Predicting the Structure of Covert Networks using Genetic Programming, Cognitive Work Analysis and Social Network Analysis[1]

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ABSTRACT

A significant challenge in intelligence analysis involves knowing when a social network description is 'complete', i.e., when sufficient connections have been found to render the network complete. In this paper, a combination of methods is used to predict covert network structures for specific missions. The intention is to support hypothesis-generation in the Social Network Analysis of covert organisations. The project employs a four phase approach to modelling social networks, working from task descriptions rather than from contacts between individual: phase one involves the collation of intelligence covering types of mission, in terms of actors and goals; phase two involves the building of task models, based on Cognitive Work Analysis, to provide both a process model of the operation and an indication of the constraints under which the operation will be performed; phase three involves the generation of alternative networks using Genetic Programming; phase four involves the analysis of the resulting networks using social network analysis. Subsequent analysis explores the resilience of the networks, in terms of their resistance to losses of agents or tasks. The project demonstrates that it is possible to define a set of structures that can be tackled using different intervention strategies, demonstrates how patterns of social network structures can be predicted on the basis of task knowledge, and how these structures can be used to guide the gathering of intelligence and to define plausible Covert Networks.

1.0 INTRODUCTION

Social network analysis is often problematic because one cannot always guarantee sufficient data to know that a network is complete [12.]. To this end, constructing networks on the basis of observed communications might provide partial views of such networks; because some communications might not be observed, or some connections might lie outside the normal scope of intelligence gathering, or some connections might represent 'noise' (in the sense that they are part of the network but not suspicious). From this, we argue that it does not make sense to speak of a 'complete' network (because there will always be the possibility of more connections than have been observed), but that it does make sense to speak of a 'useful' network. A useful network is one which provides details of the associations between key actors in the pursuit of a particular goal, and that might further influence intelligence gathering activity.

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15. SUBJECT TERMS

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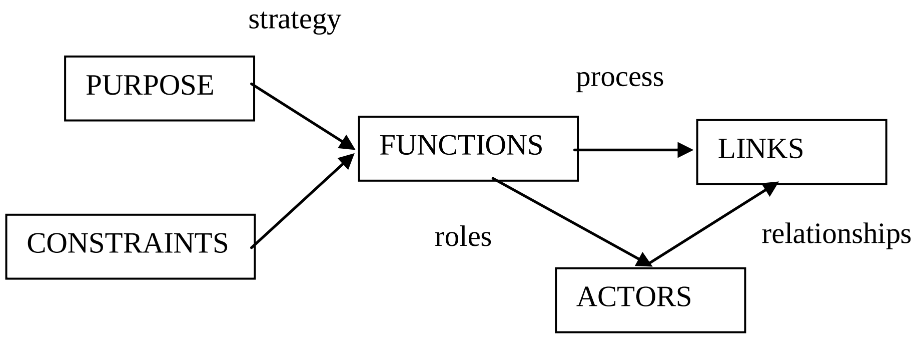


Figure 1: Initial Process Model

Figure 1 shows the process model followed in this work. We assume that networks are built and managed in pursuit of some purpose, and that functions are allocated to Actors to fulfil this purpose. The strategy provides a means of modifying functions in the light of constraints. The idea of building network structures from task models has been previously explored by [4.] and [1.]. However, this work tends to consider single networks that could represent the task model. In our work, we are concerned with the exploration of a space of possible networks.

Early studies of criminal organisations uncovered business-like 'crime families' with a core leadership involving strong family ties [5.]. However, even these crime families exhibited connections across multiple small networks often specialising on specific functions or relationships [2.], and contemporary research shows there appear to be more than one 'network' at play [17.] [16.] [19.]). A study using 'wiretap' conversations of drug networks identified 294 individuals in a loose social network with very limited connectivity, i.e., very few individuals contacted more than 2 people, and if these links were removed, the network would be able to maintain its existence through a host of 'weak-ties' [15.]. We assume, following [8.], that covert networks are not necessarily organisationally different from overt networks, i.e., a drug trafficking network will exhibit many similarities with a conventional supply-chain. What differentiates the covert from the overt network is the level of risk (personal, financial and operational) involved in their operations, and the need to retain an air of secrecy. This need for secrecy, on the one, provides a protection for core members of the network and for the network's assets, but could also compromise the ability to share information, e.g., an individual in the network might not have a clear view of all preceding and succeeding steps in the process (although this is not an unusual state of affairs in the overt supply chains). We assume that covert networks will involve short communication paths, typically based on a need-to-know basis and related to the process of tasks being followed. The approach involves four phases, as detailed in the following sections.

Phase One: Compile Intelligence: We assume that there exists a set of intelligence (either gathered through ongoing operations, or held as experience by analysts). Overall, the approach follows the model proposed by [6.]. This is similar to [9.] analysis of competing hypotheses, in that these approaches define Intelligence Analysis as an iterative process of hypothesis (or assumption) testing. Figure 2 outlines an approach which requires the Intelligence Analyst to develop intelligence gathering plans on the basis of plausible events. We take the notion of plausible events, from a Human Factors perspective, to imply the development of a task model, and the process of assumption testing to relate to the problem of crew management, i.e., how does a 'system' assign tasks to individuals in order to complete a mission, and how do these individuals interact during the course of the mission?

