11-1-2010

Framework for optimizing intelligence collection requirements

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Framework for Optimizing Intelligence Collection Requirements

by

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of
Master of Science in Computer Engineering

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Title: Framework for Optimizing Intelligence Collection Requirements

Dedication

This work is dedicated to my family and friends who have supported me in all my endeavours.

Acknowledgments

I would like to express my gratitude to Dr. Shanchieh Jay Yang for his mentorship, without whose help and inspiration I would never have finished this work.

I would like to thank Dr. Moises Sudit, Dr. Andres Kwasinski, and Jared Holsopple for their valuable advice.

Lastly I would like to acknowledge CUBRC and AFRL for providing the financial funding needed for this work.

Glossary

A

AOI Area of Interest, p. 7.

C

COA Course of Action, sequence of actions that can be performed, p. 1.

CRAs Collection Requirement Actions, actions that are performed to collect intelligence, p. 2.

D

decision support model, tools, or processes which can aid effective decision making, p. 1.

DM Decision Maker, individual with responsibility of making decisions in an operation or mission, p. 1.

DSS Decision Support System, systems which model, analyze, or visualize information to aid effective decision making, p. 1.

G

GUI Graphical User Interface, p. 12.

J

JIPOE Joint Intelligence Preparation of the Operational Environment, analytical process used in the military domain, p. 6.

P

PF Plausible Future, any event or set of events that could occur in future as anticipated by analysts or automated tools, p. 1.

Abstract

In the military, typical mission execution goes through cycles of intelligence collection and action planning phases. For complex operations where many parameters affect the outcomes of the mission, several steps may be taken for intelligence collection before the optimal Course of Action is actually carried out. Human analytics suggests the steps of: (1) anticipating plausible futures, (2) determining information requirements, and (3) optimize the choice of feasible and cost-effective intelligence requirements. This work formalizes this process by developing a decision support tool to determine information requirements needed to differentiate critical plausible futures, and formulating a mixed integer programming problem to trade-off the feasibility and benefits of intelligence collection requirements.

Course of Action planning has been widely studied in the military domain, but mostly in an abstract fashion. Intelligence collection, while intuitively aiming at reducing uncertainties, should ultimately produce optimal outcomes for mission success. Building on previous efforts, this work studies the effect of plausible futures estimated based on current adversary activities. A set of differentiating event attributes are derived for each set of high impact futures, forming a candidate collection requirement action. The candidate collection requirement actions are then used as inputs to a MIP formulation, which optimizes the plausible future mission state subject to timing and cost constraints. The plausible future mission state is estimated by assuming that the CRAs can potentially avert the damages adversary future activities might cause. A case study was performed to demonstrate several use cases for the overall framework.

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Chapter 1

Introduction

In the military domain, missions are defined to accomplish goals which can require complex decisions. As a result decision making has been studied extensively in the military to establish doctrine [3, 7, 16]. The fundamental notion in these works is the iterative cycle of Course of Action (COA) development, determination of which COA(s) to adopt, and implementation of COA(s) [23].

Intelligence collection plays a crucial role in all three fundamental phases; better intelligence collection improves decision maker's (DM's) and analyst's ability to develop and adopt effective COAs. In turn, intelligence collection requires its own set of steps: (1) anticipating plausible futures (PF), (2) determining information requirements, (3) optimizing collection based on feasibility and cost-effectiveness.

These steps are not trivial and along with the need for intelligence collection at the strategic, tactical, and operational level present a challenging problem for analysts [13]. The number of parameters and expert knowledge required to effectively carry out intelligence collection suggests the need for decision support. Decision support systems (DSS) are computerized tools which provide decision support by supplying information that can reinforce and improve a DM's effectiveness [14, 17, 20]. DSS have been implemented in many different domains such as in supply chains [2, 5], medicine [6], information fusion [15], and some existing military applications [14].

However, to properly offer decision support an understanding of the intelligence collection process is required. Intelligence collection has been studied extensively as analytical processes. Hutchins *et al.* [10] work on the Tactical Decision Making Under Stress (TADMUS) program cover the principles that are needed for decision support with regards to navy ships operating in littoral (coastline) regions of world. Where challenges such as closer proximity to enemies and swiftly unfolding events exacerbate decision making complexity. The program explored the cognitive tasks performed by humans in these military operations and subsequently discussed how decision support and (human-system) interaction design could be used to reduce the cognitive requirement on a decision maker. It was found that DSS could not adequately replicate expertise gained from experience. Since all contingencies in a situation cannot be anticipated, a human expert's intuition is needed. However, DSS can reduce search time for relevant information through graphical presentations, and reduce amount of cognitive computation required for certain tasks. This project suggests that the use of DSS can prove beneficial in a military context.

This research builds off previous works to develop a formal decision support framework for intelligence collection. The framework is composed a decision support tool that determines information requirements needed to differentiate between critical plausible futures and a mixed integer programming (MIP) optimization formulation that can trade-off between the feasibility and benefits of different intelligence requirements. In essence the the effort allows for analysts to differentiate between plausible futures via attributes to craft candidate collection requirement actions (CRAs). A set of optimal collection requirement actions are produced via the MIP formulation that can guide DMs in the decision making process.

Chapter 2

Understanding the Problem

Providing decision support for intelligence collection requires a thorough understanding of the intelligence collection process. Several works were critical in building the foundation needed to properly interpret the problem.

2.1 Generalized Information Flow Model

Yovits *et al.* [27, 28] work on the Generalized Information Flow Model acted as a starting point. As shown in Figure 2.1, Yovits tries to capture the ability of a DM to learn and adapt over time. Yovits' model relies on three hypotheses: (1) information is data of value in decision-making, (2) information gives rise to observable effects, and (3) information feedback exists so that the DM will adjust his model for later decisions.

A fundamental idea in this model is that the two sources of information come from the environment and from feedback based on observations of results from previous decisions (e.g. DM's experience). In this model, information is captured from the environment through a process called Information Acquisition and Dissemination (IAD). This is simply the process by which sensors capture data and this data is propagated to the analysts and DMs. This information is processed and provided as input to the decision maker. The decision maker uses the information available to choose a COA. The COA is executed and the results are observed. These results are compared against anticipated results and transformed into data that can be used in a feedback loop at the IAD stage. In this way the DM learns about how decisions and outcomes are related and can adjust accordingly.

The COAs in Yovits model can be viewed as options that are developed by decision makers

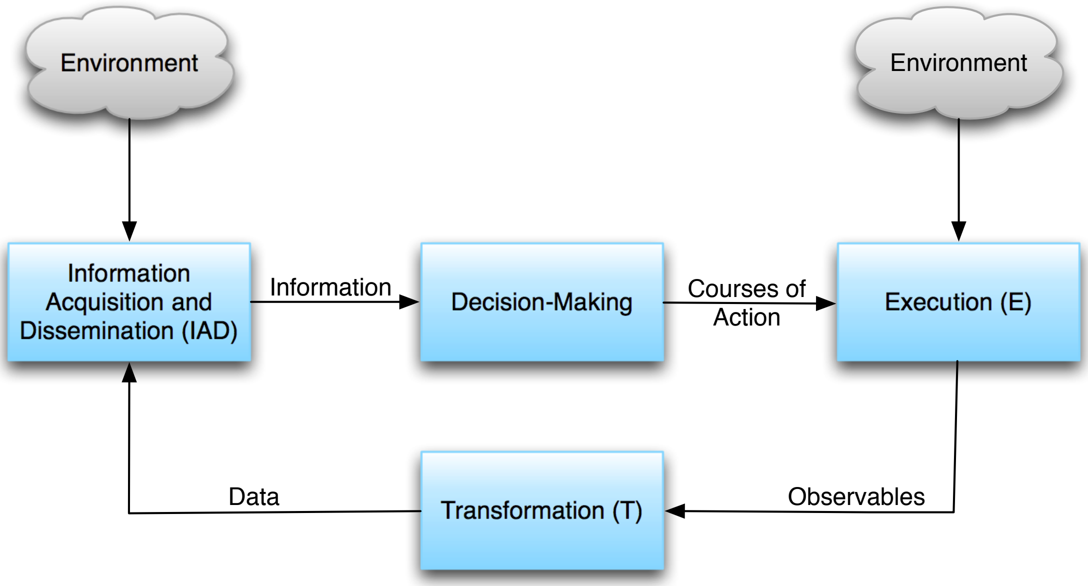


Figure 2.1: Generalized informatin flow model [28]

from the information available to them (from the environment and experience). These two elements are representative of the natural elements in human decision making: considering the current environment and anticipating future events. The generalized decision making process according to Yovits is given below:

1. DM makes a decision (chooses a COA) on the basis of all information available.

2. DM predicts some probable outcomes.

3. A comparison is made between observed results and anticipated results (feedback).

4. Updates the model of the situation from results observed.

5. Return to step 1.

Yovits asserts that DMs will always try to fulfill two main objectives: choose the best COA and learn as much as possible about the current situation. Yovits states that while classical decision making maintains that DMs will always choose to prioritize the former, this is an oversimplification. DMs may lean towards focusing on the latter because of uncertainty with current estimates or wanting to learn more about the current situation. Thus, intelligence plays a critical role in the mission planning process and selection of COAs.

Yovits also emphasizes the vital role of uncertainty in decision making and categorizes it into three categories: (1) state of nature uncertainty, (2) executional uncertainty, and (3) goal uncertainty. State of nature uncertainty is the result of uncontrollable external conditions that could influence outcomes. Examples of state of nature include: weather, governmental regulation, economy, *etc.* Executional uncertainty refers to the unknowns arising from DMs identifying available COAs (options) and outcomes of the COAs. Yovits asserts that the relationship between COAs and outcomes are probabilistic and not deterministic (even with known state of nature). Finally goal uncertainty arises from DMs having to consider outcomes and the influence they have on the end goal. Intelligence collection can be seen as a way to resolve these uncertainties to reach end goals.

As part of this work, a matrix representation was used capture a DM's decision state [28]. Figure 2.2 shows an example decision state matrix where a_m are COAs, o_n are outcomes, ω_{ij}^k is a probabilistic measure, and $v_k(o_n)$ are the effective values of the outcomes. Effective values are defined as the rating of how much an outcome moves the situation towards a desired end goal. The values of ω are subjective probabilistic measures that relate COAs to outcomes. Using this representation allows a DM to accomplish their two main tasks of choosing the best COA and learning about the situation. To choose the best COA a DM tries to maximize the sum of the effective values of the outcomes. The DM can also use the matrix to learn more about the situation by reviewing the w_{ij} values. This allows the DM to see which COA they are most uncertain about (*i.e.,* those with low w_{ij} values).

