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“Collective C2 in Multinational Civil-Military
Operations”

Representing COA with probabilistic ontologies

Topic(s): 1 - Modeling and Simulation

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14. ABSTRACT In modern day operations, planning has been an increasingly complex activity. This is especially true in civil-military scenarios, usually involving numerous and diverse actors as well as intertwining requirements that limit the solution space in nontrivial ways. Under these circumstances, decision support systems are an essential tool that can also become a liability if not properly devised or employed, and one of the critical parts of the planning process is the definition of Course of Action (COA). Although this has been widely recognized by the planning and Decision Support Systems communities, there has been little progress in designing a comprehensive methodology for COA representation that supports the diverse aspects of the Command and Control cycle. For instance, formally capturing command intent in a way that allows for automated generation of alternative COAs is still an open research topic. This paper proposes an approach for effective COA representation by means of a probabilistic ontology, as a first step towards the goal of automating the operational planning process. The current research is focused in the planning process of a Joint Force Air Component Command.					
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Abstract

In modern day operations, planning has been an increasingly complex activity. This is especially true in civil-military scenarios, usually involving numerous and diverse actors as well as intertwining requirements that limit the solution space in non-trivial ways. Under these circumstances, decision support systems are an essential tool that can also become a liability if not properly devised or employed, and one of the critical parts of the planning process is the definition of Course of Action (COA). Although this has been widely recognized by the planning and Decision Support Systems communities, there has been little progress in designing a comprehensive methodology for COA representation that supports the diverse aspects of the Command and Control cycle. For instance, formally capturing command intent in a way that allows for automated generation of alternative COAs is still an open research topic. This paper proposes an approach for effective COA representation by means of a probabilistic ontology, as a first step towards the goal of automating the operational planning process. The current research is focused in the planning process of a Joint Force Air Component Command.

Keywords: Decision-making, probabilistic ontology, Course of Action representation

1 Introduction

In spite of the domain of discourse or the characteristics of decision-makers, the identification of courses of action is a key step when planning a complex activity. Factors such as the complexity of the activity, the time available for decision-making, and the level of uncertainty involved will have a strong impact on both the definition of Courses of Action (COA) and the choice of the most suitable one. The existence of various decision-models suggests how important it is for humans to seek methods that favor choosing the best option whenever possible (BOSSE; ROY; WARK, 2007) (PHILLIPS-WREN; ICHALKARANJE; JAIN, 2008). In spite of this diversity, there is no definitive approach to the process of decision-making, and most approaches avoid

the exponential growth of the problem space by restricting the solution space and attempting to find the local optima (HAIDER; LEVIS, 2007).

Decision-making in complex situations is usually performed under uncertainty, with cost and time constraints. Further, there is a significant potential for negative results due to the presence of multiple variables and conflicting goals. In such environments, the decision-maker very often cannot reach good results (ROWE; DAVIS, 1996).

Decision Support Systems (DSS) are meant to address these issues, and have been subject of intense research and evaluation since the early 1970s (GORRY; SCOTT-MORTON, 1971). In the 80's, Herbert A. Simon (SIMON, 1987) suggested that artificial intelligence techniques could improve decision support systems by incorporating knowledge models and employing efficient AI-based algorithms (GUPTA et al., 2006). Others have also supported this idea (e.g., JACOB; MOORE; WHINSTON, 1988, LITTLE, 1986) resulting in the definition of an Intelligent Decision-Making Support System (i-DMSS). However, these new developments didn't contribute to find a definitive approach to the problem (GUPTA et al., 2006), resulting instead in further fragmentation in the field as new methodologies aimed at specific types of problems were devised.

Decision-makers in military operations, whether or not in the context of an armed conflict, also face the same above-cited issues. The process adopted by military organizations for operational planning determines steps to be performed to ensure that no aspect is overlooked. However, DSS researchers (e.g., THUNHOLM, 2006) have been questioning the efficacy of a rigid process for decision-making in situations where time is tightly restricted. In these situations, they argue, the traditional Command and Control (C2) decision cycle is not fast enough, indicating that other approaches should be considered since there is a hard limit on the ability of human planners to generate more than one efficient and effective course of action in a timely manner.

Traditional methods of generating courses of action rely on analysts (HAIDER; LEVIS, 2007) to search through mission reports and intelligence information in order to update the situational picture and assess the expected results for each generated COA.

As complexity grows, this inevitably results in a cognitive bottleneck that plagues most situational rooms in current operations, seriously limiting the decision-making process.

A generic decision-making model of a military organization can be seen in Figure 1.1, where the military decision process starts with incoming orders from the higher levels in the command structure or requests from an organization (governmental or not). In the depicted process, updates coming from the environment trigger the decision cycle, which encompasses a series of important steps whose output is a set of possible actions. These actions form the basis for defining the set of missions to be executed by the forces in order to achieve the desired effects in the environment.

Computational tools (e.g., simulation) usually support the definition of this set of missions, facilitating the assessment of how likely each combination of missions would achieve the desired effects. In other words, the output of the decision-making process is a coordinated action plan in time and space to be conducted into the environment.

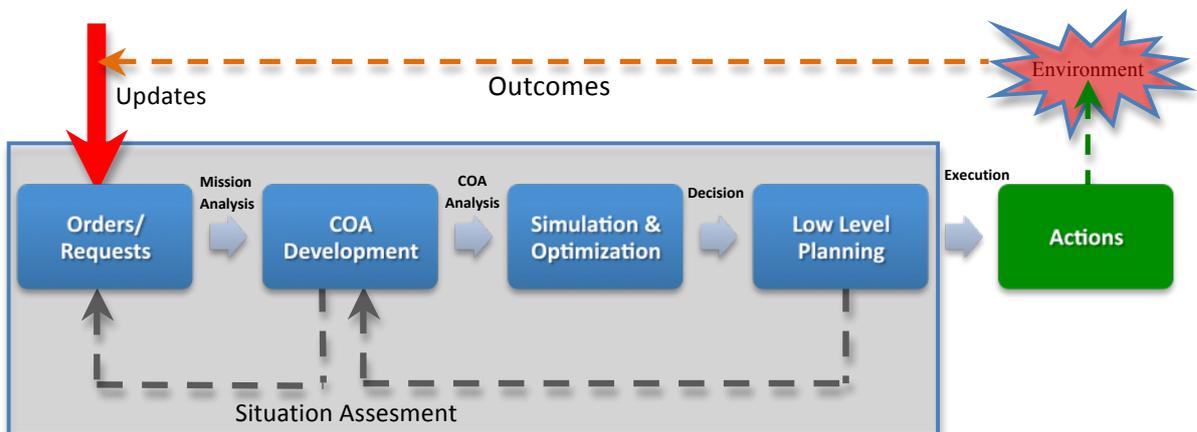


FIGURE 1.1 A generic decision-making model of military organizations.

