EXECUTIVE SUMMARY

Sensor Emplacement Network Analysis for Detection of Cross Border Tunnels

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INTRODUCTION

Since 1990, more than 116 cross-border subterranean tunnels have been discovered along the continental US borders, the vast majority between US and Mexico. Tunnels present a low probability, high threat scenario to the United States and are a known means of illicit transportation of drugs, weapons, money and people across the US border. The perpetrators engaged in illicit trafficking are intelligent, tenacious, technologically innovative and they relentlessly seek to continue to expand their profitable enterprise. In today's world, confronted with the realities of terrorism and terroristic objectives, one must also acknowledge that tunnels pose a looming threat to national security. Tunnels are also a persistent military threat. A 2007 operational needs statement (ONS) from US Central Command (CENTCOM) noted that detainees were attempting to tunnel as a means to escape from the internment facilities. Another region with an emerging subterranean threat to US Forces is in Afghanistan with the Karez, or underground aquifers built to move irrigation water from mountains to villages by normal gravity-driven flow. The Karez in Afghanistan (thought to number 6,000) present the Taliban and other insurgents with a means to cache weapons and material, infiltrate and exfiltrate the battlefield and move fighters and supplies. Furthermore, in Egypt, the flow of weapons, ammunition, and other contraband under the Egyptian border has contributed significantly to the ongoing Israeli-Palestinian conflict. Open source estimates place the number of tunnels along the Israel-Gaza border between 300 and 1000.

The objective of the study is to determine the sensor allocation that maximizes the probability and efficiency of detecting tunnel construction activity on the US border. We used a network model approach to determine plausible illicit tunnel infiltration techniques on the southern US border.

This executive summary provides a high level overview of a basic network model that enables the analysis of tunnel interdiction. The methodology was comprised of using the functional decomposition of the tunnel threat for analyzing sensor allocation. We evaluated information instances pertinent to tunnel threat behaviors to include historical tunnel locations, urbanization of border towns and tunnel attributes to support a strategy for equipping the border with a persistent tunnel defeat capability.

APPROACH TO THE TUNNEL DETECTION NETWORK MODEL.

This study coalesces exploratory data analysis, and tunnel network modeling and simulation to gain insights into sensor allocation, placement along a selected area on the US southern border. We applied operational analysis research methodologies to gain insights into these issues by evaluating notional detection technologies in order to enable the system capabilities required to detect tunnels. The goals of the study were develop a preliminary design of a prototype tunnel detection model that we named SENTRIES (Sensor Emplacement Network for Tunnel Reconnaissance & Interdiction Emulation Simulation) to developed a basic methodology that lends itself to ease of use for analysts.

DESCRIPTION OF SCENARIO

The initial, overarching detection model use case diagram is depicted in Figure 1. The overview shows a tunnel construction scenario that includes the human elements (the tunnel operator) and networked sensor system nodes.

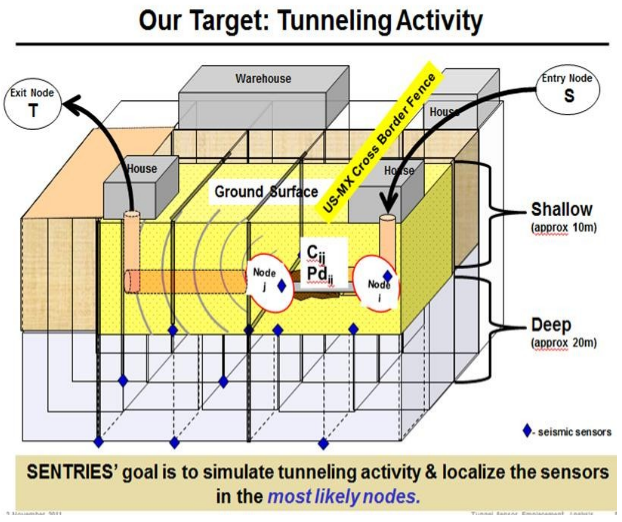


Figure 1. Detection model baseline use case scenario.

After development of the baseline use case, we applied a threat vignette to develop a sequence of events that led to the localization of sensors and subsequently interdiction of a tunneling activity. A specific signature threshold is detected up by an array of underground sensors which will be located at a given node.

Based upon these conditions, initial efforts were made at modeling the scenario in GAMS (which is suited for execution of large numbers of repetitions of parametric runs to identify likely operator's tunneling routes). A concept sketch and screenshot of the base case scenario is shown in Figures 2 and the mathematical algorithm is shown in Figure 3 below.