Llinas [12] builds off Yovits' work to develop the conceptual idea of a mathematical programming based optimization problem to model the decision making process. Llinas states that when selecting a COA a DM is basically defining a task to be carried out. The next logical step requires determining what kind of resources can be used to feasibly perform the tasks. Finally a DM must select the best or optimal resource to perform the tasks. This leads to the idea of an optimization problem. The outputs of this optimization problem are the resources that should be employed to carry out the COA.

In summary, Yovits developed a generalized model for the decision making process and ways to represent the components involved with this process as a matrix. Llinas later established that it

Relative Values		$v_k(o_1$	$v_k(o_2)$	.	.	.	$v_k(o_j)$	.	.	.	$v_k(o_n)$
Outcomes		o_1	o_2	.	.	.	o_j	.	.	.	o_n
	a_1	w_{11}^k	w_{12}^k	.	.	.	w_{1j}^k	.	.	.	w_{1n}^k
	a_2	w_{21}^k	w_{22}^k	.	.	.	w_{2j}^k	.	.	.	w_{2n}^k
	.	.	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.	.	.
Courses of action	.	.	.	.	.	.	.	.	.	.	.
	a_i	w_{i1}^k	w_{i2}^k	.	.	.	w_{ij}^k	.	.	.	w_{in}^k
	.	.	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.	.	.
	a_m	w_{m1}^k	w_{m2}^k	.	.	.	w_{mj}^k	.	.	.	w_{mn}^k

Figure 2.2: Decision state matrix [27]

is possible to use a mathematical programming based optimization problem to help achieve mission success.

2.2 Analytical Processes

There is existing doctrine which define analytical approaches to the creation and selection of COAs in the military domain. Previous efforts have also created automated tools that generate plausible futures.

Joint Intelligence Preparation of the Operational Environment [16] (JIPOE) is a systematic (structured) analytical process employed by the joint intelligence organizations. The operational environment refers to the set of conditions, circumstances, and factors that can affect a decision maker. The JIPOE process aims to provide a holistic view of the operational environment by characterizing pertinent information with regards to air, land, maritime, space, and cyberspace domains. The breadth and diversity of the domains require a large amount of subject matter expertise [16]. The analytical process will usually involve experts from several different agencies and allies cooperating together. There are four steps in the JIPOE process:

1. Define the operational environment,

2. Describe the impact of the operational environment,

3. Evaluate the adversary

4. Determine the adversary COAs

JIPOE is cyclical in nature and similar to Yovits' model reflects how analysts must constantly learn and adapt.

The first step in the JPIOE process is to define the operational environment [16]. The analysts identify the operational area and the characteristics of the operational environment that are relevant to the mission. They must keep the intent of the commander in mind to accomplish this. The analysts must define the bounds of the areas of interest (AOI), both physical and non-physical. A trade-off must be considered by analysts to determine what level of detail is needed and the amount of time that is available to accomplish it. This step also involves the analyst figuring out the intelligence gaps, priorities and shortfalls. As evidenced there are a large number of factors even within this initial step. In step two of JPIOE the impact of the operational environment is described. This involves considering all of the potential factors that could impact operations. For example how will climate, weather, sociocultural, and other factors impact operations. Also in this step the analyst must understand the relationships in the operational environment from a systems perspective, how the elements are connected and what interactions they have.

In the third step of the JPIOE process the adversary must be evaluated [16]. This is a procedure where the analysts must identify capabilities, limitations, doctrine, patterns of operation, tactics and techniques of the adversary. This space is constrained by the factors identified in step two of the process which reduces the possibilities based on the operational environment. Still it can be seen that the considerations that an analyst must make are significant. An analyst must consider adversary capabilities and define COAs that they can use to interfere with Blue's (the friendly) mission. 2 In the fourth step the adversary COAs are determined [16]. The holistic view that has been built up through the previous steps is put to use and an understanding of the the adversary's intent and strategy is developed. The analysts identify what the adversary's goal and objectives are. The analyst must then consider and create the full set of adversary COAs. Once the set of COAs have been created the analyst goes on to prioritize (rank) the COAs in order of probability of adoption. Effectively predicting what the likely set of actions the adversary will take. Given the amount of time that was determined in the previous step the analysts flesh out as much detail for each COA as possible. Finally the analysts identify initial collection requirements. This is used to identify what areas and activities need to be observed to determine which COA the adversary has adopted, effectively determining friendly (Blue) COAs.

JIPOE provides a doctrinal approach to mission planning that revolves around establishment and selection of COAs. Intelligence collection provides the essential ingredient needed for success in both phases.

Intelligence Preparation of the Battlefield (IPB) is another analytical process for threat assessment, and understanding of the environment in a geographic area [3]. The main purpose of IPB is similar to that of JPIOE as both are designed to support analyst and commander's decision making [3]. In essence IPB is the description of the effects of the battlefield and determination of the threat's COA to determine a friendlies best COA.

The main functions that are performed during IPB are essentially the same as those in JPIOE except at a finer detail. They differ specifically in their focus, JPIOE is designed to help the commander at the overall mission level whereas IPB and its finer degree of detail supports component command operations. JPIOE and IPB can be used together however these two processes should not overlap [16]. IPB can be extremely detailed, for example an individual soldier can informally perform IPB when he considers the possible actions of an enemy soldier he is about to engage. JPIOE will usually be performed at a higher level.

2.3 Automated Tools

2.3.1 INFERD

INformation Fusion Engine for Real-time Decision-making (INFERD) is a stream based processing system to update track estimates in real time as sensor messages are fed in as input [22]. The tracks used in INFERD are semantic or contextual and not kinematic and can be viewed a grouping of correlated events [22]. The system's architecture was designed to function in different domains. Two sets of inputs are provided as inputs for INFERD: a priori models, and runtime sensor data (measurement). These inputs are used in an information flow consisting of:

1. Data Alignment
2. Connotation Elicitation
3. Data Association

4. Track Update and Reporting

First sensor data from diverse sources are written to a database which is then read by INFERD. The data then goes through Data Alignment, a preprocessing step to homogenize the data [22]. This is done through a wrapper which converts each type of sensor message into a common format used by INFERD. Next in Connotation Elicitation, the *Sensor Message* is used to create an *Elicited Message* which is simply a *Sensor Message* with an additional *Model Connotation Layer* [22]. This is additional information generated using the *a priori* models provided to add more meaning to the sensor data. This could be viewed as classifying messages based on their attributes into categories. In the following step, Data Association, an estimate is made to determine which track the measurement is a part of. In addition to this, how does the new measurement associate with the existing track. The cardinality of the set of feasible tracks and elements that are produced by the data association stage is used to decide which of three kinds of processing the Track Update module takes [22]:

1. If an Elicited Message is not associated to any track, a new track is created.

2. If it's associated with a single track, message is added to that track.

3. If associated to multiple tracks, a hyper track will be created and the possible predecessor tracks are linked.

In essence, INFERD is an automated system which produces estimates of adversary activities by correlating observations and using *a priori* knowledge.

2.3.2 FuSIA

Future Situation and Impact Awareness (FuSIA) [8] is a generalized threat assessment framework applied specifically to cyber security that is able to estimate plausible presents and futures in a defined environment. FuSIA is not a predictor of future events; plausible futures are simply generated and assigned a rating.

FuSIA takes input in the form of attack tracks. The futures are generated using an ontology that represents the relationships between objects and activities in the attack tracks. Three algorithms based on the assessment of capability, opportunity, and intent are used. FuSIA assesses these three aspects separately and then combines them to generate plausible futures. A plausibility score is assigned for each generated future. The plausibility score that FuSIA generates is not a probability [8]. Plausibility scores do not have to sum to one across all the possible generated futures and is only a rating based on the current available evidence.

JIPOE, FuSIA, and INFERD provide stepping stones for formalizing the intelligence collection process as a framework. They offer components that are needed to develop a DSS for intelligence collection.

2.4 Subjective Assessments and Hierarchal Modeling of Missions

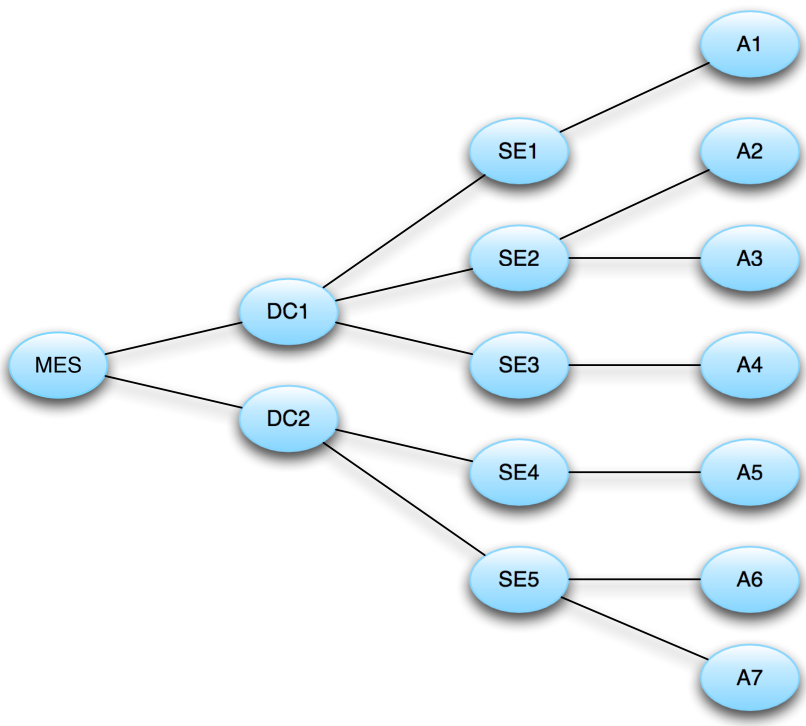


Figure 2.3: Effects Based Planning model relating Military End State (MES), Decisive Conditions (DC), Supporting Effects (SE), and Actions (A) [18]

Schubert *et al.* [9, 18, 19] formulated a subjective assessment method for mission planning, specifically in Effects Based Planning [21]. In EBP, a hierarchal plan is constructed relating Military End State (MES), Decisive Conditions (DC), Supporting Effects (SE), and Actions (A) [18] as

	Military End State	DC_1	DC_2	SE_1	SE_2	A_1	A_2	A_3	A_4
DC_1	5	0	6	0	0	0	0	0	0
DC_2	8	6	0	0	0	0	0	0	0
SE_1	0	5	2	0	0	0	0	0	-3
SE_2	0	5	8	0	0	0	0	0	0
A_1	0	0	0	3	3	0	4	-2	-3
A_2	0	0	0	3	-2	3	0	0	2
A_3	0	0	0	3	6	0	8	0	0
A_4	0	0	0	4	-2	-7	-2	0	0

Figure 2.4: Example cross impact matrix [19]

shown in Figure 2.3. The Military End State is the desired end goal of the plan. A Decisive Condition is a condition required for a transition between its phases. Supporting Effects are effects that are associated with one or many DCs. Finally, Actions are activities needed to fulfill one or many SEs. A CIM, as shown in Figure 2.4, is created in the initial planning process by subject matter experts (SMEs) as required by the type of operation. These SMEs assess how each element of the EBP process can affect each other, all the way up to the Military End State. In the CIM approach only the direct first-order influences for each object (DC, SE, A) are considered. Objects that are on the same level can influence each other bidirectionally while those on different levels are limited to unidirectional influence. The idea of influences also leads to the idea of multiplicative effects (sum of influences is greater than individual influence) which is not modeled in the CIM approach. The values in the CIM denote the influence ranging from -9 (negative influence) to 9 (positive influence) and are assigned by the aforementioned SMEs. Analysis of the CIM can lead to discovery of previously unseen synergies, alternatives, and conflicts [19].