As new information and outcomes from the environment accrue, it is essential to have a constant alignment between sub-processes, as well as between the planning and the development of COAs. Likewise, the final plan should be consistent with the orders sent from the upper echelon or requests by organizations. This dynamicity is a challenge for decision-makers, as new information may invalidate a course of action even during its planning phase, likely affecting the decision cycle and hence its ability to react to emerging situations. Thus, our research motivation is to devise an approach that allows

semi-automated planning of alternative COAs that are reliable, efficient and opportune. As a case study, we are developing the approach in support of the decision making process within the Brazilian Joint Force Air Component's C2 cycle.

This document is organized as follows: Section 1 introduced the motivation for the ongoing research. Section 2 conveys a brief literature review, while the overall approach is explained in Section 3. Finally, Section 4 concludes with some remarks on the present work.

2 Literature Review

2.1 Military Decision-Making Process

As Brazilian armed forces increase their participation in complex operations such as leading the United Nations contingent in Haiti or supporting flooding relief operations in the Santa Catarina state, their decision-making process is being forced to operate in environments for which it was not originally designed, such as peacekeeping operations, humanitarian assistance and monitoring of the national territory borders. In all these scenarios, military organizations must operate efficiently and effectively when receiving orders within its hierarchical structure or requests from other organizations.

Upon receipt of orders or requests, a planning process occurs to define which missions to accomplish totally or partially given the existing guidance and available resources. In general terms, the Brazilian Armed Forces' decision process is based largely on the US Joint Operation Planning process and its description will serve as the basis for the discussions in this work. Nonetheless, to withstand the issues mentioned in Section 1, this process must rely on decision support tools to ensure an optimal accomplishment of its goals.

Figure 2.1 depicts the planning cycle of airspace activities in a joint operation, as described in manual JP 3-30 (DOD, 2010). In the diagram, a Warning Order/Planning Directive from the Mission Analysis task at the operational level (JTF) starts the tactical level decision process of a Joint Force Component. This triggers the following sub-processes: Mission Analysis (tactical level); COA Development; COA Analysis/War

Gaming; COA Comparison; and COA Approval. These will provide the basis for the generation of Supporting Plan/Order in conjunction with the operational level.

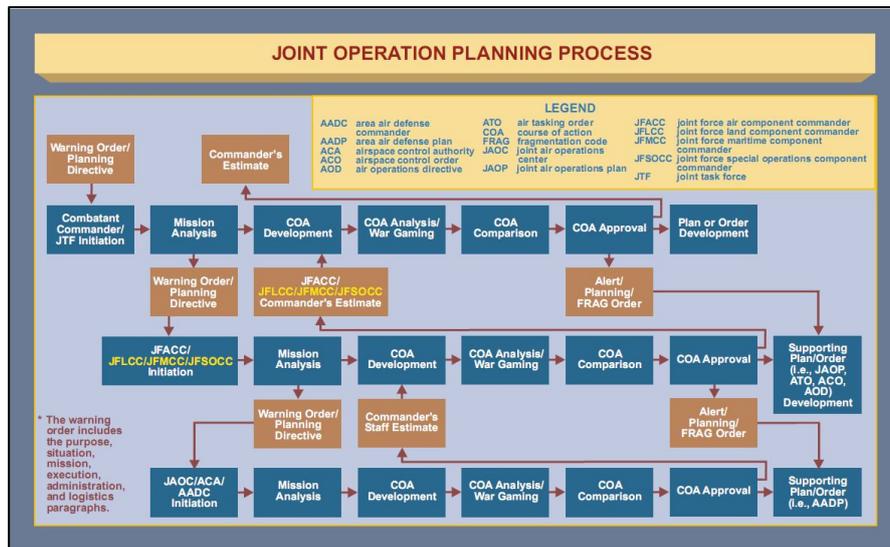


FIGURE 2.1 Joint Operation Planning Process (DOD, 2010).

The Joint Force Air Operations Center (JAOC) also receives a Warning Order/Planning Directive to develop its part of the mission planning, which has a different cycle timing (i.e., faster at the very lower tactical level). The JAOC's battle rhythm depends on the type of campaign and the defined doctrine. As a joint tactical unit it has to handle all the resources available of many different organizations under its operational control.

Each planning level (i.e., operational or tactical) will have distinct planning horizon perspectives and levels of detail (granularity) when defining their respective COAS. In general, actions at the operational level will be the goals for the tactical level. In order to reconcile these differences, it is important to understand the paradigm upon which the current military decision-making process is based: Effects Based Operation.

2.2 Effects Based Operation - EBO

Effects Based Operation (EBO) can be understood as coordinated sets of actions directed at shaping the behavior of friends, foes, and neutrals in peace, crisis, and war

(SMITH, 2002). It aims at pursuing objectives defined in terms of human behavior described in multiple dimensions and multiple levels, as well as in terms of measurement of their success based on the produced behavior. Therefore, actions encompass all available sources of a national power and create effects in anyone observing it, not only the enemies. Effects can occur simultaneously on all levels of a military operation, in the political (domestic or external) and in the economic arenas as well, are interrelated, and cumulative over time. Also, they are both physical and psychological in nature.