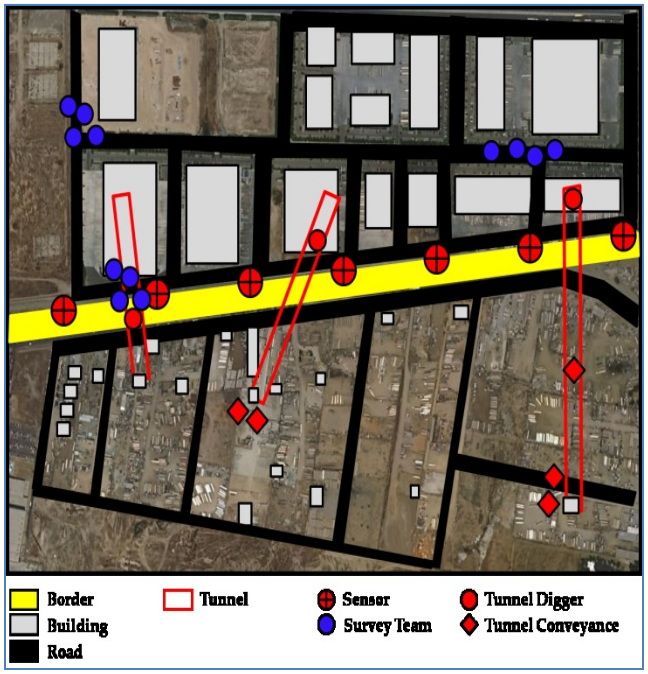
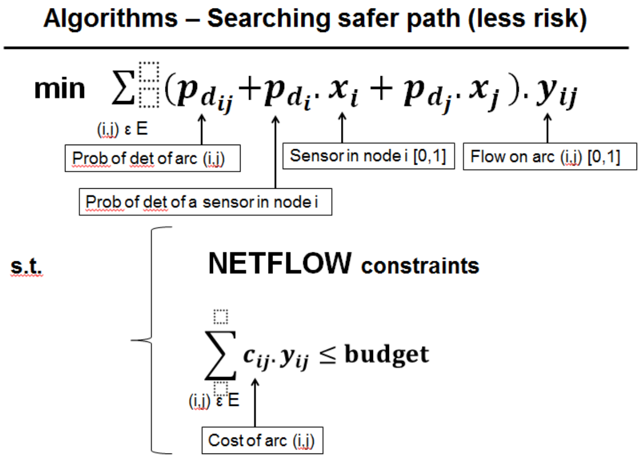


Figure 2. Network model scenario concept sketch.



Algorithms – Searching safer path (less risk)

$$\min \sum_{(i,j)\,\varepsilon\,E} (p_{d_{ij}} + p_{d_i}\cdot x_i + p_{d_j}\cdot x_j)\cdot y_{ij}$$

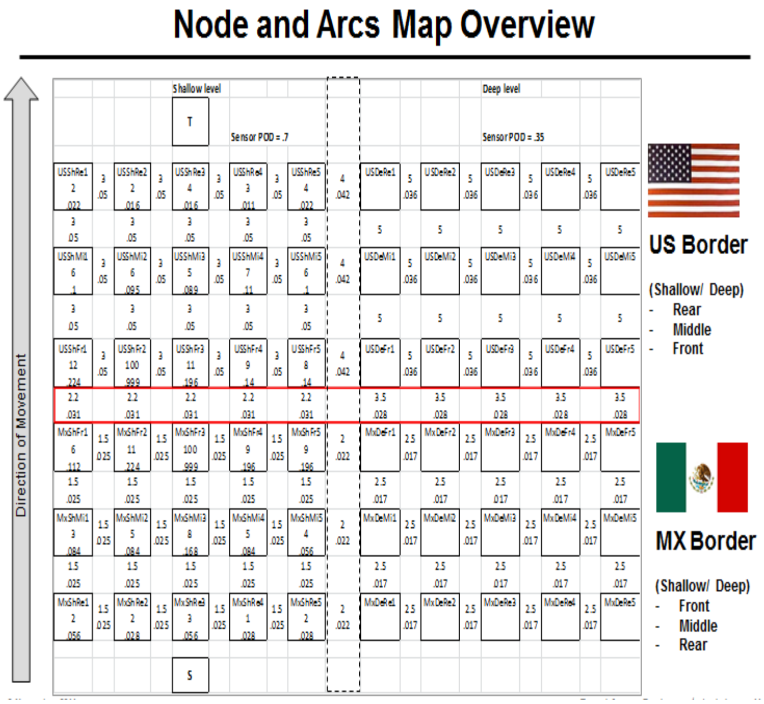
s.t. **NETFLOW constraints**

$$\sum_{(i,j)\,\varepsilon\,E} c_{ij}\cdot y_{ij} \le \textbf{budget}$$

Figure 3. Baseline Network Model.