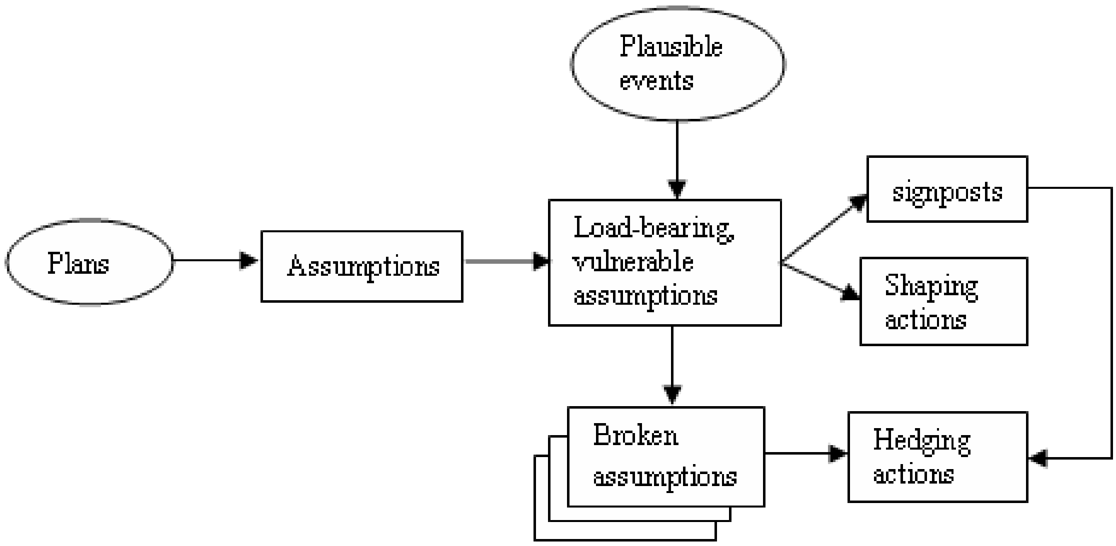


Figure 2: Assumptions-Based Planning

Phase Two: Build Task Model: A task model can be described in many different ways. At the most basic, it would simply be a flowchart showing the tasks required to achieve a given goal. At a more detailed level, it would be a process model which shows the relationship and dependencies between tasks in pursuit of a goal and some of the contextual factors which could have a bearing on performance. At a still more detailed, one could employ Cognitive Work Analysis to define the relationship between task, context and constraint. The idea of using CWA for developing task models of covert networks has been explored by [14.], but they were less concerned with either generating social networks from these models or with exploring the space of possible network structures (preferring to consider Bayesian models of how tasks might relate to available resources). The approach to task modelling in this work uses Cognitive Work Analysis [11.], and employs two function decomposition strategies: the Abstraction Hierarchy, which maps the Functions required to achieve an objective, in terms of available resources, and is used to provide an overview of the type of Mission to be analysed. This would be developed and elaborated by available intelligence and by the Intelligence Analysts knowledge and experience, and Social and Organisational Analysis of Contextual Activity, which allows the analyst to map plausible relationships between Actors and Tasks. Figure 3 shows possible functions in heroin trafficking. Different Actors are represented by different shading, functions are aligned to specific Situations, and the 'box-and-whiskers' show the possibility that Functions could occur in more than one Situation.

Situations / Functions	Farm / Plantation	Market/ Bazaar	Refinery	Border	Europe
Cultivation of poppy					
Extraction of morphine					
Bulk sale of 'pure' heroin					
Preparation of 'street grade' heroin					

Figure 3: Contextual Activity Template

Phase Three: Explore Alternative Network Structures: In order to translate from the Contextual Activity Template to a network that links Actors together, we make the assumptions that consecutive Functions require liaison between Actors and that Functions which involve more than one Actor could require liaison between these Actors. This allows an initial version of a Social Network to be constructed. However, this does not provide any indication of the number of alternative networks that could be produced, and we argue that it is necessary for the Intelligence Analyst to be able to conceive of alternative networks in order to define intelligence requirements and to consider plausible alternatives. Thus, we explore the biding of Actors to Functions through the application of Genetic Programming (GP) algorithms [13.] GPs are typically represented in the form of tree structures in which the nodes represent particular operations (see figure 4). T program seeks efficient routes through the tree to reach a given solution. In very broad terms, one can contrast a GP approach with Artificial Intelligence (AI). Imagine one wishes to develop a system which 'learns' a set of rules to run a maze. One approach in AI might be to provide some basic rules to the system and then expose it to a number of mazes. The system would apply the rules it has, and the programmer might provide feedback to the system in terms of its performance. GP takes a very different approach in that it does not assume any combination of rules but rather has components of the system which specific abilities. The components are able to respond to the maze and their 'fitness' is assessed, e.g., if a component is able to move in the maze then it survives, otherwise it dies. Over a number of trials, components can evolve, breed or otherwise develop, such that the components which survive early trials continue to tackle subsequent trials. In this way, the behaviour is not due to specification of rules but rather arises from the mapping between component behaviour and environmental conditions. The evolution of these structures is influenced by mutation and crossover (both of which can be supported easily by tree structures). Crossover occurs when two parent nodes in the tree are exchanged. Mutation occurs when a parent node in the tree is randomly selected and its sub-tree is replaced by a new one. Crossover and mutation are applied separately.

If we assume that the main problem to be solved is the efficient utilisation of available Actors in order to produce an optimal supply-chain, then one can imagine a set of algorithms that will be relate the availability of Actors (in terms of whether they are currently performing a Function) and the ability of Actors (in terms of whether they can be associated with the Function). From this, one might assume that some Actors will not be available, with the result being either a delay or a reduction in the probability of success. An application has been written in MS Visual C++ to run under Microsoft Windows XP. The model maps Actors to Function, using Genetic Programming. In this application, each mission is represented as a tree that can grow (through mutation or crossover) to a maximum size of 1000 nodes. As the GP tree is evaluated it produces a vector of real numbers. This vector is analysed and interpreted in the context of a "grammar". In this work, this grammar is defined by the binding of Actors to Tasks, e.g., "Actor #: Number of tasks, task 1...task x".

The tree structure will be populated by numbers and operators. At various points in the tree structure's iteration a 'write to file' command is issued and the product of the tree is read off. For example, the following tree combines randomly generated numbers on its branches that can be combined using operators to produce the number 4.9 (i.e., 10 – (5 + 0.1) = 4.9).