Since effects are interrelated, a created effect will tend to cascade into successions of indirect effects in ways that are not entirely predictable. In such environment, the main goal is to identify the most likely outcomes that are sufficient for planning purposes. Also, it is necessary to have some knowledge of the observers' decision-making processes in order to understand the influences upon their decisions.

During the evaluation of the operation it is necessary to adapt agilely to changing situations. Thus, the implemented process must be able to incorporate accruing information during the decision cycle.

Figure 2.2 presents EBO in the three domains of conflict (SMITH, 2002). This research concentrates on the cognitive domain, encompassing all phenomena involved in the decision process. As implied in the second block of the diagram ("Deep" understanding of situation), prior knowledge and mental models are assets to develop an understanding on how uncertainty of the shared awareness and cognitive aspects (e.g. emotions, beliefs, etc.) impact the cause and effect relations, temporal relations, and dynamic futures of a situation. Thus, performing decision-making with partial information requires approaches that can capture such nuances. In Decision Theory the decision-maker preferences, expressed in utility measures, may be combined with probabilities (RUSSEL; NORVIG, 2002).

Ontologies have been proposed as a tool to better express a domain in terms of its concepts, relations and rules (GUARINO, 1998). Within the military domain, researchers have suggested its use in support of the decision process (DARR; BENJAMIN; MAYER, 2009) (DORION; MATHEUS; KOKAR, 2005) (BOURY, 2007). Ontologies may help in contextualizing an order that was received from the

higher hierarchical level or even a request from a different organization during a civil-military operation. One limitation of ontologies is the lack of a standardized, principled support of uncertainty (COSTA, 2005), which jeopardizes its use in situation where uncertainty plays a significant role. To address this limitation, our work relies on probabilistic ontologies, which extend ontologies to capture uncertainty in a principled and standardized way.

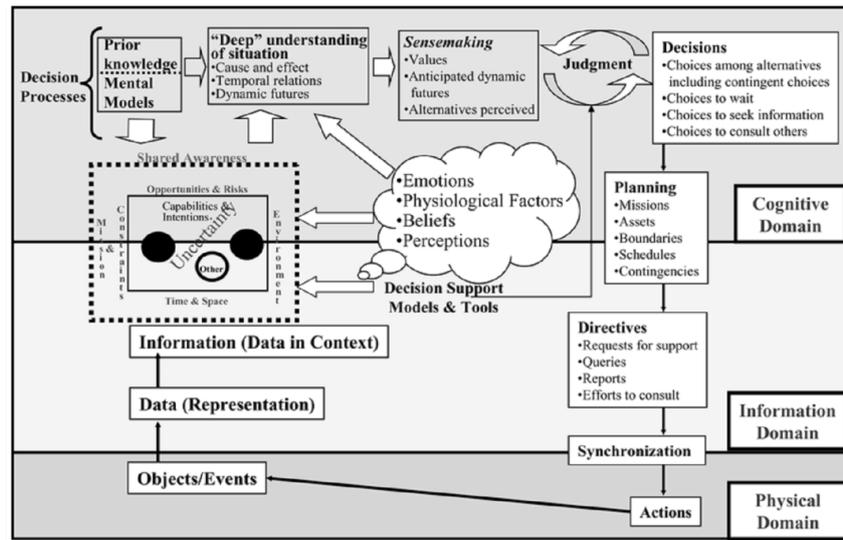


FIGURE 2.2 The Three Domains in EBO (SMITH, 2002).

2.3 Probabilistic Ontologies

A probabilistic ontology is an explicit, formal knowledge representation that extends regular ontologies to express: statistical regularities that characterize a domain; inconclusive, ambiguous, incomplete, unreliable and dissonant knowledge related to entities of the domain; and uncertainty about entities, properties, and relationships among those entities. Probabilistic ontologies are used for describing knowledge about a domain and the uncertainty associated with that knowledge in a principled, structured and shareable way (COSTA, 2005).

There are many approaches to model probabilistic domains (COSTA, 2005) (DING; PENG; PAN, 2006) (PREDOIU; STUCKENSCHMIDT, 2008) (CARVALHO, 2010). Traditional ontologies do not have built-in mechanisms for representing or inferring with uncertainty, requiring extending it with new classes, subclasses and properties that support uncertainty representation and reasoning. The PR-OWL

probabilistic ontology language (COSTA 2005) and its new version PR-OWL 2 (CARVALHO, 2010) are written in OWL and provide a consistent framework for representation and reasoning in domains with uncertainty.

The mathematical basis for both PR-OWL, and its newer version is Multi-Entity Bayesian Networks - MEBN, which integrates first order logic with Bayesian probability. MEBN provides adequate formal support for representing a joint probability distribution over situations involving unbounded numbers of entities interacting in complex ways (LASKEY, 2008). This is a major requirement to achieve principled representation of the multiple, multi-modal sensor input and their compounded interactions.

MEBN represents domain information as a collection of inter-related entities and their respective attributes. Knowledge about attributes of entities and their relationships is represented as a collection of repeatable patterns, known as MEBN Fragments (MFrag). A set of MFrag that collectively satisfies first-order logical constraints ensuring a unique joint probability distribution is a MEBN Theory (MTheory). Figure 2.3 presents an MFrag that captures, among other things, the relationship between one or more requested actions (via the input node *IsRequestedAction(act,obj,rgn,t)*) and one of their accumulated effects (via the resident node *AccumulatedEffect(act, obj, rgn)*).

An MFrag can have three different types of nodes, which are depicted in Figure 2.3. Resident nodes (yellow ovals in the figure) are the actual random variables that form the core subject of an MFrag. Input nodes (gray parallelograms in the figure) are basically “pointers” referencing to another MFrag’s resident node, providing a mechanism for connecting resident nodes between MFrag at instantiation time. Finally, Context nodes (green pentagons in the figure) are boolean random variables representing conditions that must be satisfied to make the probability distribution of an MFrag valid. By allowing uncertainty on context nodes, MEBN can represent several types of sophisticated uncertainty patterns, such as relational uncertainty or existence uncertainty.

An MFrag can be seen as a “chunk of domain knowledge” that encapsulates a pattern that can be instantiated as many times as needed to represent a specific situation.

