path segments. We refer to high level description of the path taken by the victim, which often includes only the names of the originating and destination cities (and in some cases a few intermediate cities) as a *logical path*. The red lines in Fig. 1a show some logical paths from multiple

Destination City	Originating City	Traffic Volume	Logical Path	Physical Path
C_1	C_2		$C_1 \leftarrow C_3 \leftarrow C_4 \leftarrow C_2$	$C_1 \leftarrow C_3 \leftarrow C_6 \leftarrow C_7 \leftarrow C_4 \leftarrow C_2$
C_1	C_2		$C_1 \leftarrow C_3 \leftarrow C_4 \leftarrow C_2$	$C_1 \leftarrow C_3 \leftarrow C_{12} \leftarrow C_4 \leftarrow C_2$
C_1	C_2		$C_1 \leftarrow C_3 \leftarrow C_4 \leftarrow C_2$	$C_1 \leftarrow C_3 \leftarrow C_9 \leftarrow C_{11} \leftarrow C_4 \leftarrow C_2$
C_1	C_2		$C_1 \leftarrow C_3 \leftarrow C_4 \leftarrow C_2$	$C_1 \leftarrow C_{12} \leftarrow C_3 \leftarrow C_4 \leftarrow C_2$
C_1	C_2	10 ($C_1 \leftarrow C_2$)	$C_1 \leftarrow C_3 \leftarrow C_4 \leftarrow C_2$	$C_1 \leftarrow C_3 \leftarrow C_{17} \leftarrow C_4 \leftarrow C_2$
C_1	C_2		$C_1 \leftarrow C_3 \leftarrow C_4 \leftarrow C_2$	$C_1 \leftarrow C_3 \leftarrow C_4 \leftarrow C_{20} \leftarrow C_2$
C_1	C_2		$C_1 \leftarrow C_8 \leftarrow C_2$	$C_1 \leftarrow C_3 \leftarrow C_{16} \leftarrow C_7 \leftarrow C_8 \leftarrow C_2$
C_1	C_2		$C_1 \leftarrow C_8 \leftarrow C_2$	$C_1 \leftarrow C_6 \leftarrow C_8 \leftarrow C_2$
...	...	...	...	...
...	...	...	...	...
...	...	...	...	...
C_1	C_{10}		$C_1 \leftarrow C_{24} \leftarrow C_{27} \leftarrow C_{10}$	$C_1 \leftarrow C_{24} \leftarrow C_{27} \leftarrow C_{29} \leftarrow C_{10}$
C_1	C_{10}		$C_1 \leftarrow C_{20} \leftarrow C_{10}$	$C_1 \leftarrow C_{20} \leftarrow C_{27} \leftarrow C_{10}$
C_1	C_{10}	5 ($C_1 \leftarrow C_{10}$)	$C_1 \leftarrow C_{27} \leftarrow C_{10}$	$C_1 \leftarrow C_{26} \leftarrow C_{27} \leftarrow C_{29} \leftarrow C_{10}$
C_1	C_{10}		$C_1 \leftarrow C_{10}$	$C_1 \leftarrow C_6 \leftarrow C_7 \leftarrow C_{20} \leftarrow C_{12} \leftarrow C_{10}$
C_1	C_{10}		$C_1 \leftarrow C_7 \leftarrow C_9 \leftarrow C_{10}$	$C_1 \leftarrow C_7 \leftarrow C_9 \leftarrow C_{26} \leftarrow C_{10}$

TABLE II: Mapping of Logical Paths into Physical Paths

cities, such as New York and Seattle to a single city - Las Vegas. As we obtained interdiction data only from LVMPD, the destination city of all the logical paths in Fig. 1a, is Las Vegas. We are sure that police departments of every major U.S. cities have similar human traffic incidence data. The logical paths from multiple originating cities to multiple destination cities are shown in Fig. 1b. A logical path may have been realized through many *physical paths*, for e.g., the logical path from NYC to Las Vegas (shown in Red line) in Fig. 2a, could have been realized by one of the three physical paths (shown in black dotted lines). A general scenario with a set of logical paths and their corresponding physical paths, together with the *traffic volume* on each path is shown in Table II.