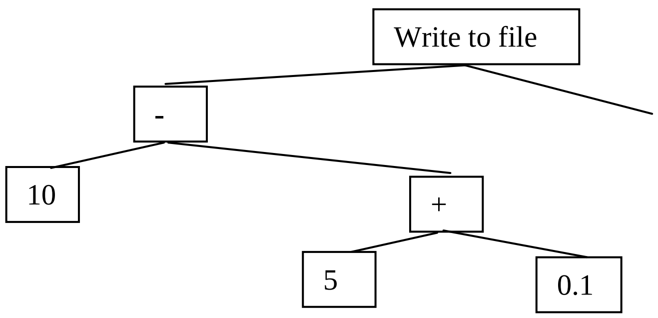


Figure 4: Example Tree Structure

In a sense, the tree represents the genome. The phenotype, in this instance, is a string of digits read from the tree, e.g.,

4.9	1.7	3.2	1.05

Figure 5: Vector String

This string of digits defines the vector of real numbers. Initially, each vector is examined from left to right. A novel aspect of our approach is that each vector will be examined in four ways (by rotating the string to produce four versions). Take, for example, figure 5 above {4.9, 1.7, 3.2, 1.05...}. For the first number in this string, 4.9, we drop the 4 and are left with 0.9. Using the range, 0 – 1, we bin this range according to the maximum number of Functions we will assign to any Actor, such as 4. So, in this case, the range 0 - 1 is divided into 4, i.e., 0.25, 0.5, 0.75, 1.0. As 0.9 is greater than 0.75 but less than 1.0 we get to the 3rd bin so the Actor will be assigned 3 Functions. In order to determine *which* Functions are assigned to this Actor, we move to the next number, 1.7. Again, we drop the 1 to have 0.7. Assume that are 20 tasks in the mission. The range 0-1.0 is binned into 20 chunks. The number 0.7 equates to class 14. So, that means that Actor 1 can do Function 14. Then we look at the next number, 3.2, which we interpret as Function 4 (because 0.2 falls on the 4th division). We repeat this with 1.05, to get 0.05 (which equates to task 1). Thus, we interpret the vector to mean: {Actor 1is assigned 3 Functions which are: 14, 4, 1}. This represents an initial solution to the binding problem. Once a sequence of tasks has been assigned, and a mission defined, the GP generates a new vector. If the vector has been previously produced, it is not analysed. By recording each novel string, the GP generates several combinations of Actors to Function (given any constraints placed on the Actors) and this combination is then run in the model (defined by the Task model). The GBG software tool, developed to support this activity, requires the following steps:

Step 1: Define Task Model: The Analyst can Add a Task to the set (on the left of the screen). Each Task can be linked to other Tasks because it provides an Output to other Tasks (or receives Input from them). In this way, the Task Model can be constructed as a sequence of dependencies between Tasks. In this work, we are only building Task Models with simple, linear dependencies. This is partly due to the source material we are using and partly due to desire to keep each element in the modelling work as simple as possible. However, there is no reason why the Task Model could not include multiple dependencies and parallel activity (but this would be the subject of subsequent research).

Step 2: Define Actors: The Analyst can Add Actors to the model. At present, the Actors can either be assigned Tasks manually or have Task assignment through the Genetic Programming (see step 3d). Future work would develop Actor capabilities so that they could be allocated to Tasks in terms of their ability to perform them.

Step 3: Build Task Model: Each Task can be further defined in terms of a Time (defined as a Gaussian distribution) and a timing model. The sequence of Tasks, taken from Step One, is shown graphically, and the timing model is used to determine whether the dependent Task will start on termination of the current Task or at some point during the Task. There are three possible points (beginning, middle, end) of the each task.

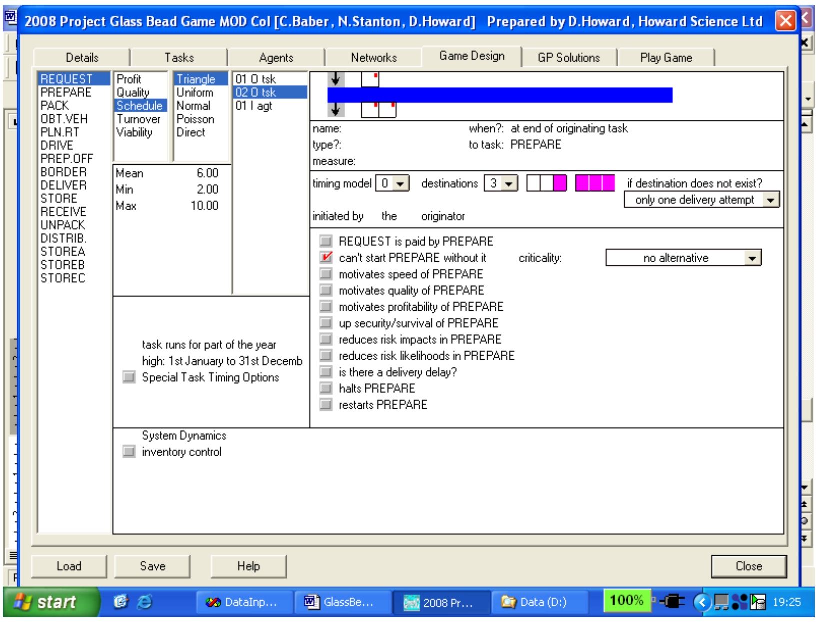


Figure 6: Defining parameters for Task Model

Step 4: Run GP: The allocation of Tasks to Actors can be assigned by the Analyst through selecting each Task (on the left) and then selecting which Actors *could* perform the Task. This results in a grid (on the right) showing the allocation of Actors to Tasks (in blue). The Genetic Program will use this information to randomly pick possible Actors for each Task in the sequence.