A Collaborative Synchronization Management Tool (CSMT) was developed [9] which incorporates the CIM as part of a tool to support EBP. The tool takes input from an XML files created by SMEs and display various views of the data via a graphical user interface. This simplifies the analysis process by presenting the data within a graphical user interface (GUI)allowing easier manipulation and interaction. The views are displays of the results of processing on the data provided by the user.

2.5 Problem in Perspective

In the military domain missions are carefully planned out and executed following a process which revolves around the creation of both adversary and friendly COAs. Existing analytical processes such as JIPOE [16] and IPB [3] define precise procedures for analysts and commanders to carry out these tasks. Intelligence collection is vital to both of these activities and requires a prescribed process itself. Due to the complexity of intelligence collection, decision support is desirable [10, 14, 15]. However, to provide proper decision support an understanding of the intelligence collection process and its components is required.

Yovits' [27, 28] and Llinas' [12] showed that intelligence collection revolves around reducing uncertainty. This is done by organizing collection requirements and performing collection activities. Yovits provided a generalized model by which this could be done. The fundamental idea ind Yovits' model is that information comes from two main sources, the environment and analyst experience. This information provides DMs with the options available to them. Improved quality of information provides a DM with more options and an improved ability to make better decisions. Llinas' builds off Yovits' work and suggests that mathematical optimization could be used to find optimal sets of actions to be performed to gather intelligence.

Thus, to provide decision support information sources that conform to the categories of environmental information (collected by sensors) and experiential (analytical) information are needed. JIPOE and IPB are analytical processes employed by the military and can provide the analytical components needed. INFERD [22] and FuSIA [8] are automated tools developed previously that process sensor data and can provide the type of environmental data required.

A model was needed in order to evaluate the influences of the data from the information sources. Schubert's work [9, 18, 19] formalized a subjective assessment method for mission planning. This work used a hierarchal model and showed it could be used as an evaluation method for how low level factors could influence a mission. The use of a hierarchy required appropriate algebraic representation and aggregation functions were found to be appropriate for combining influences as they were propagated in the hierarchy [1].

This effort ties together these ideas with novel contributions to develop an intelligence collection framework.

Chapter 3

Intelligence Collection Framework

The overall structure of the intelligence collection requirements framework is shown in Figure 3.1. The framework is composed of two main components: a plausible futures tool, and an optimization formulation. The plausible futures tool is an application that allows for attribute based analysis of plausible futures. Candidate CRAs can be derived from such analysis. These CRAs are then used in an MIP optimization formulation to select the best CRA by trading off feasibility and effectiveness. The end result is an optimized set of CRAs that can be used to aid DMs in their decision making. However there are several challenges that first need to be overcome:

- How can collection requirements be determined from plausible futures?
- How can the resulting collection requirements be represented so that they can be optimized?
- Implementing the optimization problem.

Before these challenges can be tackled an understanding of the intuition behind the framework is required. This starts with understanding what exactly are plausible futures and CRAs.

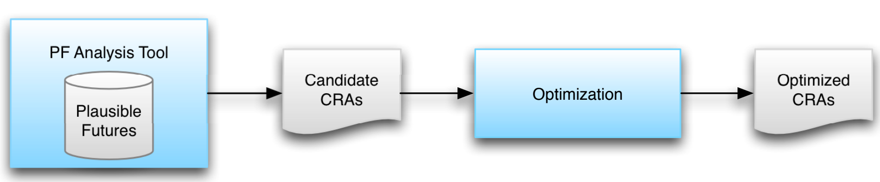


Figure 3.1: Intelligence collection framework flow

Plausible futures are likely adversary actions that can come from analytical processes such as JIPOE and IPB or automated tools such as INFERD and FuSIA. The difference between plausible futures and COAs is that plausible futures is a loosely defined term that can refer to individual actions or a generic set of actions whereas COAs strictly refer to a sequence of actions. Plausible futures can be represented as a set of characteristic attributes that are domain dependent. For this work the attributes used include:

1. ID
2. Name
3. Source
4. Target
5. Impact

A mission can be defined as a set of actions with associated assets that are responsible for their completion [12]. These assets each have a current state which measures the ability of these assets to complete a task. Consider i assets responsible for carrying out actions in a mission with the relationship between assets and actions being defined by analysts. A *current impact matrix* (S_c) can be defined which associates the i assets with a current state as shown.

$$S_c = \begin{array}{c} \\ a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{array} \begin{array}{c} state \\ \begin{pmatrix} 0.0 \\ 0.0 \\ 0.0 \\ 0.0 \\ 0.0 \end{pmatrix} \end{array}$$

Analysts can consider plausible futures each of which can impact the assets. The impact value is a subjective measure ranging from 0.0 (no effect) to 1.0 (maximum effect) conveying how a plausible future influences the health of assets. Consider i assets and j plausible futures, a *future impact matrix* (S_f) can be defined as an i by j matrix of future impact values. These plausible futures can be associated with different adversaries. Thus, the j columns can be associated any combination of adversaries.

$$
S_f = \begin{array}{c} \\ a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{array}
\begin{array}{c}
\begin{array}{ccccc} p_1 & p_2 & p_3 & p_4 & p_5 \end{array} \\
\begin{pmatrix}
0.1 & 0.0 & 0.0 & 0.3 & 0.15 \\
0.24 & 0.2 & 0.0 & 0.6 & 0.0 \\
0.33 & 0.0 & 0.0 & 0.73 & 0.0 \\
0.05 & 0.8 & 0.55 & 0.0 & 0.23 \\
0.9 & .67 & .34 & 0.8 & 0.0
\end{pmatrix}
\end{array}
$$

A Collection Requirement Action (CRA) is an action that can be taken mitigate impact from plausible futures. These actions are defined by analysts from domain knowledge. A CRA can be defined as a binary *CRA matrix* ($CRA_n(i,j)$) which associates plausible futures to assets that they affect. This allows for differentiation between candidate actions that can be taken as each action will correspond to plausible future-asset pairs. There can be overlaps in plausible future-asset pairs between CRAs. The monitoring state of plausible future-asset pairs across all selected CRAs is aggregated to form a single matrix ($\alpha(i,j)$), where $\alpha(i,j) = max(CRA_n(i,j)), \forall i, j, n$.

$$
CRA_n(i,j) = \begin{array}{c} \\ a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{array}
\begin{array}{c}
\begin{array}{ccccc} p_1 & p_2 & p_3 & p_4 & p_5 \end{array} \\
\begin{pmatrix}
0 & 0 & 0 & 0 & 0 \\
0 & 1 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array}
$$

During mission planning there may be a large number of candidate actions that can be taken. For each asset there are multiple plausible futures that could influence its health. An aggregation function is used to evaluate the aggregate impact across all plausible futures, since an asset can only have one state. If a CRA is taken (i.e. the action is selected and carried out as prescribed by analysts) the influence on assets from a plausible future is considered mitigated. In effect the impact from these CRAs are known and are accounted for in the health of the assets. The health of assets in the future is a function of the aggregate from all plausible futures that have been accounted for by CRAs as shown in Equation 3.1.

$$y(i) = AGG_j(S_f(i,j)\alpha(i,j)) + S_c(i)(1 - max_j(\alpha(i,j))), \forall i,j \tag{3.1}$$

In evaluating which CRA should be selected an analyst should consider which of the candidate CRAs (if performed) would avert the most impact. Fundamentally the optimal CRA is the one which can avert the most impact.

The following sections detail the inner workings of overall framework.

3.1 Determining CRAs from Plausible Futures

The overall flow of the framework begins with finding the differentiating attributes using the plausible futures analysis tool. This process can be performed analytically by analysts without the aid of any tool. However, a support tool is necessitated due to the possibly overwhelming number of plausible futures. The purpose of the decision support tool is to provide a facility for viewing large numbers of plausible futures efficiently and simplify the analyst's task of identifying differentiating attributes to enable the creation of candidate CRAs. User interaction and insight is heavily influenced by the GUI components of the tool, careful consideration was made to use appropriate components and avoid common interface errors [4, 11].

In implementation, plausible futures are stored in a MySQL database. Table 3.1 shows an example set of plausible futures and how they are stored as rows of attributes in a relational database. Figure 3.2 shows an example MySQL query for retrieving plausible futures. In essence the data is gathered based on defined relationships and attributes. The plausible futures were organized using the following hierarchy:

1. Activities

2. Plausible futures

Table 3.1: Example plausible futures

Activity	**Future**	**Event**	**Source**	**Target**	**Impact**	**Plausibility**	**Reliability**
A1	F1	1	Database Services on SAA server	Network Services on JADOCS	0.25	0.33	0.3
A1	F2	2	Unix on Super Client	Microsoft Windows on AOC weapons System Server	0.62	0.52	0.49
A2	F1	1	Network Services on IWS	Microsoft Windows on C2D0 Tac C2 Dm Expert	0.21	0.49	0.74
A3	F1	1	Database Services on Super Client	Network Services on Exercise Control	0.06	0.37	0.8
A3	F2	2	Microsoft Windows on IWS	Unix on Super Client	0.14	0.73	0.74
A3	F2	2	Network Services on Domain Server	Microsoft Windows on C2PC	0.08	0.73	0.6
A4	F1	1	UNIX on Oracle Server	Microsoft Windows on AOC Weapons System Server	0.61	0.46	0.5
A5	F1	1	Network Services on Team Training Bay	Microsoft Windows on AOC Weapons System Server	0.04	0.53	0.69
A6	F1	1	Microsoft Windows on Team Training Bay	Unknown	0.68	0.40	0.34
A7	F1	1	UNIX on SAA Server	Microsoft Windows on AOC Weapons System Server	0.81	0.91	0.75
A7	F2	1	Network Services on Intelligence Information Ops Training Bay	Network Services on JADOCS	0.39	0.91	0.06
A7	F2	2	Microsoft Windows on AOC Weapons System Server	UNIX on Sybase Server	0.7	0.91	0.7

```sql
SELECT fact.id,
       fact.activityid,
       a1.name         AS activityname,
       fact.futureid,
       fact.eventid,
       e1.name         AS entityname,
       e2.name         AS targetentityname,
       e2.id,
       e2.entitytypeid AS targetentitytypeid,
       t1.TYPE         AS typename,
       fact.impact,
       fact.reliability,
       fact.fused
FROM   entities e1,
       entities e2,
       entitytypes t1,
       activities a1,
       (SELECT f.*
        FROM   futures f
               INNER JOIN (SELECT activityid,
                                  Max(eventid) AS maxeventid
                           FROM   futures
                           GROUP  BY activityid) groupedactid
                 ON f.activityid = groupedactid.activityid
                    AND f.eventid = groupedactid.maxeventid) AS fact
WHERE  e1.id = fact.entityid
       AND e2.id = fact.targetentityid
       AND a1.id = fact.activityid
       AND t1.id = e2.entitytypeid
ORDER  BY fact.activityid,
          fact.futureid,
          Field(typename, "Mission", "Submission", "Step", "Host",
          "HostCluster", "Application", "Service", "Version"),
          e1.name ASC;
```

Figure 3.2: Example of gathering plausible futures from a database

3. Events

Activities are groupings of related plausible futures, and events are discrete actions within plausible futures.