From the interdiction perspective, the law enforcement authorities need to know (or estimate) which one of the many physical paths that correspond to a logical path, most likely taken by the trafficker. In order to make that estimate, our interdiction model makes a few assumptions: (i) each path segment has (a) *cost of travel*, and (b) an *interdiction probability* associated with it; (ii) Trafficker has a *travel budget* that cannot be exceeded. Within these parameters, we assume that the trafficker will choose the *least risky path* (i.e., the path with the the smallest interdiction probability), that is *within the trafficker's budget*. This setting gives rise to the *Logical-to-Physical Path Mapping Problem* (LPPMP), which is discussed in detail in Section V.

Using the solution to the LPPMP, the Law Enforcement Authorities (LEAs) can estimate the path the trafficker most likely took between a source-destination city and set up check points accordingly. The *traffic flow volume* of a logical path is the number of victims that are transported through that path. After mapping each logical path into a physical path, one can compute the traffic flow through each path segment (i.e., an edge of the network graph), which is the summation of the traffic volumes of each of the paths that use this edge. From the LEA perspective, this quantity is the *payoff* associated with interdiction of that edge. Like the trafficker, LEAs also has a budget referred to as the *Interdiction Budget*. The goal of the LEAs is to maximize *Interdiction Payoff* subject to the constraint that the interdiction cost doesn't exceed Law Enforcement Interdiction Budget (LEIB). This scenario gives rise to "Interdiction Payoff Maximization Problem" (IPMP), which is discussed in detail in section VI.

III. U.S. Interstate Network Graph Data Generation and Visualization

For the purpose of evaluating our algorithms on real road transportation infrastructure in U.S., we wanted to have access to a network graph, which closely resembles the U.S. interstate highways. As no such graph is readily accessible, we created such a network graph, referred to as the *U.S. Interstate Network Graph* (USING) ourselves. In this graph, the nodes represent either (i) the largest city in each state, or (ii) intersection point (city) of two interstate highways. Two nodes are connected by an edge if the corresponding cities have an interstate highway

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segment connecting them. The network constructed following these rules have 280 nodes and 475 edges and is shown in Fig. 2b.

It may be noted that an interstate on the US map can be represented by multiple edges. For instance, I-10 runs from Los Angeles through Phoenix, Casa Grande and many other cities all the way to Jacksonville. In USING, each segment of I-10 (e.g., between LA and Phoenix, Phoenix and Casa Grande, etc.) will be represented by an edge. Each edge has attributes such as *Trafficker's Travel Cost* (TTC), *probability of interdiction* (g), and *Law Enforcement Interdiction Cost* (LEIC), associated with it.

In constructing the data set for USING, we use the Googlemaps API. We start with a major city (node) and determine what other major cities or interstate intersections are neighbors of this city. If there is another major city (node) or an interstate intersection neighboring this node, we draw an edge between these two nodes. After determining all the neighbors of a node, we then go to each of its neighbors in manner typical of a *Breadth First Traversal*, and then find their neighbors in the same fashion, until all the intersection of interstates and major cities are connected. A snapshot of USING created following the process is shown in Fig. 2b.

IV. Problem Formulation

The *Logical to Physical Path Mapping Problem* (LPPMP), and the *Interdiction Payoff Maximization Problem* (IPMP) are studied with respect to the USING network. The problems are defined as follows. The following items are provided as the input for the LPPMP and IPMP problems.