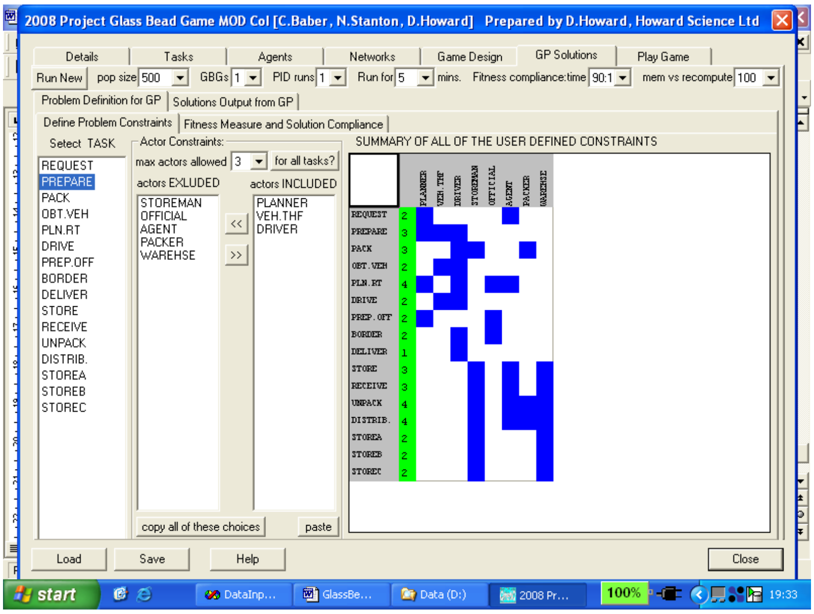


Figure 7: Assigning Tasks to Actors

Step 5: Explore Results: The GBG tool generates permutations of Actors and Functions and selects those which result in the mission being completed. These permutations can then be visualised in terms of the allocation of function to actors, the timeline of the process, or the communications between actors (see figure 8).

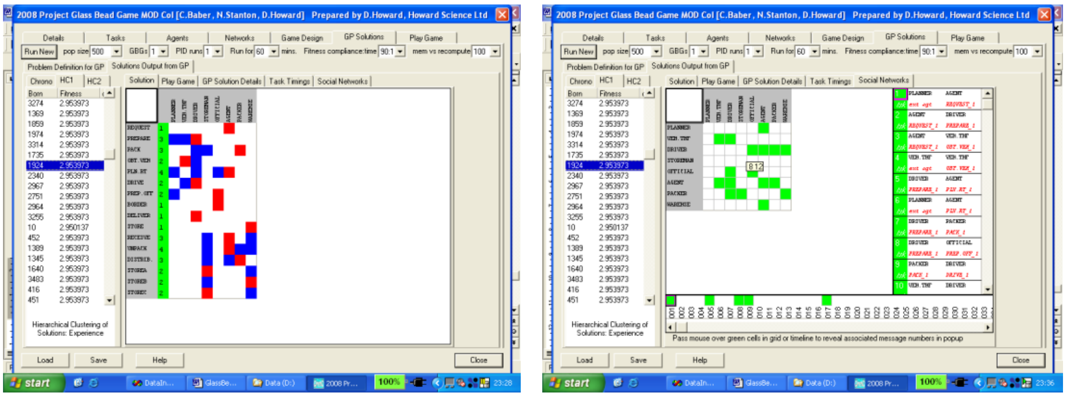


Figure 8: Output Analysis from GBG (resulting task model and social network matrix for model) The task model, on the left, shows the Actors who could be assigned a given Function (in blue) and the Actors who the GP solution actually assigns (in red). Thus, the algorithm offers alternatives, in terms of who might perform the Functions, but only selects one person to do the work. This echoes the earlier discussion of covert network structure.

Phase Four: Compare and Analyse Social Networks: The communication between actors, produced by GBG, can be saved as a .csv file (for wither specific instances or as an amalgamation of instances which share common features). In this part of the work we employed the *WESTT* tool developed under the HFI-DTC [10.]. The .csv file is edited in MS Excel and then saved as a MS Excel before being imported into WESTT for analysis. As figure 9 shows, the WESTT tool produces a social network diagram and performs several analyses related to the connections and distance between actors in the network.

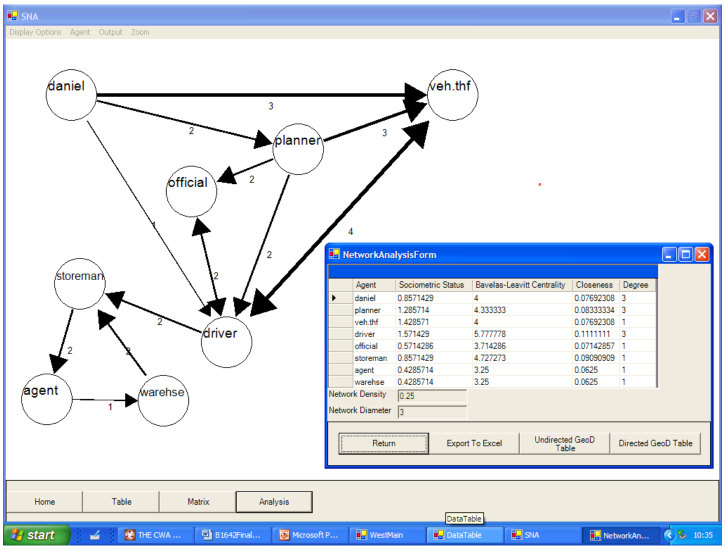


Figure 9: Example of Social Network Analysis in WESTT

2.0 CASE STUDY: MARIJUANA SMUGGLING NETWORK

Objective: compare networks generated from task models, using *gbg*, with network compiled from intelligence (taken from [18.]).