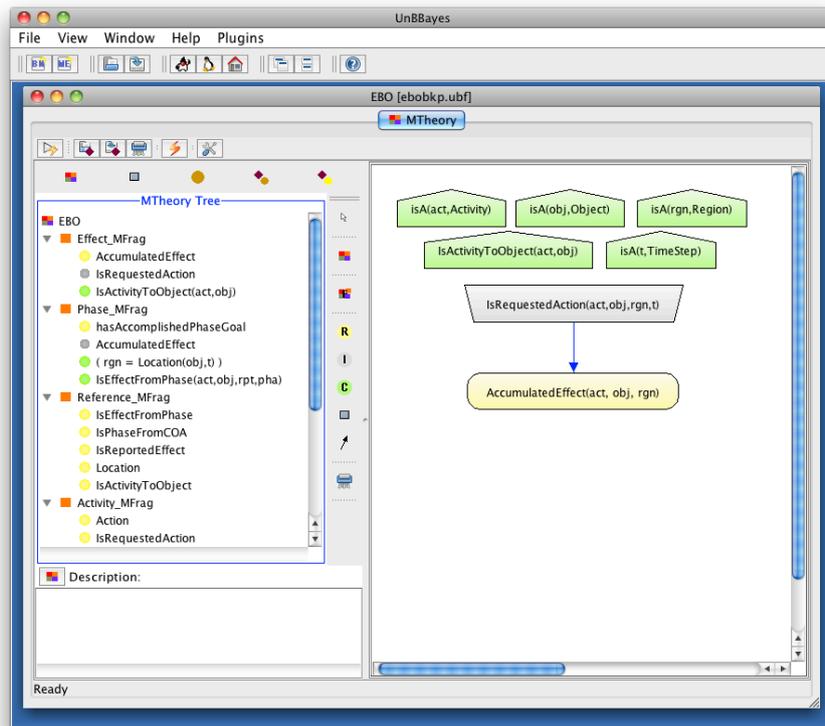


FIGURE 2.3 MFrag exemplifying an action and its outcome.

That is, the MFrags of an MTheory are templates from which a Bayesian Network (BN) - technically, a Situation Specific Bayesian Network, or SSBN - can be formed in response to a query. This provides a composable modeling framework, which can be used to represent the specificities of the decision-making process for building COAs.

Figure 2.3 is a screen shot of UnBBayes (UNBBAYES, 2011)¹, an open-source, Java-based probabilistic reasoner application developed jointly by Mason and the University of Brasilia. UnBBayes-MEBN provides both a graphical user interface for building MTheories and a probabilistic reasoner for performing inference in particular situations. UnBBayes-MEBN uses the PR-OWL probabilistic ontology language to represent MTheories.

In our approach, we employ traditional and probabilistic ontologies to formally describe prior knowledge supporting EBO’s “Deep” understanding of situation. PR-OWL interoperates with ontologies represented in OWL, providing a means to represent

¹ The UnBBayes version used in this paper was 4.2.2, which was the latest available from the UnBBayes sourceforge page. The authors acknowledge the kind support provided by the developers of the UnBBayes-MEBN plugin, Rommel Carvalho and Shou Matsumoto.

statistical regularities and probabilistic information associated with attributes and relationships of entities represented in an ontology. That is, PR-OWL provides a structured, sharable, logically coherent formalism for describing knowledge about a domain and the associated uncertainty.

2.4 Related Work

Section 2.3 stated many important concepts from EBO (SMITH, 2002) that are being addressed in our research. The proposed approach includes the ability to:

1. Model effects that are cumulative over time;
2. Identify the most likely outcomes that are sufficient for planning purposes;
3. Implement a process that incorporates accruing information during the decision cycle; and
4. To develop an implementation that captures how uncertainty of the shared awareness and cognitive aspects impact the cause and effect relations, temporal relations and dynamic futures of a situation.

The work in (HAIDER; LEVIS, 2007) presents an approach for effective COA identification in dynamic and uncertain scenarios based on evolutionary algorithms. Uncertainty is modeled using timed influence nets (TIN), which are instances of Dynamic Bayesian Networks (DBNs).

The work in (DARR; BENJAMIN; MAYER, 2009) describes an ontology to support modeling COA plans that are consistent with US Army and Marine Corps doctrine. It is structured into a core ontology that includes definitions of common COA planning concepts and multiple domain-specific ontologies. The work describes the context that a COA-ontology supports showing three phases during an operation with three possible COAs. The approach utilizes a forward chaining reasoning algorithm to identify the possible activities in each state and a backward chaining reasoning to determine what activities can achieve an end-phase outcome.

Another aspect presented by the ontology is the Preferential Dominance that allows outcomes to be pruned, reducing the computational complexity. Although the paper only described a preliminary design of the ontology and some of the inference rules employed, it showed the possibilities of using ontologies to establish templates for COA planning. This can be an opportunity to improve automation in planning.

The work presented in (MOFFAT; FELLOWS, 2010) analyses decision-making as the core of the new generation of simulation models. It focuses on models designed to respond the growing demand of the UK Ministry of Defense (MoD), which is pushing for a shortening of its decision cycle. The range of the models is from the single environment (tactical engagement) to the whole joint campaign, and across a number of coalition partners. The models are being implemented in WISE (Wargame Infrastructure and Simulation Environment) and address previously identified gaps in the representation of commanders' decision-making process.

Research on COA decision support tools includes (BÉLANGER; GUITOUNI; PAGEAU, 2009) and (WAGENHALS; HAIDER; LEVIS, 2006), which provide different approaches to help decision-makers generating effective COAs. Such tools improve the ability to generate alternative COAs, and are being used also to support COA analysis.

The work in (MATHEUS et al., 2009) and (BOURY, 2007) describes an ontology representation of temporal aspects in scenarios that include threat evaluation or enemy modeling. In addition to addressing a knowledge representation problem, this work also considers the interoperability aspects that surface when putting together different domain representations formalized as OWL ontologies.