(i) A graph $G = (V, E)$, where $V = \{v_1, \ldots, v_n\}$ and $E = \{e_{i,j} | v_i \ is \ adjacent \ v_j \ in \ G = (V, E)\}$ (USING is an example of such a graph)
(ii) Three parameters, (a) *Law Enforcement Interdiction Cost* $LEIC(e_{i,j})$, (b) *Trafficker's Travel Cost* $TTC(e_{i,j})$, and (c) *Probability of Interdiction* $g(e_{i,j})$ is associated with each edge $e_{i,j} \in E$. For simplicity, $TTC(e_{i,j})$ is equal to the distance between the cities i, j (computed using Googlemaps API).
(iii) Human trafficking incidence data from single/multiple cities over a fixed time period (say, one year) is shown in Table I. It may be noted that each row of this table corresponds to a *logical path* from the originating to the destination city. The traffic volume on path P_k, i.e., the number of victims transported over this path, denoted by $TV(P_k)$, is also available in this data set.
(iv) Two budget parameters, one for the trafficker B_T and one for the law enforcement B_{LE}.
From input data items (i)-(iv), the following items can be computed.
(i) Law Enforcement Interdiction Payoff for a path P_k, $LEIP(P_k)$, is equal to the volume of traffic that can be reduced if the path P_k is interdicted (disrupted), i.e, $LEIP(P_k) = TV(P_k)$.
(ii) Law Enforcement Interdiction Payoff for an edge $e_{i,j}$, $LEIP(e_{i,j})$, is equal to the volume of traffic that can be diminished if the edge $e_{i,j}$ is interdicted. It may be noted interdiction of an edge $e_{i,j}$ will disrupt all the paths that use the edge $e_{i,j}$, i.e., if P' a subset of the set of paths that use $e_{i,j}$, then

$$LEIP(e_{i,j}) = \sum_{\substack{P_k \in P' \\ e_{i,j} \in P_k}} TV(P_k)$$

(iii) Probability of an edge $e_{i,j} \in E$ *not being interdicted*, $h(e_{i,j}) = 1 - g(e_{i,j})$
(iv) The path P_k is disrupted only if at least one of the edges that is a part of the path P_k is interdicted. Accordingly, the probability of P_k *being disrupted*

$$r(P_k) = 1 - \prod_{e_{i,j} \in P_k} h(e_{i,j})$$

(vii) Thus, the probability of P_k *not being disrupted*

$$s(P_k) = 1 - r(P_k) = \prod_{e_{i,j} \in P_k} h(e_{i,j})$$

V. Logical to Physical Path Mapping

The goal of the LPPMP is to map a given logical path to one of the many physical paths that correspond to that logical path. As shown in Fig. 2a, the logical path shown in Red can be realized (mapped onto) by any one of the three physical paths shown in Black dotted lines. As discussed earlier, in our model we assume that the trafficker has a travel budget, B_T, and the trafficker would choose the least risky path (i.e., the path where the interdiction probability is the minimum), subject to the budget constraint. Accordingly, the LPPMP becomes the

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Budget Constrained Minimum Risk Path Selection Problem (BCMRPSP).

Note that, each logical path has a specified source node (origin city), a sink node (destination city) and zero or more intermediate cities. In the following, we assume that the logical path is specified with source and sink nodes only (i.e., with zero intermediate cities). The scenario where the number of intermediate cities is non-zero can easily be extended from the one with zero intermediate nodes.

BCMRPSP must establish a path from the source to the sink node, such that the cost of the path is at most B_T and interdiction probability is minimum (or, non interdiction probability is maximum). In Section IV, it was established that the probability of a path P_k not being interdicted (disrupted) is $s(P_k) = \prod_{e_{i,j} \in P_k} h(e_{i,j})$, where $h(e_{i,j})$ is the probability of the edge $e_{i,j}$ not being interdicted. Thus the BCMRPSP becomes the problem of finding a path P_k from the source to sink, whose travel cost is at most B_T and $s(P_k)$ is largest among all possible paths from the source to the sink. The BCMRPSP belongs to a family of path computation problems known as the "Constrained (or Restricted) Shortest Path Problem" (CSPP) [7]. One difference between the CSPP and BCMRPSP is that the objective function for the CSPP involves an *additive operator* (i.e., the objective function is of the form `Maximize` $\sum_{e_{i,j} \in P_k} f(e_{i,j})$), whereas, in the BCMRPSP the objective function involves a *multiplicative operator* (i.e., the objective function is of the form `Maximize` $\prod_{e_{i,j} \in P_k} h(e_{i,j})$). However, the as $\prod_{e_{i,j} \in P_k} h(e_{i,j})$ is maximized when $log \prod_{e_{i,j} \in P_k} h(e_{i,j})$ is maximized, the goal of BCMRPSP can be realized by replacing the multiplicative operator by an additive operator and maximizing $\sum_{e_{i,j} \in P_k} log\ (h(e_{i,j}))$. In the following, we provide an Integer Linear Programming (ILP) formulation for the BCMRPSP. We include a binary variable $x_{i,j}$ for each edge $e_{i,j} \in E$. This binary variable takes the following values:

$$x_{i,j} = \begin{cases} 1, & \text{if edge } e_{i,j} \text{ is in the path } P_k \\ 0, & \text{otherwise} \end{cases}$$

$$Max \sum_{i,j} (log\ h_{i,j}) \times x_{i,j} \tag{1}$$

$$\sum_{i,j} TTC(e_{i,j}) \times x_{i,j} \leq B_T \tag{2}$$

$$\sum_{j} x_{i,j} - \sum_{j} x_{j,i} = 1, i = s \tag{3}$$

$$\sum_{j} x_{i,j} - \sum_{j} x_{j,i} = -1, i = t \tag{4}$$

$$\sum_{i,j} x_{i,j} - \sum_{i,j} x_{j,i} = 0, \forall i \neq s, j \neq t \tag{5}$$

The objective function selects a path which maximizes the probability of not being interdicted, Eq. 2 is the budget constraint of the trafficker and Eqs. 3-5 generate the path from source to destination. We use the ILP formulation for computing the physical paths corresponding to the logical paths obtained from the LVMPD data set and executing them on USING. The results of our logical to physical path mapping is presented in Section VII.

VI. Interdiction Payoff Maximization

The goal of the Interdiction Payoff Maximization Problem (IPMP) is to reduce the human traffic flow to the largest possible extent, subject to law enforcement interdiction cost not exceeding budget B_{LE}. We provide an optimal solution for IPMP using ILP. An IPMP instance is made up of
(i) A graph $G = (V, E)$, where $V = \{v_1, \ldots, v_n\}$ and $E = \{e_{i,j} | v_i\ is\ adjacent\ v_j\ in\ G = (V, E)\}$
(ii) $\mathcal{P}$: Set of physical paths $P_1, \ldots, P_r$ computed from the logical paths from the LVMPD data set.
In addition, the following parameters discussed in section IV are used for solving IPMP.
(iii) $LEIC(e_{i,j})$: Law Enforcement Interdiction Cost for edge $e_{i,j}$
(iv) B_{LE}: Law enforcement budget
(v) $[D(e_{i,j})]_{\mathcal{P}}$: The subset of paths in $\mathcal{P}$ that will be disrupted if the edge $e_{i,j}$ is interdicted in the graph $G = (V, E)$.
(vi) $[LEIP(e_{i,j})]_{\mathcal{P}}$: Interdiction payoff from the edge $e_{i,j}$ with respect to the path-set $\mathcal{P}$.
(vii) $LEIC(E')$: Interdiction cost of the edge set $E' \subseteq E$ = $\sum_{e_{i,j} \in E'} LEIC(e_{i,j})$

We associate a binary variable $x_{i,j}$ with each edge $e_{i,j} \in E$ and another binary variable y_k with each

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City Name	Adjacent Cities									
	Adjacent City 1			Adjacent City 2			···	Adjacent City k		
	City Name	Interstate	Distance	City Name	Interstate	Distance	···	City Name	Interstate	Distance
Phoenix	Flagstaff	17	200	Los Angeles	10	400	···	···	···	···
Albuquerqee	Flagstaff	40	250	Denver	25	300	···	···	···	···