One of the main design decisions was how to display plausible futures efficiently. A tree table was the final design choice since the plausible futures were hierarchal in nature. Each of the plausible futures are associated with an activity which is the likely event that could occur. The individual plausible futures for each activity are defined for individual targets along with an estimated impact value. Figure 3.3 shows the main window of the tool. Since the plausible futures are stored as rows in the database it made sense to translate this to the graphical interface as a tree table as well. The ability to collapse and expand particular activities allows for analysts to focus either on individual activities or large collection of them.

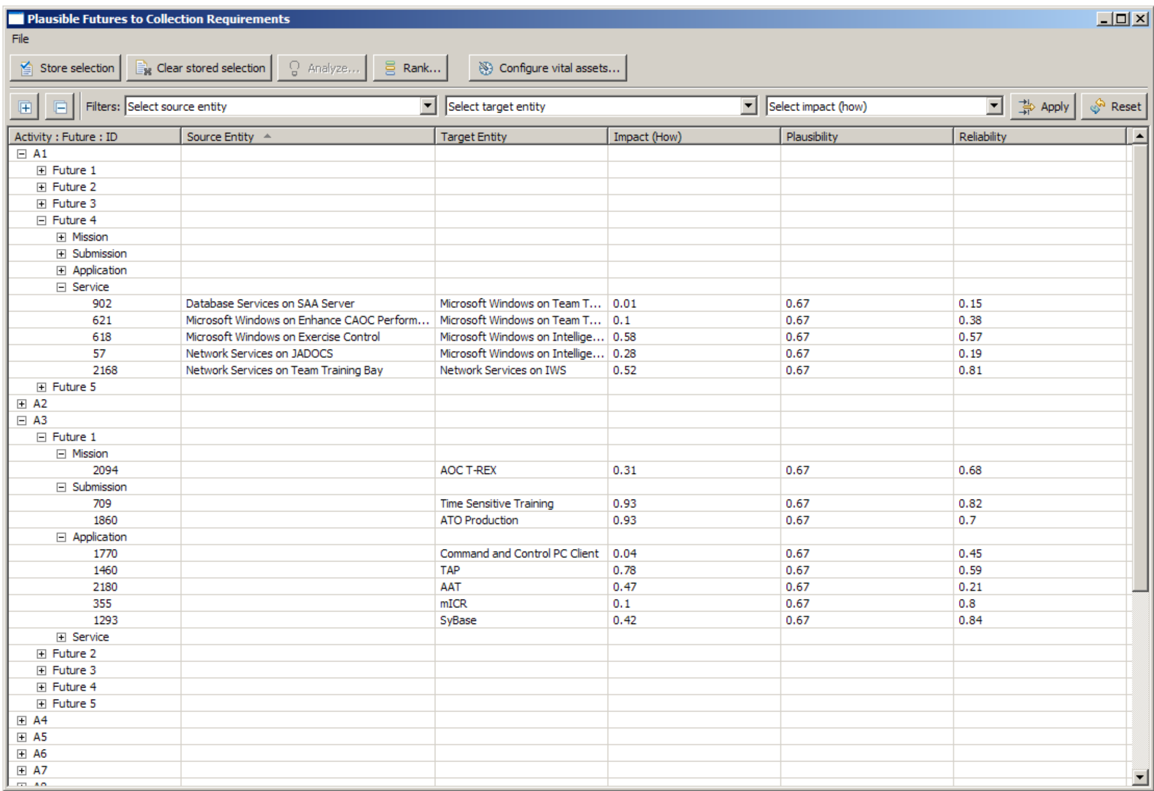


Figure 3.3: Plausible futures conversion tool

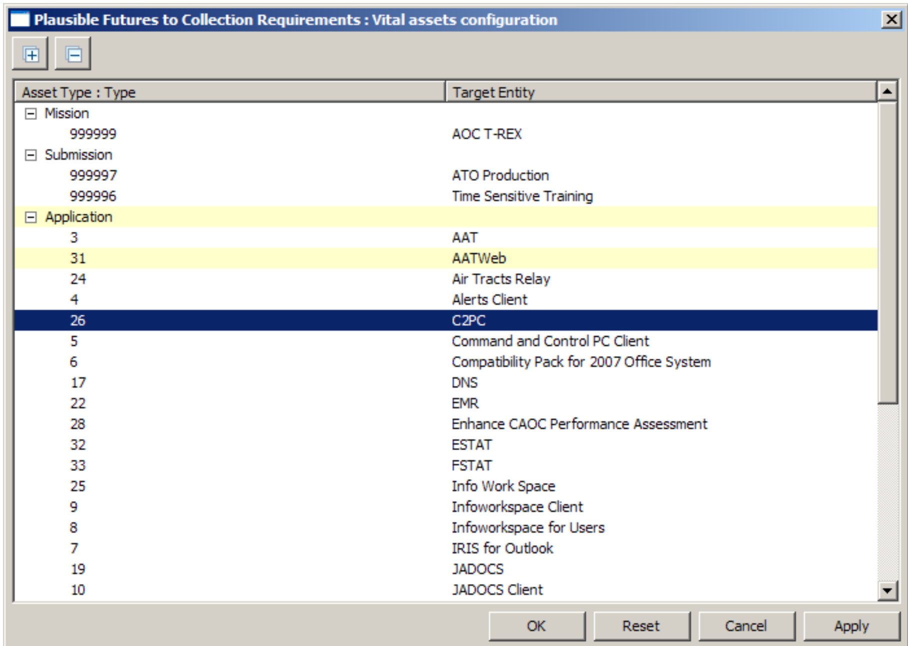
The key features of the decision support tool are: (1) identification of critical futures based on attributes, (2) allows for analysis of plausible futures based on attributes, and (3) ability to rank of plausible futures by criteria.

3.1.1 Identification of critical plausible futures

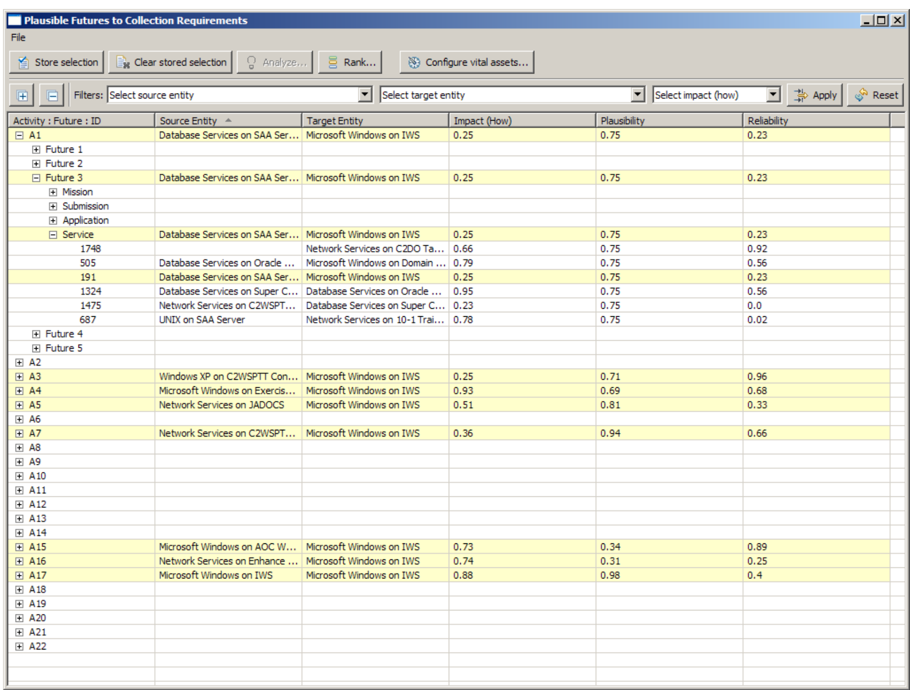
Analysts have insight into assets/entities in a mission which are critical to mission success. Critical plausible futures are those which have attributes that involve these type of entities. Having these critical futures emphasized draws an analysts attention and helps them to identify plausible futures. Thus, the tool allows analysts to configure which assets they consider critical and subsequently highlights them in the interface.

The analyst can configure what attribute (specifically target) they think are critical to the success of the operation as seen in Figure 3.4a. This results in the plausible futures which involve this attribute being highlighted in the GUI. This reduces the effort the analyst needs to spend identifying plausible futures of interest as the number of plausible futures increases. They can spend a minimum amount of time up front identifying the attributes that they consider vital and allow the tool to identify the critical plausible futures for them. In implementation, this is accomplished by keeping a list of vital attributes that are configured by the user in a singleton object. The singleton guarantees that there is only ever one instance of the list. As the display of the plausible futures occurs each attribute is checked against the list to determine whether it is critical plausible future or not. Figure 3.4b shows the vital attributes configuration reflected in the main window.

Since the display is tree based, data is also rolled up so that at the highest level the analyst can see vital assets with maximum impact in the display as seen in Figure 3.4b. This functionality is implemented using the code seen in Figure 3.5. This code recursively traverses the complete hierarchal tree of all plausible futures in the display and checks to see if each node is one which involves a critical entity. A *RowAggregator* object is used to track the maximum values at each level in the hierarchy. This object stores the current maximum impact value and as the traversal occurs each node is checked and the maximum value is updated if a new max is found. This results in the hierarchal rollup which shows the analyst at each level the maximum impact to a critical asset (Figure 3.4b). The interface draws the analysts attention to certain plausible futures by both highlighting plausible futures and displaying maximum impact values.