Model design

The model design methodology will help us to gain insights on sensor system behavior and its interaction with key factors. The goal is to gain such insights from factors that influence the disruption of tunnel construction and respective costs incurred by the operator. We used GAMS to implement the baseline network model and identify tunneling routes that will minimize the operator's probability of detection. During model development, we also created notional node and sensor probability detection factors (shown in Table 1) that defined both the characteristics and performance capabilities of sensors and the tunneling activities performed by an operator.



Node and Arcs Map Overview

				Shallow level										Deep level				
				T		Sensor POD = .7								Sensor POD = .35				
USShRe1 2 .022	3 .05	USShRe2 2 .016	3 .05	USShRe3 4 .016	3 .05	USShRe4 3 .011	3 .05	USShRe5 4 .022	4 .042	USDeRe1	5 .036	USDeRe2	5 .036	USDeRe3	5 .036	USDeRe4	5 .036	USDeRe5
3 .05		3 .05		3 .05		3 .05		3 .05		5		5		5		5		5
USShMi1 6 .1	3 .05	USShMi2 6 .095	3 .05	USShMi3 5 .089	3 .05	USShMi4 7 .11	3 .05	USShMi5 6 .1	4 .042	USDeMi1	5 .036	USDeMi2	5 .036	USDeMi3	5 .036	USDeMi4	5 .036	USDeMi5
3 .05		3 .05		3 .05		3 .05		3 .05		5		5		5		5		5
USShFr1 12 .224	3 .05	USShFr2 100 .999	3 .05	USShFr3 11 .196	3 .05	USShFr4 9 .14	3 .05	USShFr5 8 .14	4 .042	USDeFr1	5 .036	USDeFr2	5 .036	USDeFr3	5 .036	USDeFr4	5 .036	USDeFr5
2.2 .031		2.2 .031		2.2 .031		2.2 .031		2.2 .031		3.5 .028		3.5 .028		3.5 .028		3.5 .028		3.5 .028
MxShFr1 6 .112	1.5 .025	MxShFr2 11 .224	1.5 .025	MxShFr3 100 .999	1.5 .025	MxShFr4 9 .196	1.5 .025	MxShFr5 9 .196	2 .022	MxDeFr1	2.5 .017	MxDeFr2	2.5 .017	MxDeFr3	2.5 .017	MxDeFr4	2.5 .017	MxDeFr5
1.5 .025		1.5 .025		1.5 .025		1.5 .025		1.5 .025		2.5 .017		2.5 .017		2.5 .017		2.5 .017		2.5 .017
MxShMi1 3 .084	1.5 .025	MxShMi2 5 .084	1.5 .025	MxShMi3 8 .168	1.5 .025	MxShMi4 5 .084	1.5 .025	MxShMi5 4 .056	2 .022	MxDeMi1	2.5 .017	MxDeMi2	2.5 .017	MxDeMi3	2.5 .017	MxDeMi4	2.5 .017	MxDeMi5
1.5 .025		1.5 .025		1.5 .025		1.5 .025		1.5 .025		2.5 .017		2.5 .017		2.5 .017		2.5 .017		2.5 .017
MxShRe1 2 .056	1.5 .025	MxShRe2 2 .028	1.5 .025	MxShRe3 3 .056	1.5 .025	MxShRe4 1 .028	1.5 .025	MxShRe5 2 .028	2 .022	MxDeRe1	2.5 .017	MxDeRe2	2.5 .017	MxDeRe3	2.5 .017	MxDeRe4	2.5 .017	MxDeRe5
				S														

US Border

(Shallow/ Deep)
- Rear
- Middle
- Front

MX Border

(Shallow/ Deep)
- Front
- Middle
- Rear

Table 1. Notional factors representing the node layout for both shallow and deep plausible sensor locations.

The mode layout represents a selected area along the United States/Mexico border with representative road and building infrastructure as previously depicted in Figures 1 and 2. We have identified 60 nodes (plus S and T notional nodes), 30 in US and 30 in Mexico. The nodes are located in two levels: Shallow and Deep levels (which are about 10 and 20 meters below the surface respectively). The letter configuration in the top of the node box describes the location of node, for example:

- US/Mx: node is in the US or Mexico side
- Sh/De: node in Shadow/Deep level
- Fr/Mi/Re: node in Front/Middle/Rear position with respect to the border line.
- Node numbers 1 to 5: order of the nodes in each line.

It is assumed that the tunnel operator cannot move in a diagonal fashion.