Table 2.1 shows an overview of related work cited in this section and how they relate with the four EBO concepts that are emphasized in our approach. To address all the aspects raised above, our approach leverages many concepts and ideas implemented on these works.

TABLE 2.1 Related Work Summary Based on the Four Addressed EBO Concepts

Work	EBO Concept			
	1	2	3	4
HAIDER; LEVIS, 2007	X		X	X
DARR; BENJAMIN; MAYER, 2009		X	X	X
MOFFAT; FELLOWS, 2010		X	X	X
BÉLANGER; GUITOUNI; PAGEAU, 2009		X	X	X
WAGENHALS; HAIDER; LEVIS, 2006	X		X	X
MATHEUS et al, 2009			X	X
BOURY, 2007			X	X

3 Proposed Approach

Our overall research aims to support the Joint Operation Planning Process (JOPP) at the level of a Joint Force Component Command ([Section 2.1](#)). Figure 3.1 shows JOPP from the research development’s point of view. The process was divided into six steps, each one with its own role and task to be achieved. The present paper addresses the third step, namely the uncertainty representation during the process of COA determination. For the purpose of this work, the representation of command intent and the description of causal relations will be considered as given. The steps from 4 through 6 are beyond the scope of this paper.

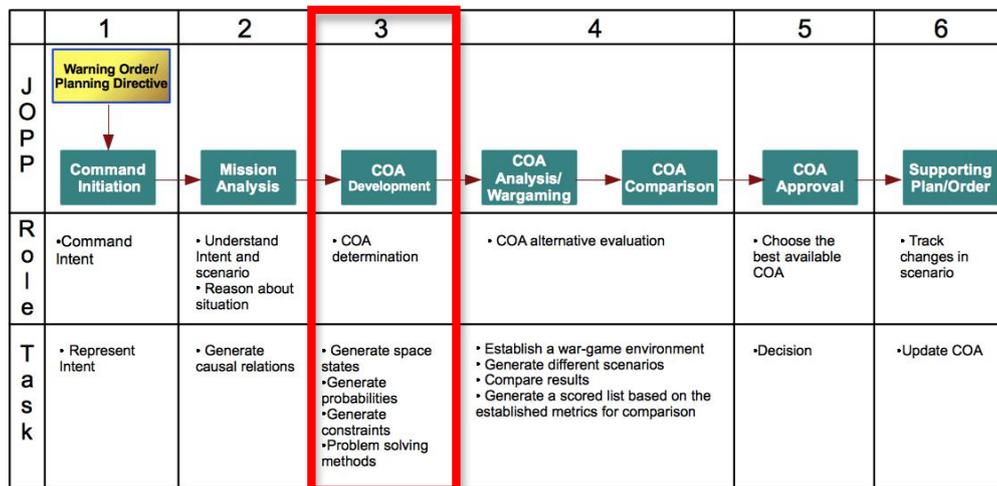


FIGURE 3.1 – The six steps of the Joint Operations Planning Process.

3.1 COA Development Input

The process of COA development demands a high level of situation awareness. Command intent, intelligence reports, Geographic Information Systems support, and information about own units and resources are the main input of this step. As the OODA paradigm (Observe-Orient-Decide-Act) describes, in order to ask for information and to establish a COA it is important to understand the what the situation is and its meaning to one’s goals.

As previously mentioned our approach relies on ontologies for describing and updating the necessary information to support a planning cell from a military

organization in acquiring and maintaining a high level situational awareness. This requires a formal representation of concepts about time, space, actions, effects, resources and uncertainty over a dynamic future. Figure 3.2 presents a probabilistic ontology about COA development.

The five MFrag of the COA MTheory describe the probabilistic part of the domain knowledge and show the causal relations between its main concepts.

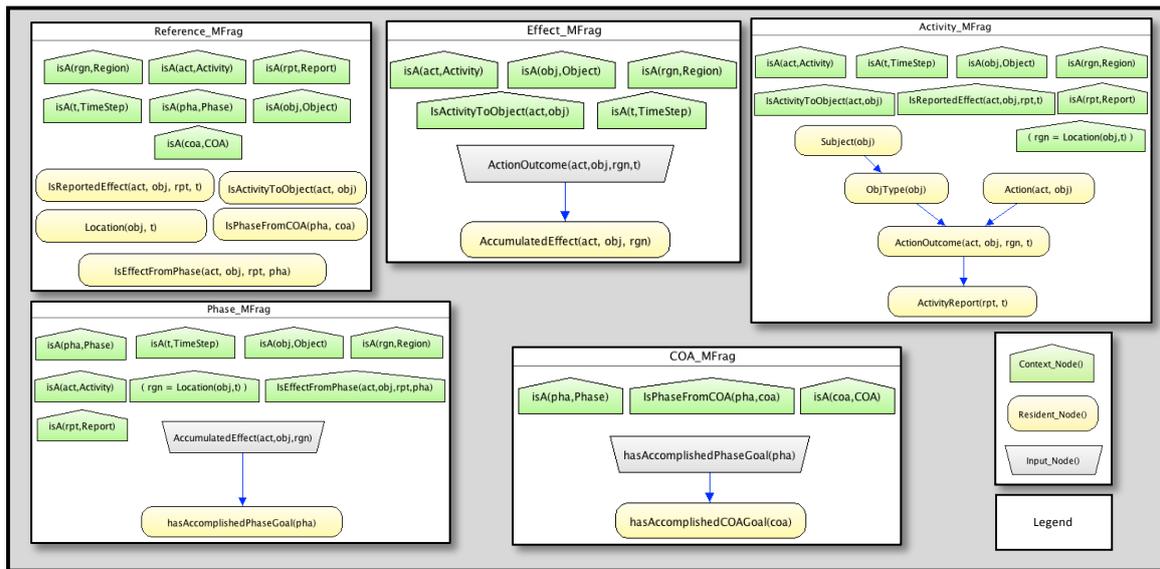


FIGURE 3.2 – COA MTheory.