Outline**:** The analysis of drug smuggling rings in [18.] focused on the export rings and the import rings. The book does not detail the growing and processing of the cannabis, nor does it detail much about the distribution and sales after the main wholesaling. The main research is concerned with the interaction of the export ring with the import ring, and the manner in which the Customs and Drug Enforcement Agencies attempt to detect, infiltrate and defeat these rings.

Compile Intelligence: Daniels negotiates with farmers and landowners for the price of cannabis, and buys-off the military, police and narcotics control. He also puts investors and financiers together to fund shipments. His deals could be in the order of 20 tons of Thai Sticks at a time. He arranges for all of the cannabis to be brought to a central warehouse where it was compacted and vacuum packed to preserve it. Daniels also has a system organised to prevent searching of his crates containing cannabis at the port. He has a blue crest stamped 'passed' onto a tag. All crates with this tag were not inspected by the customs men, in return for payment. By bribing the military, police and narcotics control personnel at all levels he received tip-offs as well as assistance in his smuggling operations. The Import Ring is the 'Coronado Company' in table 1. The four main players in the 'Coronado Company' are Villar (who handled procurement and negotiations), Weber (who was the pilot and mechanic), Otero (who was the beach-master and organised the landing and offloading of cannabis), and Acree (who was in charge of sales and distribution). They employ people to captain the ship for bringing cannabis into the country, and also employ an offload crew to get the cannabis off the ship to a safe stash house. The 'Coronado Company' has a communications house with a high power antenna and a ship-to-shore radio, so that movement of the coast guard could be reported and the drop off could be arranged.

Create Task Model: The task model begins with an outline of actors and the functions with which they are associated. For the purposes of this analysis, this information is taken from a reading of [18.] and presented in table 1. Figure 10 shows that there is mixture of 'discrete', 'inter-dependent' and 'multiple' (i.e., several Actors could perform a specific Task) role allocation in the function-situation matrix, and the relationships between Actors is illustrated by figure 11.

Table 1: Actors and Functions in Case Study Two

Agent Role	**Description**
Farmers	Grows marijuana using traditional farming techniques
Landowners	Own the land on which the farmer grows marijuana
Military	Mostly army in Thailand, may be used to protect transport of marijuana to dockside
Police	May provide intelligence of impending operations and steer operations away from Daniels
Narcotics officers	May provide intelligence of impending operations lso do not search cargo with 'Passed inspection' labels on them in return for payment
Investors	Putting up money to finance shipment in return for cut of the profits
Financiers	People lending money to the investors
Daniels	Key link between the Export ring and Import ring; specialises in putting all the people together and stays in the background of the operation, but takes large profits for himself.
Chris (captain)	Experienced sailor, hired on an occasional basis for a large fee
Villar (procurement)	Skilled negotiator and has multiple languages. Understands about the quality of marijuana.
Weber (mechanic)	Skilled mechanic, looks after all the equipment
Otero (beachmaster)	Offloading the marijuana from the ship to the stash house.
Acree (sales)	Has a wide sales and distribution network.
Del Mar (distribution)	One of the distribution networks.
Offload crew	The team that work under Otero.
Truck drivers	Drivers of trucks.
Guards	People used to guard the marijuana at various points on its journey.