In order to be able to determine the probability of detection "Pd_{ij}" and the Costs of the edges "C_{ij}" (in cost units) shown in Table 1, we used the following criteria:

- Pd_{ij} and the Costs of the tunnel paths in the Mexican side are half the value than the ones in the US side (notional values were assigned to each node for computational feasibility)
- The probability of detection (Pd_{ij})of the arcs located in deep levels are 30 percent lower than the ones from the shallow level.
- The Costs (C_{ij}), of the arcs located in deep levels are 70 percent higher than the ones from the shallow level.
- The arcs between the notional node "S" and every node in the shallow level have a cost and a probability of detection dependent to the location of the node. This configuration is similarly for the exit notional node "T".

SUMMARY

As expected, the operator's probability of success (POS) is affected by the number of sensors. We noticed that the resilience curve decreases monotonically as the sensors preclude the operator to continue on a less risky tunnel path.

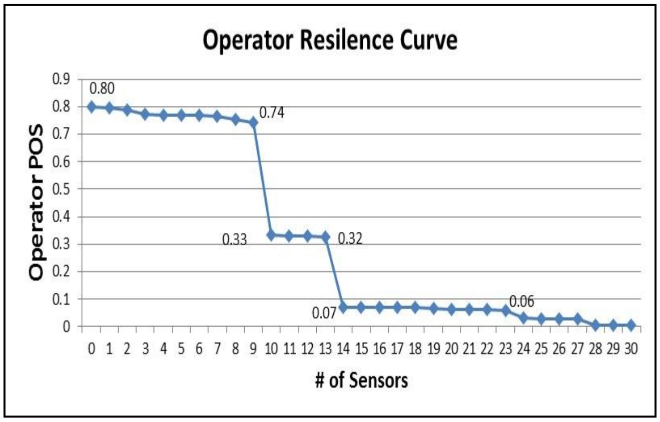


Figure 4. After nine sensors, the operator is forced to cross a node with a sensor and drastically reduce his POS from 0.74 to 0.33.

The Critical Budget is the resource required by an operator to be able to fulfill the tunnel construction with his best probability of success. The model enable's the visualization of the negative effects on the operator's POS when the budget is reduced (see Figure 5 below).

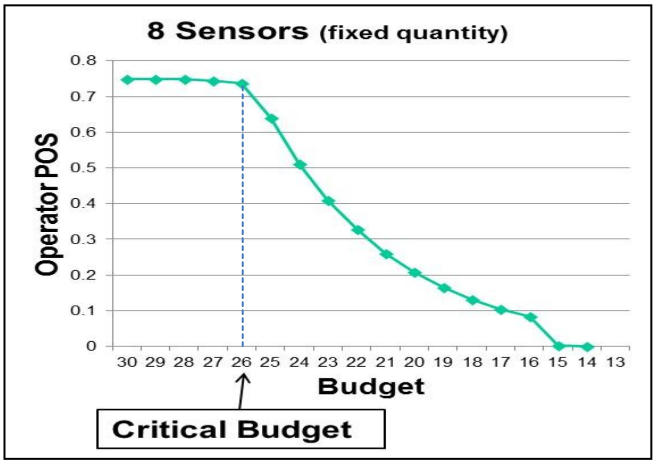


Figure 5. A budget that is lower than the operator's Critical Budget will negatively impact the POS.

In conclusion:

- Operator consistently selects less risky routes (based on a limited budget).
- The model provides a quantifiable method to estimate the operator's critical budget.
- This model provides the sensible number of sensors required to drastically reduce the operator's POS.

Analysis of Base Case

The outputs of interest consist of the possible sensor system allocations for a given tunnel interdiction scenario. The outputs are highly multivariate, consisting of all sensor systems positions, dispositions, and strengths as well as the perception of tunnel location. That is, the output is a Common Operational Picture (COP) comprised of the adversary and/or tunnel interdiction assets. The MOEs that may be derived from the network model include; sensor assets and money allocation (i.e. operator budget). In this manner we determine the constraints that will drive a future response.

Further Work

The challenges to tunnel defeat are attributed to the vast lengths of the border, varied geologies that degrade persistent monitoring and geophysical resolution of subsurface anomalies, as well as the unknown quantity of existing tunnels. The tunnel interdiction mission must be addressed in a comprehensive manner in order to be successfully implemented. This means embracing a heterogeneous system of systems approach that allows both passive and active sensing, command and control, and robotics for post discovery interrogation. Before committing to a particular technical solution, a cost-benefit study and an analysis of systems study that takes into account operational performance associated with GIS locations, risk assessment associated with GIS location, man power requirements, projected training, maintenance costs, and sustainability factors will provide the necessary oversight and will demonstrate due diligence in specifying a system solution.

Within the context of systems engineering and analysis, network modeling for tunnel detection systems shows great promise as a method to enhance the evaluation of multiple detection systems under various conditions. In addition, further work may include developing and testing a DOE capability and designing a user interface appropriate to the skill level of the operator, the required response times, the resource allocations, and the operational environment.