TABLE III: Human Trafficking Incidence Data in Local Law Enforcement Records of City C_1

path $P_k \in \mathcal{P}$. The binary variable $x_{i,j} = 1$, if the edge $e_{i,j}$ is *interdicted*, otherwise $x_{i,j} = 0$. The binary variable $y_k = 1$, if the path P_k is *disrupted*, otherwise $y_k = 0$. The set of edges that make up the path P_k is denoted by $E_k \subseteq E$. If any edge $e_{i,j} \in E_k$ is interdicted, then the path P_k is disrupted.

$$Max \sum_{P_k \in \mathcal{P}} LEIP(P_k) y_k \tag{6}$$

$$\sum_{\forall e_{i,j} \in E} LEIC(e_{i,j}) x_{i,j} \leq B_{LT} \tag{7}$$

$$y_k = 1, \ \ \texttt{if} \ \ x_{i,j} = 1 \ \ \texttt{and} \ \ e_{i,j} \in P_k \tag{8}$$

Equation 8 can be re-written in the form

$$y_k = 1, \ \ \texttt{if} \sum_{e_{i,j} \in P_k} x_{i,j} \geq 1 \tag{9a}$$

The above constraint involves a *logical* term *if*, and can be replaced by the following constraints and that do not involve any logical term.

$$y_k \leq \sum_{e_{i,j} \in P_k} x_{i,j} \tag{9b}$$

$$\forall e_{i,j} \in P_k, \ \ y_k \geq x_{i,j} \tag{9c}$$

$$\forall y_j, 1 \leq j \leq r \quad y_j = 0/1 \tag{10}$$

$$\forall x_{i,j}, 1 \leq i, j \leq n, \quad x_{i,j} = 0/1 \tag{11}$$

$$\sum_j x_{i,j} - \sum_j x_{j,i} = 1, i = s \tag{12}$$

$$\sum_j x_{i,j} - \sum_j x_{j,i} = -1, i = t \tag{13}$$

$$\sum_{i,j} x_{i,j} - \sum_{i,j} x_{j,i} = 0, \forall i \neq s, j \neq t \tag{14}$$

Eq. 6 maximizes the interdiction payoff for the LEAs. Eq 7. ensures that the LEA operates within their budget. Eqs. 8-14 ensure that a path is interdicted iff all the edges in the path have been interdicted. We use the above ILP formulation for finding the set of edges whose interdiction will maximize the Interdiction Payoff for the Law Enforcement, without violating the budget constraint. The results of our experiments are discussed in Section VII.

VII. Experimental Results

The results of our experimental evaluation of *Logical to Physical Path Mapping* and *Interdiction Payoff Maximization* problems are presented in Tables IV and V respectively. In Table IV, columns 1 through 4 indicate the originating city, intermediate cities (if known), destination city (Las Vegas) and the shortest distance between the originating and destination cities respectively. It may be noted that we have used the USING network for our experimentation and the shortest path length between the cities is computed from this graph. The column 5 in Table IV indicates the tolerance level over the shortest path distance, the trafficker might be willing to accept, in order to reduce the interdiction probability. As shown in Table IV, if the originating and destination city IDs. are 79 and 10 respectively (Kansas City and Las Vegas in USING) and the trafficker chooses to use the shortest path between these two cities, the interdiction probability is 0.999. However, if the trafficker is willing to take a slightly longer path (at most 25% more than the shortest path length), the interdiction probability can be reduced to 0.951. However, further increase in tolerance, i.e., allowing 50% over the shortest path length may not reduce interdiction probability any further. In the four originating-destination city pairs whose results are presented in Table IV, it can be seen that for pairs 1, 3 and 4, the interdiction probability can be lowered by taking a slightly longer path (up to a certain limit), whereas for the pair 2, increase in