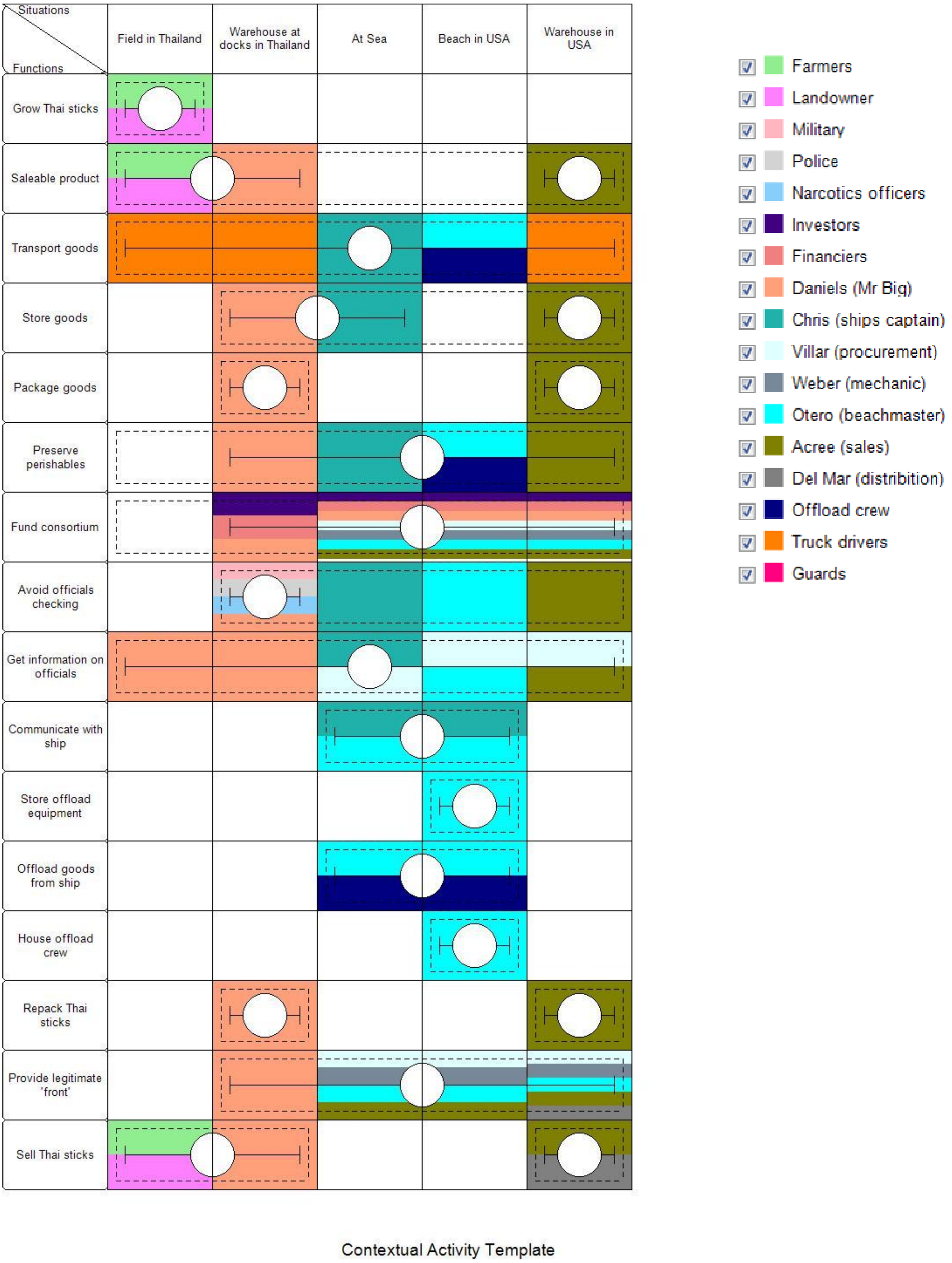


Figure 10: Contextual Activity Template for Case Study

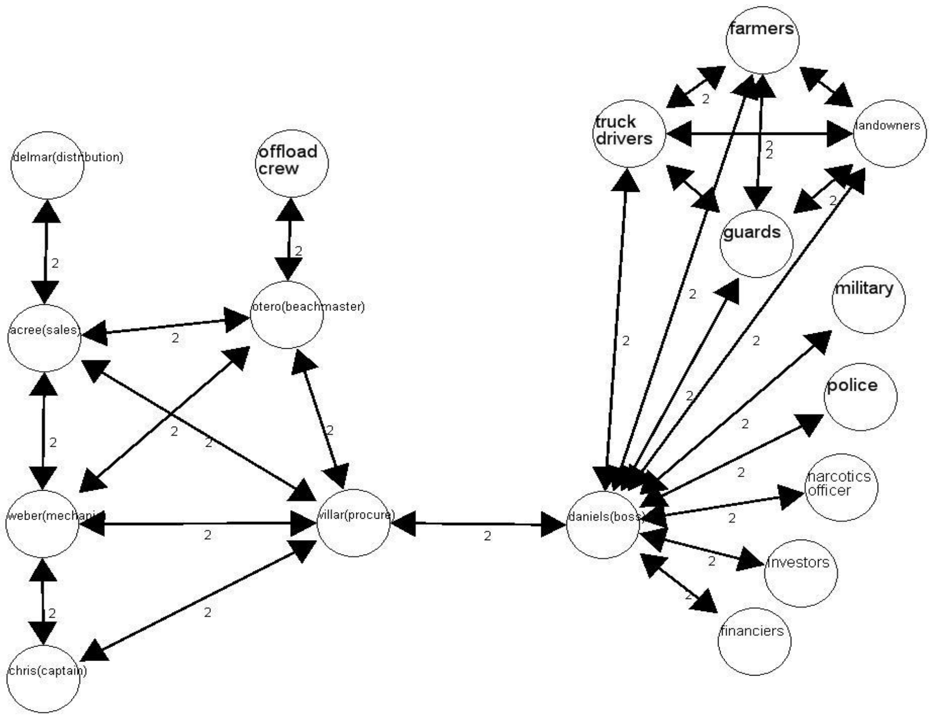


Figure 11: Social Network constructed from initial 'intelligence'

Explore alternative network structures: It was assumed that there would be a degree of constraint in the allocation of Tasks to Actors. The construction of the GBG model involved translating table 1 into a process model and assigning Actors to Tasks based on figure 12. This would provide sufficient constraint on the binding between Actors and Tasks to reduce to number of connections. One possible problem with this approach is that the Task Model we were using is quite simplistic (on the basis of the details provided in the source material), and one might anticipate a more robust Task Model to be developed from Intelligence materials.

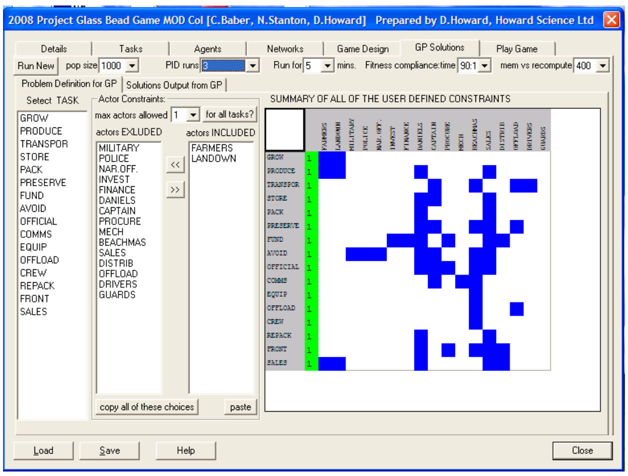


Figure 12: GBG model for Case Study Two

Having created the process model and defined plausible actors for each task, the model was run with a population of 1000 over 3 runs. This produced 16 solutions for run 1, 15 solutions for run 2, and 18 solutions for run 3. Overall, the solutions had a range of fitness scores, as shown in table 2.

Table 2: Number of Solutions for different Fitness Score

Fitness Score	Number of Solutions
2.99151	38
2.99123	3
2.99068	4
2.99041	1
2.98986	1
2.98904	2

The 38 solutions with maximum score we saved and used to populate WESTT for subsequent analysis.

Compare and Analyse Social Networks: Each network was subjected to basic Social Network Analysis, using metrics that relate to the number of connections for each node and the distance between nodes in the network. The results of this analysis are compared against metrics produced from review of [18.].