The Reference MFrag conveys the main concepts from the COA MTheory. Consequently, these concepts will serve as the basis for the major part of context nodes of other MFrag. The Activity MFrag describes the causal relation from an action over an object. One important component is the node $ActionOutcome(act, obj, rgn, t)$, which represents the probability of the requested action during the COA determination. From the node's parameters, one can derive that the outcome will be dependent on the action, the object of the action, the region, and the time where it occurs.

The Effects MFrag describes the accumulated effect resulting from an action over an object located in some region of the scenario. This knowledge is captured by the node $AccumulatedEffect(act, obj, rgn)$ and shows the model's ability to represent effects that are cumulative over the time (1st EBO's addressed concept). The Phase MFrag describes the likelihood of accomplishing the phase's goal as a function of the accumulated effects on all objects in the defined space. Note that the input node

AccumulatedEffect(act,obj,rgn) is in fact a pointer to the corresponding resident node in the Effect MFrag (same name).

To illustrate how MEBN semantics work, let's assume that a query was posed about a likelihood of accomplishing a phase goal given the accumulated effects of a combination of a given action-object-region. Further, let's assume that this combination produced five accumulated effects. In this case, the SSBN formed to answer the query will have the Effect MFrag instantiated five times (i.e., one for each combination and associated effect) and the *hasAccomplishedPhaseGoal(pha)* will have five parent nodes that are copies of the *AccumulatedEffect(act,obj,rgn)*, one for each combination of these parameters.

The COA MFrag has the same idea as the Phase MFrag, but applied to the outcome of the interested COA. Finally, the Activity MFrag deals with the 4th item from the EBO's addressed concepts. It shows a cause and effect relation in which the *Action()* and the *ObjType()* nodes influence the *ActionOutcome()* node, which is the expected outcome from the activity.

As MEBN has the expressiveness of First Order Logic (LASKEY, 2008), it is important to constrain each MFrag to reduce the combinatorial explosion during the SSBN construction, when each random variable can be replaced by the possible instances from the knowledge base (KB). Also, because of MEBN's *open world assumption*, all non mentioned literals are unknown (RUSSEL; NORVIG, 2002) and must be described in the context nodes. Thus, all available information should be provided to the KB in order to reduce the search space and improve decidability.

Each new instance added to the knowledge base can be processed during a Query. Therefore, the generated reports can be used to incorporate new information during the COA development, even after the planning has already started (3rd EBO's addressed concept). The challenge is then to identify the most likely outcomes that are sufficient for planning (2nd EBO's addressed concept).

As in any Bayesian approach, a MEBN model includes the *a priori* knowledge stored in local probability distributions. At this point a query would result in the reasoner applying Bayes rule to calculate the marginal distributions. During the campaign, as new information accrues, the same process is used to calculate the

posterior probabilities, which represent the best knowledge possible to support new planned actions given the information available.

3.2 COA Determination

The developed MTheory will help COA determination by answering queries about the evidence available in or provided to the knowledge base. The probabilistic part of the KB was modeled with seven classes as showed in Table 3.1. The model also has the local probability distribution tables (LPD) for the resident nodes of interest. Table 3.2 presents the Effect’s LPD as an example.

After all instances and LPDs are included in the KB, a query can be posted to the model to assess a specific outcome. The Specific Situation Bayesian Network – SSBN (Laskey 2008) presented in Figure 3.4 is the result of a query on the planned outcome of the AirStrike phase [*?hasAccomplishedPhaseGoal (?AirStrike)*]. In the resulting SSBN, there are planned effects accumulated from *T0*, *T1* and *T2* for the activity *Attack_Bridge* to object *Target1_Bridge* and the activity *Air_Defense_Suppression* over object *Target2_AAA*. The same inference process will happen to the COA evaluation.

TABLE 3.1 Knowledge base descriptions for COA determination

Class	Description	Individuals
Activity	The possible type of missions during an operation	Air_defense_Supression, Attack_Bridge, Attack_Runway, Reconnaissance
COA	The course of action we are interested in	AirSuperiorityCampaign,
Object	The subject of the action	Target1_Bridge, Target2_AAA
Phase	The phases within a COA	AirStrike
Region	The region where the subject is	Sector_ALFA1, Sector_GAMA2
Report	The evidence with the information about the Object, Activity, Phase, Region and TimeStep.	Rpt0,Rpt1, Rpt2
TimeStep	The time when activities should occur (time is considered discrete)	T0,T1,T2

TABLE 3.2 Effect’s LPD

Effect	Action								
	Recon	Attack	SEAD	Recon	Attack	SEAD	Recon	Attack	SEAD
High	.70	.60	.80	.60	.50	.55	.55	.20	.40
Medium	.20	.20	.10	.25	.30	.20	.30	.30	.35
Low	.05	.15	.05	.10	.15	.15	.10	.35	.20
None	.05	.05	.05	.05	.05	.10	.05	.15	.05
	Soft			Medium			Hard		
	ObjType								

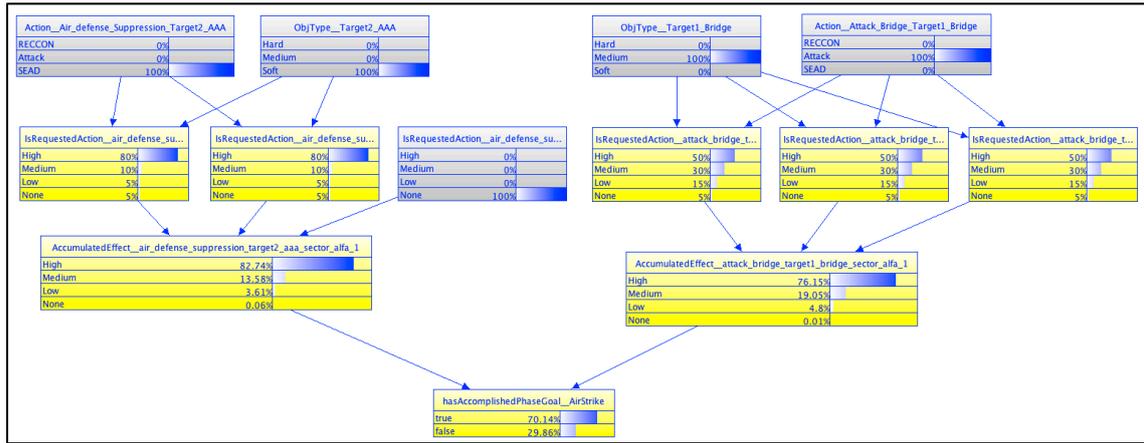


FIGURE 3.4 – SSBN for the query *?hasAccomplishedPhaseGoal(?AirStrike)*.