(a) Configuration



(b) Display

Figure 3.4: Configuring and display of important attributes

```java
public static RowAggregator recursivelyUpdateData(TreeItem startingItem) {
    // all items in the tree must have children item the length might
    // just be zero, so this is a safety check to make sure the selection
    // is part of the tree and not some random item
    // default to false to indicate the color should not be changed from
    // the default background
    RowAggregator aggregator = new RowAggregator();
    if (startingItem.getItems() != null) {

        Object itemData = startingItem.getData();
        if (itemData != null && itemData instanceof EventRow) {
            Long curID = ((EventRow) itemData).getTargetEntityID();
            if (VitalAssetsManager.getInstance().isVitalAsset(curID)) {
                // if this node is a vital asset return true
                aggregator.set((EventRow) itemData);
            }
        }

        // recurse over the children, if no children the loop stops
        TreeItem[] children = startingItem.getItems();
        for (int i = 0; i < children.length; i++) {
            TreeItem child = children[i];
            aggregator.combine(recursivelyUpdateData(child));
        }

        // if there is a max then set the values for it at this point
        if (!(itemData instanceof EventRow)) {
            if (aggregator.getAggregate().size() == 1) {
                EventRow max = aggregator.getAggregate().get(0);
                startingItem.setText(1, max.getSourceEntityName());
                startingItem.setText(2, max.getTargetEntityName());
                startingItem.setText(3, Double.toString(max.getImpact()));
                startingItem.setText(4, Double.toString(max
                        .getPlausibility()));
                startingItem.setText(5, Double.toString(max
                        .getReliabililty()));
            } else if (aggregator.getAggregate().size() > 1) {
                // if there is no max we use a utility method to create some
                // text
                // to reflect this that does not have a max
                EventRow parsedRow = parseMultiAggregate(aggregator
                        .getAggregate());
                startingItem.setText(1, parsedRow.getSourceEntityName());
                startingItem.setText(2, parsedRow.getTargetEntityName());
            }
        }
    }

    return (aggregator);
}
```

Figure 3.5: Determining which attributes affect plausible futures most

3.1.2 Analysis of plausible futures using attributes

Using the plausible futures tool, the user can also perform analysis for a select set of plausible futures that they want to consider from the larger overall set. This allows for observations such as overlaps in attributes between plausible futures. A possible benefit from this is that a single action might suffice to mitigate the impact of multiple plausible futures if they share attributes.

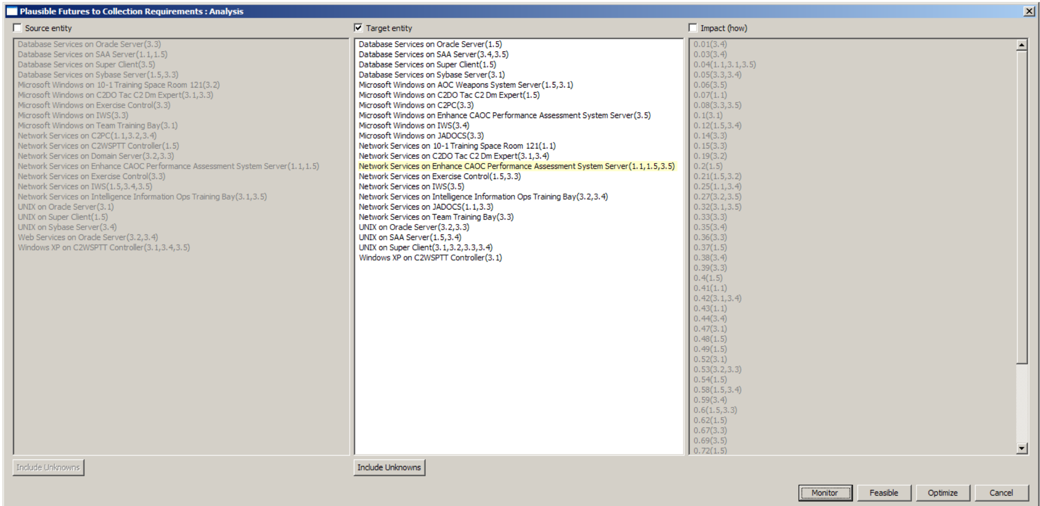
Figure 3.6a displays the attribute selection screen that is displayed when analysis is performed on a set of plausible futures. This panel shows all of the attributes related to the selected plausible futures as well as the activities they belong to. When an analyst looks at the panel they can see which attributes are shared between plausible futures by the labels beside each attribute. For example, it can be seen that the target entity attribute *'Microsoft Windows on AOC Weapons System Server'* is involved in two plausible futures (1.5, 3.1). The highlight on *'Network Services on Enhance CAOC Performance Assessment System Server'* denotes that this target entity has previously been marked as critical by the analyst which helps to draw attention.

The analyst selects attributes they are interested in and can monitor. This brings up a new dialog as seen in Figure 3.6b, which displays the plausible futures that involve the selected attributes. Rows highlighted in blue are plausible futures that were part of the initial set selected by the analyst. Gray highlighted rows are other plausible futures that involve the selected attributes but were not part of the initial set selected by the analysts. The results pane provides a complete set of plausible futures that are effectively covered by CRAs performed on the selected attributes.

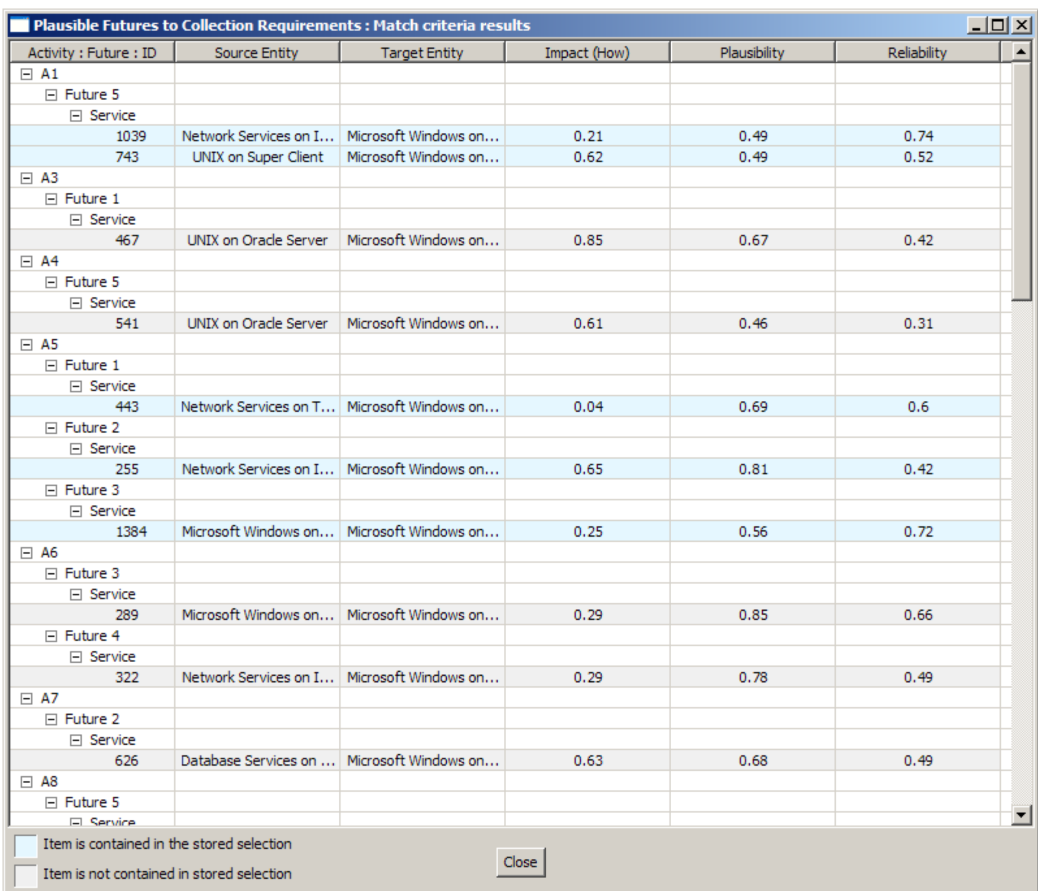
3.1.3 Ranking plausible futures

A ranking feature was also implemented so that analysts could view the top *N* ranked plausible futures based on a specified criteria. The ranking of plausible futures provides another quick way for analysts to identify important plausible futures. The criteria for the ranking is based on either subjective assessments or algorithmically. The ranking panel also displays a column which identifies other plausible futures (that are also ranked or not ranked) that share common attributes with the ranked plausible future. This allows for analysts to easily identify important CRAs that could cover multiple plausible futures resulting in more efficient CRAs.

Using the plausible futures tool an analyst can intelligently craft candidate CRAs such as shown in Figure 3.8. CRAs are represented as matrices of binary values where one denotes a plausible