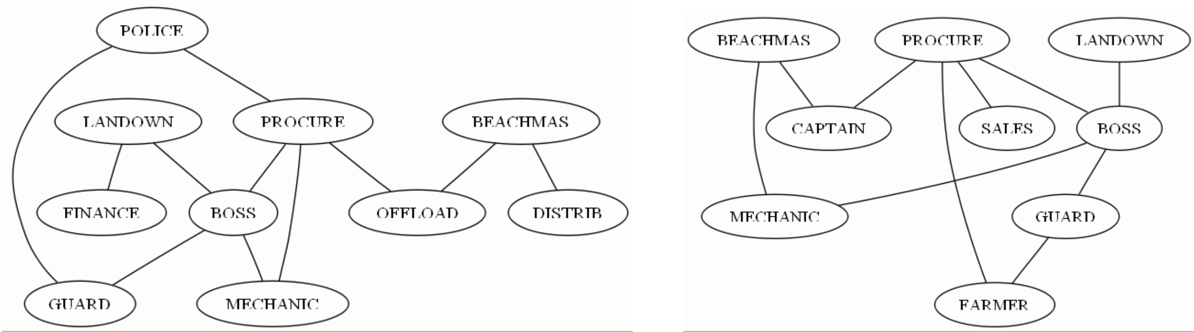
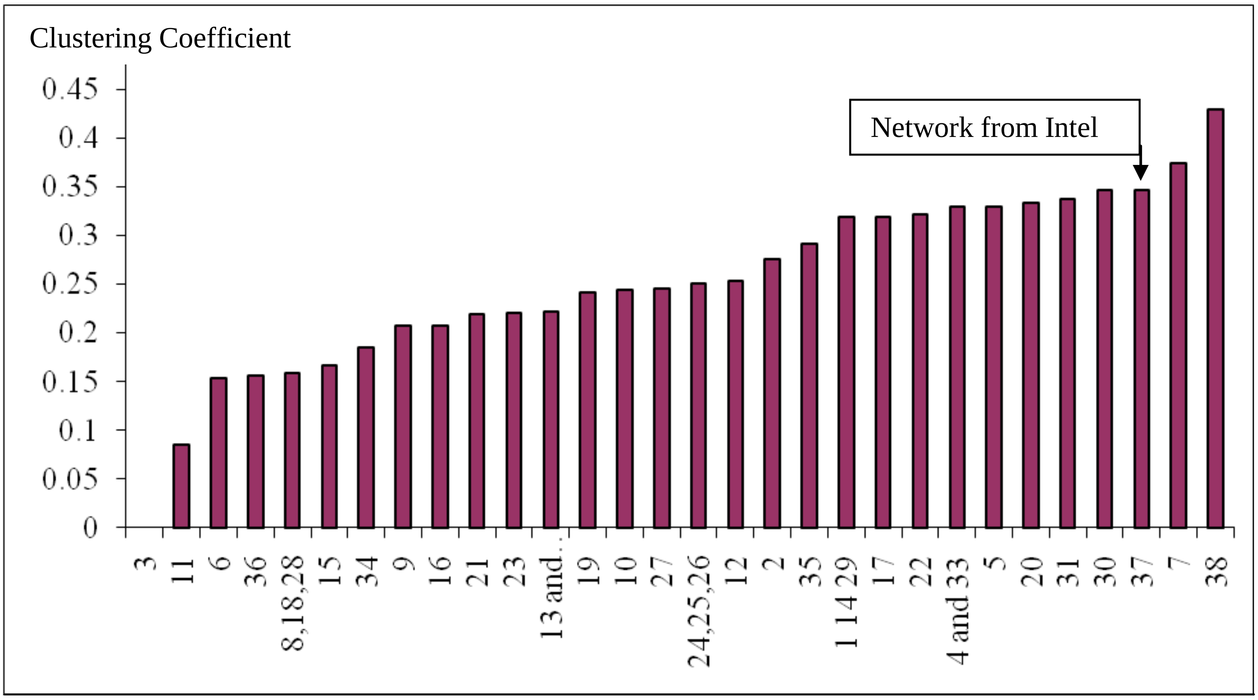


Figure 13: Examples of Social Networks derived from GBG Tool

Figure 10 shows the network that could be derived from a reading of [18.]. Broadly, it shows what looks like a clique centred on Daniels, and another clique centred on the Beachmaster. One possible explanation of the structure of the network shown in figure 19 is the desire to maintain separation between Actors other than the key Actors. Thus, the ‘production’ Actors (in the top right of the figure) have no connection with the ‘distribution’ Actors (in the top left of the figure). Another explanation might simply be that the source material was focussing primarily on the role of Daniels (the ‘Boss’) and the Coranado Company (involving named individuals in an import ring). Both Daniels and the Beachmaster were identified in table 1 as being key players in this network (the other key players being Mechanic and Procurement). Figure 10 contains more actors than each of the networks shown in figure 13. This can be explained simply by virtue of the fact that the networks produced in figure 13 were developed to perform the specified tasks and had a limit on the number of actors who could perform a task, whereas figure 10 does not represent the performance of a specific task so much as the summation of all contacts mentioned in the book. While we have assumed a network structure that links Actors on the basis of Functions, this produces small networks with little redundancy. If we follow the description of ‘structural holes’ put forward by [3.], then we might assume that there are information and resilience benefits to be gained from larger networks with many non-redundant contacts.

Clustering Coefficients: A series of routines, using PySNA a Social Network Analysis library in Python[i], was used to read the output files generated by the *GBG* tool, in order to construct models, calculate clustering coefficients and perform simple resilience analysis (figure 14).



Network identification numbers

Figure 1410: Graph showing networks by clustering coefficient

Figure 14 shows the results of the analysis. One can see that the network model from the source material lies towards the right hand side of the figure, and that the GBG model produces many networks with much lower clustering coefficients. In part this is because the Task Model we have used implies a linear chain of activity which could require limited connection between Actors. A more detailed Task Model, in which Tasks are either performed in parallel or in which there are 'dummy' Tasks could lead to a more highly connected network. However, it is worth noting that an aim of the covert network must be to maintain sufficient connectivity to operate with minimal connection of critical Actors and maximal separation of key Tasks.