The SSBN in Figure 3.4 does not fully support the decision process, since no information on utility and alternatives is considered. Thus, to provide full support to the COA determination process it is necessary to resort to Multi-Entity Decision Graphs (MEDGs) (LASKEY, 2008), which is the extension of MEBN that includes support to decision-making. MEDGs are for MEBNs what Influence Diagrams (ID) are for Bayesian Networks.

Further, in response to a query, a MEDG will generate an influence diagram (technically, a Situation Specific Influence Diagram, or SSID). Figure 3.5 shows an influence diagram generated by UnBBayes after exporting the SSBN.

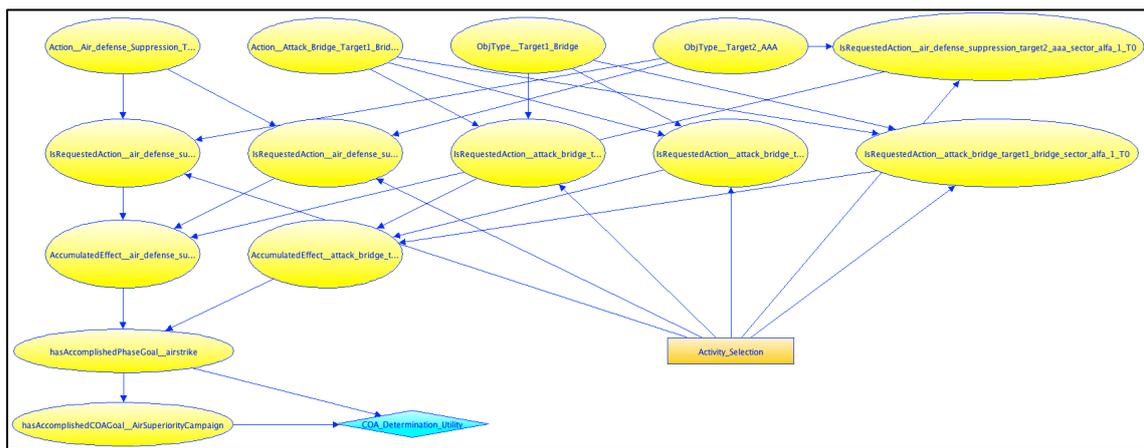


FIGURE 3.5 – Influence Diagram for COA Determination.

The COA representation based on hybrid ontologies written in PR-OWL has the ability to describe the characteristics of the domain of interest that would support the

automated planning phase of the decision process, while addressing the four major aspects of the EBO.

4 Conclusions

The described work on COA representation addresses many aspects of Effects Based Operations representation. However, to fully support EBO it is necessary to have the ability to describe cumulative effects, temporal relations, dynamic futures, as well as the most likely outcomes that are sufficient for planning and incorporate novel information during the decision cycle.

The present paper describes a work in progress for which there are, as yet, no validated results. The research presented here mainly addresses the cognitive domain of the problem, but includes verification and validation of the chosen COAs with support of Modeling and Simulation. The main approach is to improve the COA representation by means of a probabilistic ontology language to model the domain of interest and provide a description of the planning process.

The adopted decision model was the Joint Operation Planning Process at the level of a Joint Force Component Command, which has to produce a complete COA with phases and actions to reach the desired end-state. The process was divided into six steps and this paper focuses on the third step, COA Determination representation.

The model was implemented using PR-OWL (COSTA, 2005), a probabilistic ontology that is being supported by UnBBayes, a graphical modeling tool that includes a PR-OWL plugin (UNBBAYES, 2011). The knowledge base was described and a small example was introduced to show the applicability of the ontology modeling.

Future work includes incorporating the planning formalism and also the command intent description. This will result in a complete description of the decision-making process using a model that will reduce ambiguity and will support automated reasoning to generate conformant plans.

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Representing COA with probabilistic ontologies

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Outline

- Introduction
- Literature Review
- Related Work
- Proposed Approach
- Summary

Introduction

- Planning Operations is an increasingly complex activity
- Different approaches have been suggested to support Course of Action development
- There is no unique solution
- In this work, we propose Probabilistic Ontologies as an efficient alternative to support COA development