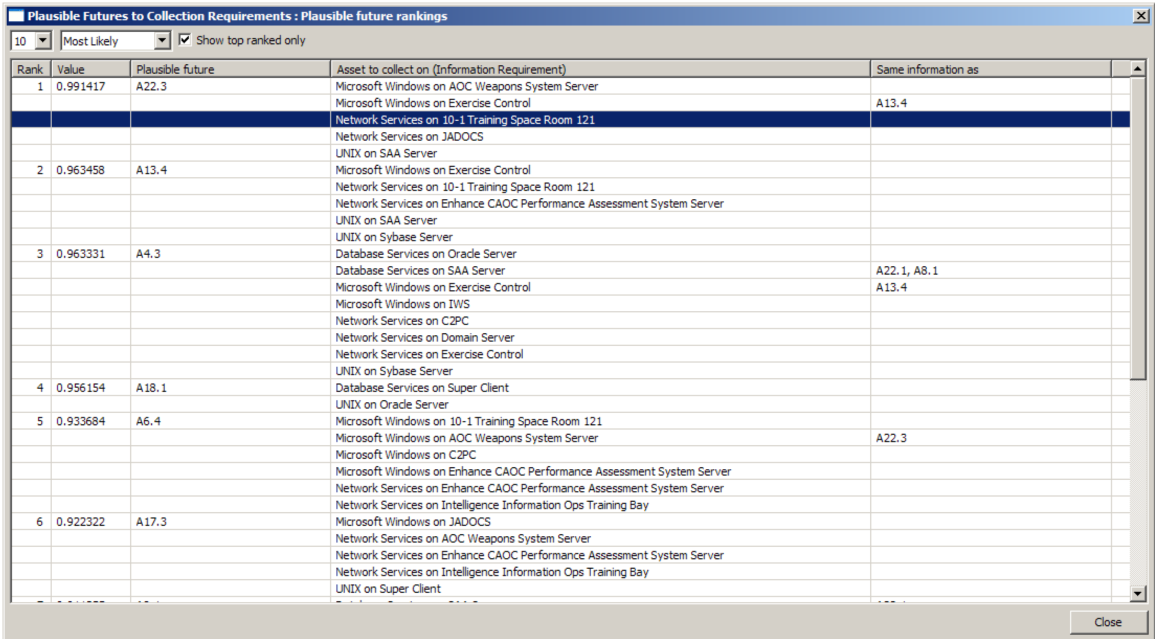


(a) Selection of attributes to compare



(b) Results of analysis

Figure 3.6: Analysis of sets of plausible futures



Plausible Futures to Collection Requirements : Plausible future rankings

10 | Most Likely | Show top ranked only

Rank	Value	Plausible future	Asset to collect on (Information Requirement)	Same information as
1	0.991417	A22.3	Microsoft Windows on AOC Weapons System Server	
			Microsoft Windows on Exercise Control	A13.4
			Network Services on 10-1 Training Space Room 121	
			Network Services on JADOCS	
			UNIX on SAA Server	
2	0.963458	A13.4	Microsoft Windows on Exercise Control	
			Network Services on 10-1 Training Space Room 121	
			Network Services on Enhance CAOC Performance Assessment System Server	
			UNIX on SAA Server	
			UNIX on Sybase Server	
3	0.963331	A4.3	Database Services on Oracle Server	
			Database Services on SAA Server	A22.1, A8.1
			Microsoft Windows on Exercise Control	A13.4
			Microsoft Windows on IWS	
			Network Services on C2PC	
			Network Services on Domain Server	
			Network Services on Exercise Control	
			UNIX on Sybase Server	
4	0.956154	A18.1	Database Services on Super Client	
			UNIX on Oracle Server	
5	0.933684	A6.4	Microsoft Windows on 10-1 Training Space Room 121	
			Microsoft Windows on AOC Weapons System Server	A22.3
			Microsoft Windows on C2PC	
			Microsoft Windows on Enhance CAOC Performance Assessment System Server	
			Network Services on Enhance CAOC Performance Assessment System Server	
			Network Services on Intelligence Information Ops Training Bay	
6	0.922322	A17.3	Microsoft Windows on JADOCS	
			Network Services on AOC Weapons System Server	
			Network Services on Enhance CAOC Performance Assessment System Server	
			Network Services on Intelligence Information Ops Training Bay	
			UNIX on Super Client	

Close

Figure 3.7: Ranking of plausible futures based on attributes

future influences an asset, which implicitly means that an action can be taken to mitigate the impact from the plausible future.

3.2 Evaluating Mission Impact Using CRA Matrices

As previously state, a *current impact matrix* and a *future impact matrix* is used to represent the state of assets. The current impact matrix is the current state of the assets, and future impact matrix is the possible state of the assets if plausible futures occur. Actions (candidate actions) can be

$$\begin{array}{c c} & \begin{array}{ccccc} p_1 & p_2 & p_3 & p_4 & p_5 \end{array} \\ \begin{array}{c} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{array} & \begin{pmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 \end{pmatrix} \end{array}$$

Figure 3.8: Example CRA matrix created after use of the decision support tool which defines how plausible futures (p) influence assets (a)

$$\begin{array}{c} \\ a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{array}\begin{array}{c} state \\ \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \end{array}$$

(a) Current impact matrix

$$\begin{array}{c} \\ a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{array}\begin{array}{c} \begin{array}{ccccc} p_1 & p_2 & p_3 & p_4 & p_5 \end{array} \\ \begin{pmatrix} 0.2 & 0.0 & 0.8 & 0.0 & 0.64 \\ 0.5 & 0.0 & 0.0 & 0.89 & 0.55 \\ 0.0 & 0.0 & 0.5 & 0.26 & 0.78 \\ 0.0 & 0.98 & 0.0 & 0.8 & 0.0 \\ 0.8 & 0.34 & 0.0 & 0.2 & 0.4 \end{pmatrix} \end{array}$$

(b) Future impact matrix

Figure 3.9: Representing current and future asset states

performed to mitigate the impact from plausible futures, this mitigated impact can be viewed as the benefit from performing the action. Optimization occurs on the premise of maximizing the mitigated impact to the mission, not the difference in the states of the assets. The candidate actions are represented algebraically as CRA matrices as shown in 3.8, which uses a binary value to show whether a plausible future influences an asset or not.

So in essence, if a CRA is taken (carried out) than the impact from the plausible future is accounted for and effectively replaces the current impact value in our consideration.

Equation (3.1) selects between the current impact value and a plausible future impact value (Figure 3.9) based on a decision variable of whether or not a CRA was taken and therefore the impact was mitigated. A mission model is used to propagate the low level impacts from this evaluation to the overall mission.

The concept of a mission model has been seen in previous works such as Schubert *et al.* work on CIMs and effect-based planning [9, 18, 19]. The framework defines a mission hierarchy (model) based on an analyst's expertise as shown in Figure 3.10. The analyst creates the hierarchy *a priori* to model the relationships and interactions from assets up to the overall mission. The mission hierarchy defined by the framework does not consider influences by elements at the same level of the hierarchy. The number of possible combinations of influences as well as their multiplicative effects are difficult to take into account and thus not within the scope of this work.

The hierarchy is asset based, the assumption is that within any given mission ultimately the assets allow for the mission to be accomplished by carrying out tasks [12]. The definition of an asset is purposely loose for generalization purposes. An asset is any entity of value to the mission; this could be a soldier, an unmanned aerial vehicle, a server, a service on a server, *etc.* Figure 3.9

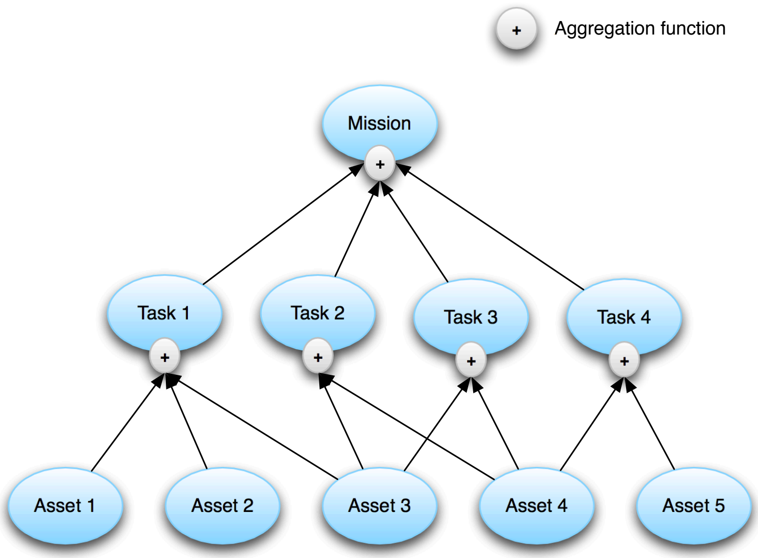


Figure 3.10: Mission hierarchy tree.

shows an the impact matrices which forms the lowest level of input for the mission hierarchy. Where the impact values for each asset is a value from [0.0, 1.0] with 1.0 being the maximum impact and 0.0 being no impact. These values are also absolute and not a delta value and can be viewed as the state of the asset.

3.3 Aggregation Functions

Forward propagation of impacts occurs via aggregation functions such as a weighted average or Yager's Ordered Weighted Average [24] [26] [25]. The use of a hierarchy necessitates the use of functions that can produce representative values from a large number of inputs, aggregation functions provide this utility. The different levels in a hierarchy can be viewed as progressively becoming more complex as the number of entities each level encapsulates increases. Aggregation functions facilitate this representation efficiently and selection of appropriate aggregation functions to model relationships in a mission is a significant task.

Aggregation functions (operators) are simply functions with special properties [1]:

Definition 3.3.1. An aggregation function is a function of n $>$ 1 arguments that maps the (n-dimensional) unit cube onto the unit interval $f : [0, 1]^n \rightarrow [0, 1]$, with the properties

(i) $f(\underbrace{0, 0, \dots, 0}_{\text{n times}}) = 0$ and $f(\underbrace{1, 1, \dots, 1}_{\text{n times}}) = 1$

(ii) $x \leq y$ implies $f(x) \leq f(y)\ \forall x, y \in [0, 1]^n$

3.3.1 Ordered Weighted Average

An aggregation function of particular interest are Ordered Weighted Averages (OWA) [24–26] as OWA can be used to represent different logical relationships. OWA is exactly the same as a simple weighted average however the $\searrow$ subscript indicates that inputs are first sorted in descending order. This allows OWA to represent different relationships depending on how the weighting vector is specified. This flexibility is desirable in a model as it simplifies implementation and allows analysts to create different relationships efficiently.

Definition - Ordered Weighted Average. For a given weighting vector $\mathbf{w}, w_i \geq 0, \sum w_i = 1$, the OWA function $[1, 24]$ is given by

- $OWA_w(\mathbf{x}) = \sum_{i=1}^{n} w_i x_{(i)} = \langle \mathbf{w}, \mathbf{x}_\searrow \rangle$

$$w_{max} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$
$$\mathbf{x}_\searrow = \begin{bmatrix} 5 & 4 & 3 & 2 & 1 \end{bmatrix}$$

$$w_{top2} = \begin{bmatrix} 0.5 & 0.5 & 0 & 0 & 0 \end{bmatrix}$$
$$\mathbf{x}_\searrow = \begin{bmatrix} 5 & 4 & 3 & 2 & 1 \end{bmatrix}$$

Since OWA can be used to formulate different relationships analysts can change the weights of the function as parameters rather than using explicit logical functions.

3.4 Optimization Formulation

The final step in the framework is the ability to optimize the set of CRAs to select the best based on feasibility, effectiveness, and maximizing mission success.

Equation 3.3 defines a cost constraint which limits the amount of feasible CRAs that can be taken based on resources available. Equation 3.4 is a timing constraint that limits which CRAs can be taken based on turnaround time.

Variables
$X(n) = \begin{cases} 1, & \text{If CRA } n \text{ is selected} \\ 0, & \text{o.w.} \end{cases}$
$A_{max}(j) =$ whether plausible future j has maximum impact
$T_{max}(i) =$ whether asset i has maximum impact
$M_{max}(l) =$ whether task l has maximum impact
$\alpha(i,j) = \begin{cases} 1, & \text{asset } i \text{ for plausible future } j \text{ is monitored} \\ 0, & \text{o.w.} \end{cases}$
$y(i) =$ aggregated impact on asset i
$D_{task}(l) =$ aggregated impact on task l
$D_m =$ aggregated impact on mission

Parameters
$c_n =$ cost of executing X_n
$t_n =$ time alotted for X_n to complete
$T =$ max turnaround time
$B =$ total budget
$A_n(i,j) =$ monitored stated for asset i, plausible future j
$S_c(i) =$ current impact for asset i
$S_f(i,j) =$ future impact for asset i, plausible future j

Objective:

$$\text{Maximize } D_m \tag{3.2}$$

Subject to:

$$\sum_{i=1}^{n} X_n \cdot c_i \leq B \tag{3.3}$$

$$X_n \cdot t_n \leq T, \forall n \tag{3.4}$$

$$\alpha(i,j) \geq X_n \cdot CRA_n(i,j), \forall i,j,n \tag{3.5}$$

$$\alpha(i,j) \leq \sum_{i=1}^{n} X_n \cdot CRA_n(i,j), \forall i,j \tag{3.6}$$

$$\begin{aligned} y(i) = {} & max_j(S_f(i,j)\alpha(i,j)) \\ & + S_c(i)(1 - max_j(\alpha(i,j))), \forall i,j \end{aligned} \tag{3.7}$$

$$\sum_{k=1}^{i} T_{max} = i - 1 \tag{3.8}$$

$$y(i) \leq D_{task}(l), \forall i,l \tag{3.9}$$

$$D_{task}(l) \leq C \cdot T_{max}(l,i) + y(i), \forall i,l \tag{3.10}$$

$$\sum_{k=1}^{l} M_{max} = l - 1 \tag{3.11}$$

$$D_{task}(l) \leq D_m, \forall l,m \tag{3.12}$$

$$D_m \leq C \cdot M_{max}(l) + D_{task}(l), \forall l,m \tag{3.13}$$

The optimization formulation incorporates all of the ideas previously mentioned.