Testing Resilience: In addition to considering clustering, the PySNA tool allowed the exploration of resilience. In this analysis we simply removed Actors one at a time from the network to explore the impact on the number of links. Figure 16 illustrates the impact of removing Actors from the Network developed from the source material. One can see that removing the key Actors (using SNA metrics from the highest to lowest score) has a dramatic a rapid destruction of the network (the pink line in figure 15).

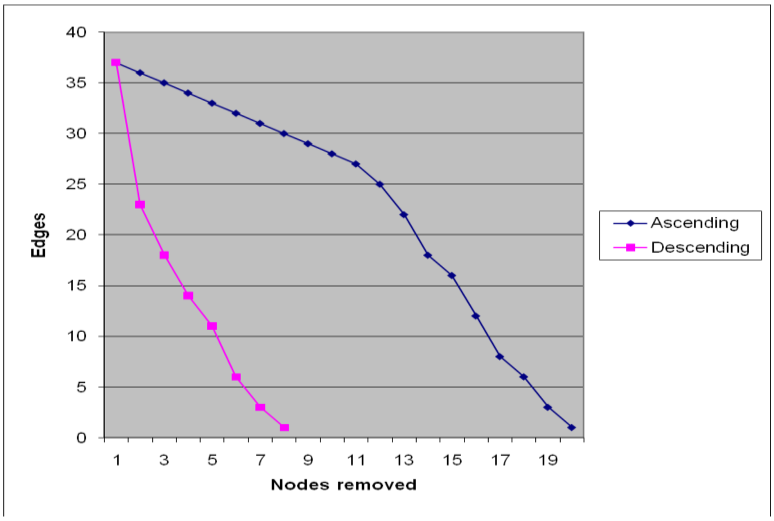


Figure 15: Removing Key and Peripheral Actors from the source material Network

This is to be expected because the highly connected Actors hold the network together and their removal leads to rapid destruction, i.e., removing 'Daniels' splits the network into two separate regions and removes a bunch of Actors who only connect to this Actor.Removing Actors from the periphery (i.e., with low SNA scores) has limited impact and implies that the network could continue functioning with the removal of some dozen or so Actors before problems occur. The point of interest is that such 'targeted destruction' of the network relies on both the opportunity to attack the network and the identification of high status nodes. It also implies, perhaps, that all networks can be attacked in a similar manner but this is not the case. Some networks might require targeted destruction whereas others could be dealt with through random attack. Applying this resilience analysis to all of the networks produced by the GBG model, we see varying effects of targeted and random attacks. This is illustrated by graphs in figure 16. The blue and pink lines represent ascending and descending SNA scores (as in figure 16) and the other lines represent 3 different random attacks, i.e., removing Actors irrespective of their scores. For the Low Clustering Coefficient, it seems as if there is little to choose between the various approaches and that all attacks result in a similar, linear degradation with the number of nodes removed. This means that for around 12 or so networks produced by the GBG tool, a random attack would be sufficient to disrupt them. For the Medium and High Clustering Coefficient Networks, the picture is a little more complicated. Some random attacks would result in similar performance to the removal of high status nodes, others would be slightly less effective. However, the random attacks tend to lead to faster disruption than the removal of the low status nodes. This implies that it might be possible to disrupt such networks without high investment in intelligence gathering.

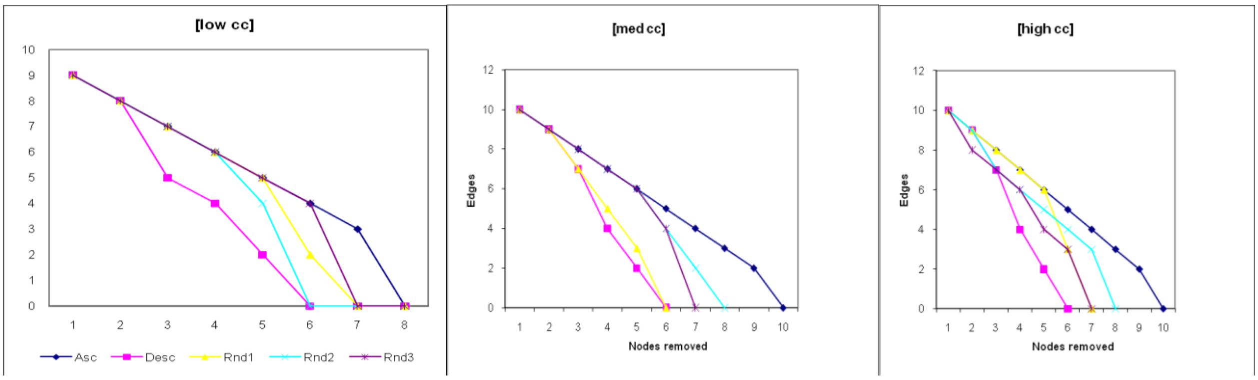


Figure 116: Comparison of Targeted and Random Attack on Networks with Different Clustering Coefficients

Both sets of networks suggest that removal of the high status nodes while obviously leading to rapid disruption to the network might not be key to attacking the networks produced by the GBG model. Of course, there is a strong caveat to be made here: the GBG model is only as good as the Task Model that informs it. This points to further work which would involve the analyst in conducting 'what-if' assessments of different network types in order to further explore assumptions of how the network might *function* and how it might be *disrupted*. Thus, is possible to evolve social networks on the basis of function-actor mappings and to provide opportunities for exploring disruption. Current work is exploring situations in which tasks can be allocated to several individuals on the basis of the knowledge, skill and ability, such that loss of individuals need not compromise the network. Initial explorations suggest that, as one might expect from scale-free networks, only a few nodes represent significant losses to the network and many other nodes can be lost with little cost.

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