Logical Path			Shortest Path (SP) Length (in miles)	Percentage Tolerance over SP	Physical Path	Interdiction Probability
Originating City	Intermediate Cities	Destination City				
79	None	10	1571.46	0	79, 170, 66, 55, 44, 30, 20, 12, 16, 10	0.999
				25	79, 94, 104, 55, 44, 41, 30, 20,12, 16, 10	0.951
				50	79, 94, 104, 55, 44, 41, 30, 20,12, 16, 10	0.951
15	14	10	648.37	0	15, 14, 2, 5, 10	0.694
				25	15, 14, 2, 5, 10	0.694
				50	15, 14, 2, 5, 10	0.694
17	31, 1	10	1835.13	0	17, 25, 31, 21, 13, 6, 3, 5, 10	0.9980
				25	17, 25, 36, 31, 21, 13, 6, 12, 16, 10	0.9963
				50	17, 25, 36, 31, 21, 13, 6, 12, 16, 10	0.9963
59	71, 60, 25	10	2338.97	0	59, 69, 71, 60, 49, 37, 25, 17, 11, 6, 3, 5, 10	0.99993
				25	59, 60, 71, 60, 49, 37, 25, 21, 13, 6, 12, 16, 10	0.9986
				50	59, 60, 71, 60, 49, 37, 25, 21, 13, 6, 12, 16, 10	0.9986

TABLE IV: Logical to Physical Path Mapping Table

Time Period	Physical Paths (Traffic Volume)	Interdiction Budget	Interdiction Payoff
2011	2, 5, 10 (6)	100	11
	12, 16, 10 (1)	200	13
	7, 2, 5, 10 (1)	300	14
	15, 14, 2, 5, 10 (1)	400	15
	23, 15, 14, 2, 5, 10 (1)	500	15
	14, 2, 5, 10 (1)	600	15
	24, 16, 10 (1)	700	15
	79, 170, 66, 55, 44, 30, 20, 12, 16, 10 (1)	800	15
	108, 188, 106, 97, 80, 95, 79, 170, 66, 55, 44, 30, 20, 12, 16, 10 (1)	900	15
	71, 69, 59, 72, 168, 226, 161, 51, 41, 28, 155, 12, 16, 10 (1)	1000	15
2012	14, 2, 5, 10 (1)	100	11
	7, 2, 5, 10 (3)	200	12
	44, 30, 20, 12, 16, 10 (1)	300	13
	71, 69, 59, 72, 168, 226, 161, 51, 41, 28, 20, 155, 12, 16, 10 (1)	400	13
	2, 5, 10 (1)	500	13
	98, 97, 88, 95, 79, 94, 104, 55, 44, 30, 20, 12, 16, 10 (1)	600	13
	23, 15, 14, 2, 7, 2, 5, 10 (1)	700	13
	32, 23, 15, 14, 2, 5, 10 (1)	800	13
	32, 23, 15, 14, 2, 5, 10 (1)	900	13
	79, 170, 66, 55, 44, 30, 20, 12, 16, 10 (1)	1000	13
	11, 17, 25, 21, 13, 8, 4, 7, 2, 5, 10 (1)	1100	13

TABLE V: Interdiction Payoff Maximization Table

tolerance doesn't reduce the interdiction probability. The entries in column 6 provide the physical path corresponding the logical path defined by the originating, destination and the intermediate cities.

Table V shows the results of Interdiction Payoff Maximization for 2011 and 2012. During 2011 and 2012, there were 144 and 120 recorded incidences of trafficking respectively in Las Vegas, of which only 22 and 32 had the origin and destination city information respectively. An origin-destination city pair corresponds to a logical path. As out of 22 and 32 logical paths, only 10 and 11 paths were *distinct*, in Table V, we present the results of these distinct paths only. The total traffic volume on these distinct paths were 15 and 13 respectively. Table V shows how increase in Law Enforcement Interdiction Budget results in increase in Interdiction Payoff, up to a certain point. For 2011, when the interdiction budget is increased from 100 to 400 in steps of 100, the interdiction payoff increased from $11 \rightarrow 13 \rightarrow 14 \rightarrow 15$. Any further increase in the interdiction budget doesn't result in any higher payoff because with a budget of 400, the entire traffic volume carried by the 10 paths (15) was interdicted and there was no room for any further improvement in interdiction payoff. The experiments were conducted on a 2.30 GHz processor computer with 16GB RAM utilizing Python and Gurobi.

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