3.4.1 Logical Constraints

Logical constraints need to be algebraically formulated to be used in MIP solvers such as Gurobi. For example, consider $D_asset(i) = max(y(i,j))$ which can be written as shown below:

$$\sum_{k=1}^{j} A_{max} = j - 1 \tag{3.14}$$

$$y(i,j) \leq D_{asset}(i) \tag{3.15}$$

$$D_{asset}(i) \leq C \cdot A_{max}(i,j) + y(i,j) \tag{3.16}$$

Constraints 3.14, 3.15, 3.16 enforce a max relationship as the aggregation function for asset damage. The following example illustrates the logic which create the max relationship.

If A_{max} is a matrix of binary decision variables (*i.e.,* values are bounded from 0 to 1).

$$A = \begin{bmatrix} 0 & 1 & 1 & 1 & 1 \end{bmatrix}$$

$$y(i,j) = \begin{bmatrix} 4 & 3 & 5 & 1 & 2 \end{bmatrix}$$

If A has a value of zero corresponding with four in $y(i,j)$ then 3.15 is violated since 3.16 forces D_{asset} to be four. In fact for all values except five this constraint is violated. When A has a value of zero corresponding with five, D_{asset} is bounded on top to be 5 and it is indeed greater than or equal to all other elements which satisfies constraint 3.15. The constant C is just a sufficiently large constant that should be much greater than all values in $y(i,j)$. Since the values in the impact matrix fall between zero and one, a value of one can be used as the constant. Due to computation concerns the smallest value constant possible should always be used based on analysis of the inputs.

A logical mininum constraint can be constructed in a similar fashion by putting the binary variable (in 3.16) to the lower bound and changing the addition to subtraction. So that the constraint forces the minimum value to fixed only when.

$$\sum_{k=1}^{j} A_{min} = j - 1 \tag{3.17}$$

$$D_{asset}(i) \leq y(i,j) \tag{3.18}$$

$$y(i,j) - 1 \cdot A_{min}(i,j) \leq D_{asset}(i) \tag{3.19}$$

```
// Constraint that ensures only one element in aMax
// will be zero and all others are 1
//
// : sum(aMax_j) == n - 1
for (int i = 0; i < numAssets; i++) {
        GRBLinExpr exprLHS = new GRBLinExpr();
        for (int j = 0; j < numFutures; j++) {
                exprLHS.addTerm(1.0, aMax[i][j]);
        }
        model.addConstr(exprLHS, GRB.EQUAL, numFutures - 1, "");
}

// Ensures that the assetImpact is bounded on the bottom
for (int i = 0; i < numAssets; i++) {
        GRBLinExpr exprRHS = new GRBLinExpr();
        exprRHS.addTerm(1.0, assetImpact[i]);

        for (int j = 0; j < numFutures; j++) {
                GRBLinExpr exprLHS = new GRBLinExpr();
                exprLHS.addTerm(1.0, y[i][j]);
                model.addConstr(exprLHS, GRB.LESS_EQUAL, exprRHS, "");
        }

}

// Ensures that the assetImpact is bounded from the top
for (int i = 0; i < numAssets; i++) {
        GRBLinExpr exprLHS = new GRBLinExpr();
        exprLHS.addTerm(1.0, assetImpact[i]);

        for (int j = 0; j < numFutures; j++) {
                GRBLinExpr exprRHS = new GRBLinExpr();
                exprRHS.addTerm(1.0, y[i][j]);
                exprRHS.addTerm(1000, aMax[i][j]);
                model.addConstr(exprLHS, GRB.LESS_EQUAL, exprRHS, "");
        }
}
```

Figure 3.11: Gurobi implementation of logical max constraint

Figure 3.11 shows how logical constraints (in this case max) can be written in Gurobi. The figure shows that writing constraints in a modeling package requires the use of for loops to replicate the $\forall(i, j)$ condition. The model is represented as a single object and all variables are for defined for this model. The model is solved via a *model.optimize()* method call.

3.5 Implementation of Optimization Problem

After the set of CRAs have been determined and the mission hierarchy used to evaluate how these CRAs impact the overall mission. The next logical step is to optimize and select a subset of the CRAs based on the tradeoff of feasibility and cost-effectiveness. This problem was formulated as a mixed integer programming problem based on the requirements of the inputs: the selection of CRAs is binary and the evaluation of mission impact values is continuous.

There are many different optimization packages available for MIP problems. However, in implementation the most important step is to start at the algebraic formulation to determine the requirements needed from the package chosen. From Chapter 3.4 the requirements are that the package can solve MIP type problems, and be able to handle a large number of constraints. The most well known commercial solvers were considered: Lindo, CPLEX, Microsoft Solver Foundation. The problem with selecting these packages are that they are expensive. Gurobi is a recently released optimization package that is available commercially but also offers free academic licenses. These packages each have different interfaces for creating the model. Lindo uses a modeling language called LINGO, and CPLEX can be used with OPL. The modeling languages closely reflect algebraic formulations and simplify the implementation of algebraic expressions. Alternatively, all packages have s which allows for standard programming with languages such as Java, C++, C#, and Python. Gurobi was selected as the package of choice due to easy access. Microsoft Excel also includes a Solver which was used a simple alternative used for prototyping and smaller problems.

Algorithm 1 Gurobi optimization problem setup

```
create parameter matrices
model.create()
create and add decision variables to model
define constraints
model.optimize()
```

Figure 1 presents the basic flow for setting up an optimization problem in Gurobi. These implementation details complete the needed steps to develop the intelligence collection framework.

Chapter 4

Case Study

A case study was performed to evaluate the frame work. The case study emulated the processes an analyst would perform using the framework to demonstrate its capabilities.

4.1 Scenario: Hostage Rescue

A hostage rescue scenario was considered involving a special forces team sent to rescue hostages being held by a terrorist group. A helicopter is to be used for transporting the team and extracting the team and rescued hostages.

Mission
A special forces team is sent to rescue a group of hostages being held by terrorists. The operation uses a helicopter for transport.

In planning the mission an analyst can anticipate the the following plausible futures.

Plausible Futures
The terrorists could acquire weapons to use against the special forces team (p_1)
Terrorist scouts perform surveillance on friendly forces (p_2)
Terrorist combatants utilize their intelligence on friendlies to lay an ambush (p_3)
The terrorists decide to relocate the hostages (p_4)
The terrorists decide execute the hostages (p_5)

From the friendly analyst's perspective the following assets are of interest to the overall mission (*i.e.,* these assets are required to achieve mission success).

ID	Plausible Future	Source	Target	Impact
1	Acquire weapons	Terrorists leadership	Special forces	0.9
2	Acquire weapons	Terrorists leadership	Hostages	0.6
3	Acquire weapons	Terrorists leadership	Helicopter	0.8
4	Acquire weapons	Terrorists leadership	Landing site	0.55
5	Acquire weapons	Terrorists leadership	Friendly base	0.6
6	Surveillance	Terrorist scouts	Special forces	0.7
7	Surveillance	Terrorists scouts	Hostages	0.2
8	Surveillance	Terrorists scouts	Helicopter	0.55
9	Surveillance	Terrorists scouts	Landing site	0.75
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.

(a) Plausible futures

ID	Attribute name
1	Special forces
2	Hostages
3	Helicopter
4	Landing site
5	Friendly base

(b) Assets

Figure 4.1: Attribute-based analysis of plausible futures

Assets
Special forces team (a_1)
Hostages (a_2)
Helicopter (a_3)
Landing site for helicopter (a_4)
Friendly base (a_5)

Finally, a set of tasks need to be accomplished to successfully complete the hostage rescue.

Tasks
Land safely in drop off zone (t_1)
Secure terrorist base (t_2)
Capture terrorists (t_3)
Rescue hostages (t_4)
Return to base (t_5)

An analyst can arrive at estimated impacts of plausible futures to assets. These estimates can be derived from an analyst's experience, intuition, and with the aid of automated tools.

Figure 4.2 shows the estimated future impacts from plausible futures. An analyst can arrive at these estimates from experience, intuition, and with the aid of automated tools.

$$
\begin{array}{l}
 \\
\text{Special forces} \\
\text{Hostages} \\
\text{Helicopter} \\
\text{Landing site} \\
\text{Friendly base}
\end{array}
\begin{array}{c}
\begin{array}{ccccc}
\text{Acquire weapons} & \text{Surveillance} & \text{Ambush} & \text{Relocate} & \text{Execute}
\end{array} \\
\begin{pmatrix}
0.9 & 0.7 & 0.85 & 0.6 & 0.3 \\
0.6 & 0.2 & 0.5 & 0.7 & 1 \\
0.8 & 0.55 & 0.8 & 0.1 & 0.05 \\
0.55 & 0.75 & 0.9 & 0.15 & 0.05 \\
0.6 & 0.5 & 0.2 & 0.3 & 0.05
\end{pmatrix}
\end{array}
$$

Figure 4.2: Future impact matrix

$$
\begin{array}{c|c}
 & p_1 \; p_2 \; p_3 \; p_4 \; p_5 \\
\begin{array}{c} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{array} &
\begin{pmatrix}
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 1 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array}
$$

(a)

$$
\begin{array}{c|c}
 & p_1 \; p_2 \; p_3 \; p_4 \; p_5 \\
\begin{array}{c} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{array} &
\begin{pmatrix}
1 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array}
$$

(b)

$$
\begin{array}{c|c}
 & p_1 \; p_2 \; p_3 \; p_4 \; p_5 \\
\begin{array}{c} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{array} &
\begin{pmatrix}
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0
\end{pmatrix}
\end{array}
$$

(c)

$$
\begin{array}{c|c}
 & p_1 \; p_2 \; p_3 \; p_4 \; p_5 \\
\begin{array}{c} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{array} &
\begin{pmatrix}
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array}
$$

(d)

$$
\begin{array}{c|c}
 & p_1 \; p_2 \; p_3 \; p_4 \; p_5 \\
\begin{array}{c} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{array} &
\begin{pmatrix}
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0
\end{pmatrix}
\end{array}
$$

(e)

Figure 4.3: The set of candidate CRAs: (a) CRA 1 - State of hostages, (b) CRA 2 - Determine weapons capability, (c) CRA 3 - Determine adversary intelligence level, (d) CRA 4 - Relocate hostages, and (e) CRA 5 - Secure landing site

An analyst must then consider a set of collection requirement actions that are derived from the plausible futures. The developed plausible futures tool facilitates this process. Figure 4.1(a) shows example plausible futures as well as their corresponding attributes. From the analysts point of view the friendly assets would be critical to mission success. Analysis can be performed using the plausible futures tool. If the analyst selects the special forces team and hostages as vital to the mission. The result would be that the analyst's attention would be drawn to the plausible futures which involve these assets. The analyst notice that one of the highest impact plausible futures (*i.e.,* terrorists acquire weapons) involves this asset so a CRA that monitors this plausible future would be advisable.

The collection requirement (CRA 1) that is derived is that the weapons capability of the terrorists must be monitored. Appropriate actions must be defined by the analyst to determine what weapons the adversary has access to. A subjective relative cost is assigned to the CRA of 0.5 (with a range of 0 to 1.0). To differentiate between the different CRAs so cost and time required for each CRA can be assigned relative to each other. Figure 4.3(a) shows the matrix representation of this CRA. The values in the matrix reflect the analyst's intuition regarding which assets could be influenced if this collection requirement is selected. In this case if the weapons capability of the terrorists is not determined the weapons could in turn be used against the special forces team, the helicopter, and possibly hostages. For simplification the time required for all CRAs to be performed in the case study was set at relative value of 0.5 units. The timing constraint in this case study is used limit feasible number of actions.

A second CRA (CRA 2) would be to determine the state of the hostages. An analyst can expect that the terrorists would communicate and give demands which would mean determining this information is relatively low cost so a value of 0.10 can be subjectively assigned. Figure 4.3(b) shows the matrix representation of this CRA. Intuitively if the hostages are executed or relocated then they would be impacted, the matrix reflects this idea.

The analyst would likely also want to know about the terrorist's intelligence level on friendlies. This forms the third CRA (CRA 3) as shown Figure 4.3(c). Due to the complexity of determining such information the cost of this CRA is rated high relative to the others at 0.75. The matrix shows that if surveillance has occurred it would likely impact the friendly base as well, special forces team, and likely the planned landing site.

Collection requirements could also be related to each other. For example, if the terrorists have adequate intelligence on friendly forces they might choose to relocate the hostages. This would require a new CRA (CRA 4) to determine the location of the hostages. Since the operational areas of the terrorists can be determined from previous activity and their are known areas of interest this CRA would have a relatively low cost at 0.25. A constraint would be required in the formulation so that this CRA is dependent on CRA 3 (*i.e.,* $CRA4 \leq CRA3$). This effectively orders the selection of CRAs. This is a powerful idea that along with the timing constraints can add a temporal aspect to the formulation. The matrix in Figure 4.3(d) shows that if the hostages or relocated the special forces team, hostages, and landing site will be impacted.

Similarly, if the intelligence level of the terrorists is sufficient they might choose to lay an ambush for the special forces team. Therefore to successfully complete the hostage rescue a CRA is needed to determine the security of the landing site. Since this should be a well defined action the cost is set at 0.3. Figure 4.3(e) shows the intuition that if an ambush occurs the special forces team, helicopter, and landing site would be influenced.

The aggregation function to use for aggregating impacts to assets from plausible futures is selected to be a max function as shown in Equation (4.1). The choice of aggregation function is based on an analyst's expert knowledge. In this case, the analyst desires to know what is the greatest possible benefit from monitoring plausible futures. The analyst can use a min function if they want to evaluate the minimum benefit, or other aggregation functions based on the desired behavior.

$$y(i) = max_j(S_f(i,j)\alpha(i,j)) + S_c(i)(1 - max_j(\alpha(i,j))), \forall i, j \tag{4.1}$$

Once the aggregation function for assets has been selected, the aggregation functions for tasks must also be created by the analyst as shown in Equations (4.2) - (4.6). These functions effectively represent asset responsibility for tasks. For example, Equation (4.2) defines the relationship between assets and the task of landing safely in the the drop off zone. Intuitively the special forces team, helicopter, and landing site are needed.

$$D_{t_1} = 0.8 \cdot max(a_1, a_3, a_4) + 0.1 \cdot a_2 + 0.1 \cdot a_5 \tag{4.2}$$

$$D_{t_2} = 0.9 \cdot a_1 + 0.1 \cdot WA(a_2, a_3, a_4, a_5) \tag{4.3}$$

$$D_{t_3} = 0.9 \cdot a_1 + 0.1 \cdot WA(a_2, a_3, a_4, a_5) \tag{4.4}$$

$$D_{t_4} = 0.6 \cdot a_1 + 0.4 \cdot a_2 \tag{4.5}$$

$$D_{t_5} = 0.7 \cdot max(a_1, a_2, a_3, a_4) + 0.3 \cdot a_5 \tag{4.6}$$

Finally since all tasks are equally needed for successful completion of the mission the aggregation function for the mission is defined as shown in Equation (4.7).

$$D_m = 0.2 \cdot t_1 + 0.2 \cdot t_2 + 0.2 \cdot t_3 + 0.2 \cdot t_4 + 0.2 \cdot t_5 \tag{4.7}$$

4.2 Results

This scenario was then optimized and the results as constraints were altered are shown in Table 4.1. The results show that until the cost and timing constraints are relaxed sufficiently, they limit the selection of which actions can be selected. As the budget rises the objective value also rises as expected. Since the time required for each CRA is set to 0.5 units, the time constraint effectively limits how many CRAs can be performed. Once the budget is great enough to make the optimal CRAs feasible the optimal CRAs are selected. In the first set of results where the max time constraint is 0.5 units, and only one CRA can be selected it can be seen that determining the weapons capability of the adversary is the optimal action to take with an objective value of 0.776. Intuitively this makes sense as this will reveal the threat that adversaries pose to the rescue team. When the timing constraints are 1.0 and two CRAs can be selected the optimal choices are learning the state of the hostages and determining the weapons capability of the adversary with an objective value of 0.834. Finally, at a timing constraint of 1.5 when three CRAs can be selected the optimal set of CRAs is to learn the state of the hostages, determine the weapons capability of the adversary, and determine the level of intelligence that the adversary has on friendlies. It can be seen that as the budget increases additional actions are feasible but the previous optimal solution is always involved in the larger set.

Since the size of the CRA set was small for this case study it was verified that each solution was unique however this is not guaranteed. The MIP formulation is also sensitive to initial conditions which needs to be taken into account.

4.3 Limitations

Ideally for a intelligence collection framework of this nature, user experiments would be conducted with military analysts. These experts would be able to identify and give a more accurate estimation of the framework performance.

It was intended that the framework would utilize OWA operators throughout to model different logical relationships such as max, min, top N, *etc.* However a solution for the sorting required to implement OWA operators was not found. Therefore explicit logical constraints were used instead. If OWA operators could have been used instead this would simplify the modeling required since OWA operators can be implemented once and different relationships represented with by changing the weighting vectors as parameters. Using explicit logical constraints forces the user to come up with the constraints which is not as simple.

Relationships were explored as combinations of weighted averages, maximum, and minimum. The use of OWA would have increased flexibility for analysts in defining relationships in the mission model.

Table 4.1: Optimization results with varying parameters

Budget	Max Time	State of hostages	Weapons capability	Intelligence level	Relocate hostages	Secure landing site	Total Cost	Total Time	Obj. value
0.25	0.5	1	0	0	0	0	0.1	0.5	0.25
0.50	0.5	0	1	0	0	0	0.5	0.5	0.776
0.75	0.5	0	1	0	0	0	0.5	0.5	0.776
1.00	0.5	0	1	0	0	0	0.5	0.5	0.776
1.25	0.5	0	1	0	0	0	0.5	0.5	0.776
1.50	0.5	0	1	0	0	0	0.5	0.5	0.776
1.75	0.5	0	1	0	0	0	0.5	0.5	0.776
2.00	0.5	0	1	0	0	0	0.5	0.5	0.776
0.25	1	1	0	0	0	0	0.25	0.5	0.25
0.50	1	0	1	0	0	0	0.5	0.5	0.776
0.75	1	1	1	0	0	0	0.6	1	0.834
1.00	1	1	1	0	0	0	0.6	1	0.834
1.25	1	1	1	0	0	0	0.6	1	0.834
1.50	1	1	1	0	0	0	0.6	1	0.834
1.75	1	1	1	0	0	0	0.6	1	0.834
2.00	1	1	1	0	0	0	0.6	1	0.834
0.25	1.5	1	0	0	0	0	0.1	0.5	0.25
0.50	1.5	0	1	0	0	0	0.5	0.5	0.776
0.75	1.5	1	1	0	0	0	0.6	1	0.834
1.00	1.5	1	1	0	0	0	0.6	1	0.834
1.25	1.5	1	0	1	0	1	1.15	1.5	0.864
1.50	1.5	1	1	1	0	0	1.35	1.5	0.887
1.75	1.5	1	1	1	0	0	1.3	1.5	0.887
2.00	1.5	1	1	1	0	0	1.3	1.5	0.887

Chapter 5

Conclusion and Future Work

This thesis contributes a intelligence collection framework to act as decision support for military analysts. A large focus of the effort was devoted to the proper interpretation of the problem needed to develop the intuition required for to create the framework.

A decision support tool was developed to allow analysts to create candidate CRAs from plausible futures. These CRAs were optimized via a novel MIP formulation in order to select the best set of CRAs by trading off feasibility and effectiveness. Finally, a case study was performed in order to evaluate the framework.

5.1 Future Work

This section describes several ideas related to this work that could be explored in future research.

5.1.1 Fully integrated decision support system

The framework currently is not fully integrated. It would be desirable to create a single application that integrates tightly the whole framework. The application would combine the existing decision support tool and optimization formulation as a singular tool. Gurobi has a Java interface which could allow for easy integration with the Java decision support tool.

5.1.2 Exploring feedback in collection requirements

The results of this thesis can be used to plan alternatives or responses. An natural extension of this work would be to explore how the results of these planned responses can be used as inputs to the framework. Such an extension would likely have work on a data set that contains complete scenarios, responses, and results of these responses. An alternative would be to create a simulator capable to simulating such scenarios.

5.1.3 Generalizing framework to other domains

The essence of the framework is a mathematical model capable deciding between a set impact values. This is very generic and should be applicable to other domains. Further research could explore such a generalization.

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