Introduction

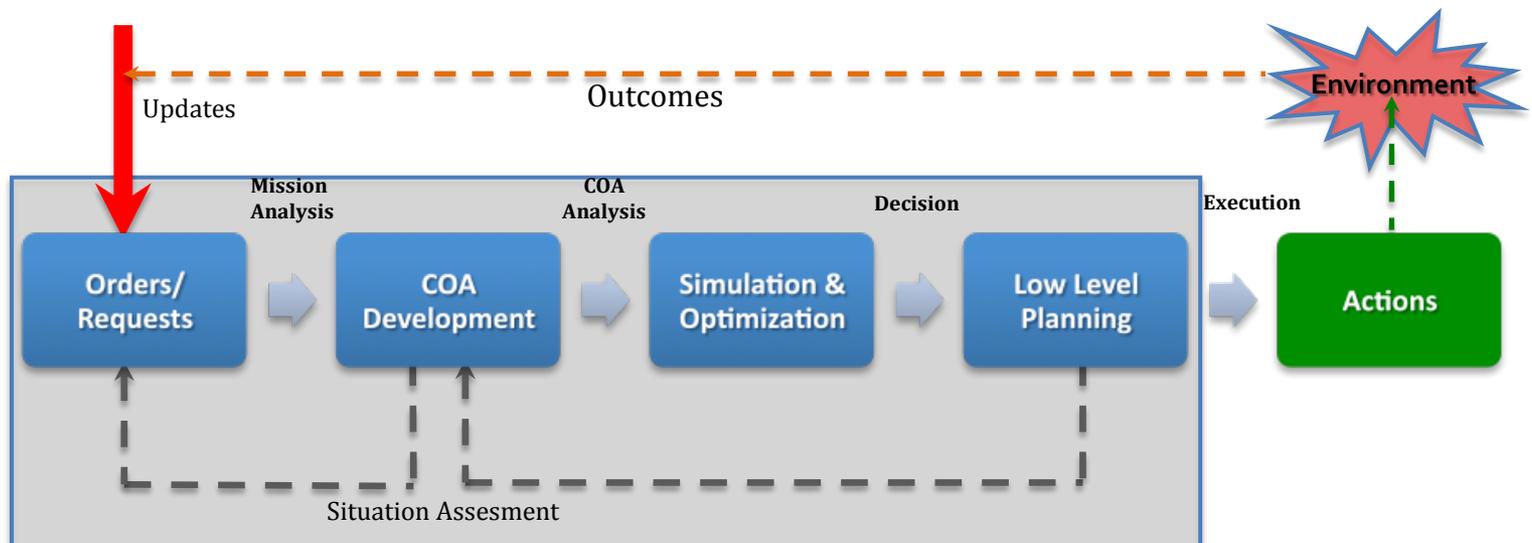
- Decision-making in complex situations
 - Uncertainty
 - Cost and time constraints
 - Significant potential for negative results (existence of multiple variables and conflicting goals)
- Decision Support Systems (DSS)
 - A way to address above issues
 - Research and evaluation since early 1970s
 - AI-based algorithms (i-DMSS)

Introduction

- Generic Military Decision process

Do while environment *is not* in the desired end-state:

- i. Receive incoming orders (hierarchy) or requests
- ii. Generate Plan (output is a set of possible actions)
- iii. Execute plan in order to achieve the desired effects (actions)
- iv. Compute changes in environment (updates)

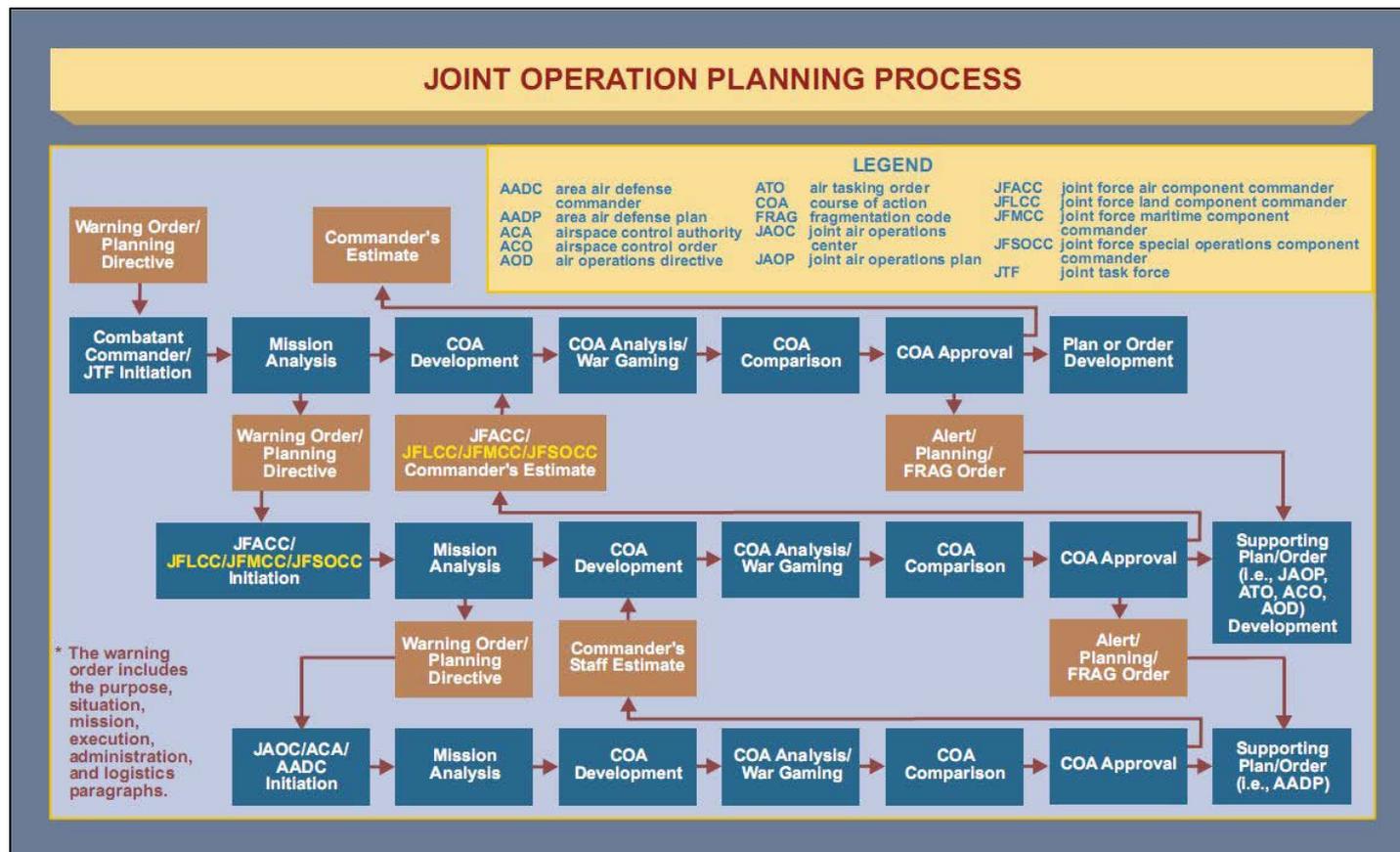


Literature Review

- Military Decision-Making Process
 - Brazilian Armed Forces characteristics (OOTW)
 - Increase participation in Haiti
 - Supporting relief operations
 - Monitoring the national borders
 - Decision process largely similar to the US Joint Operation Planning Process
 - Case Study – Joint Air Operations

Literature Review

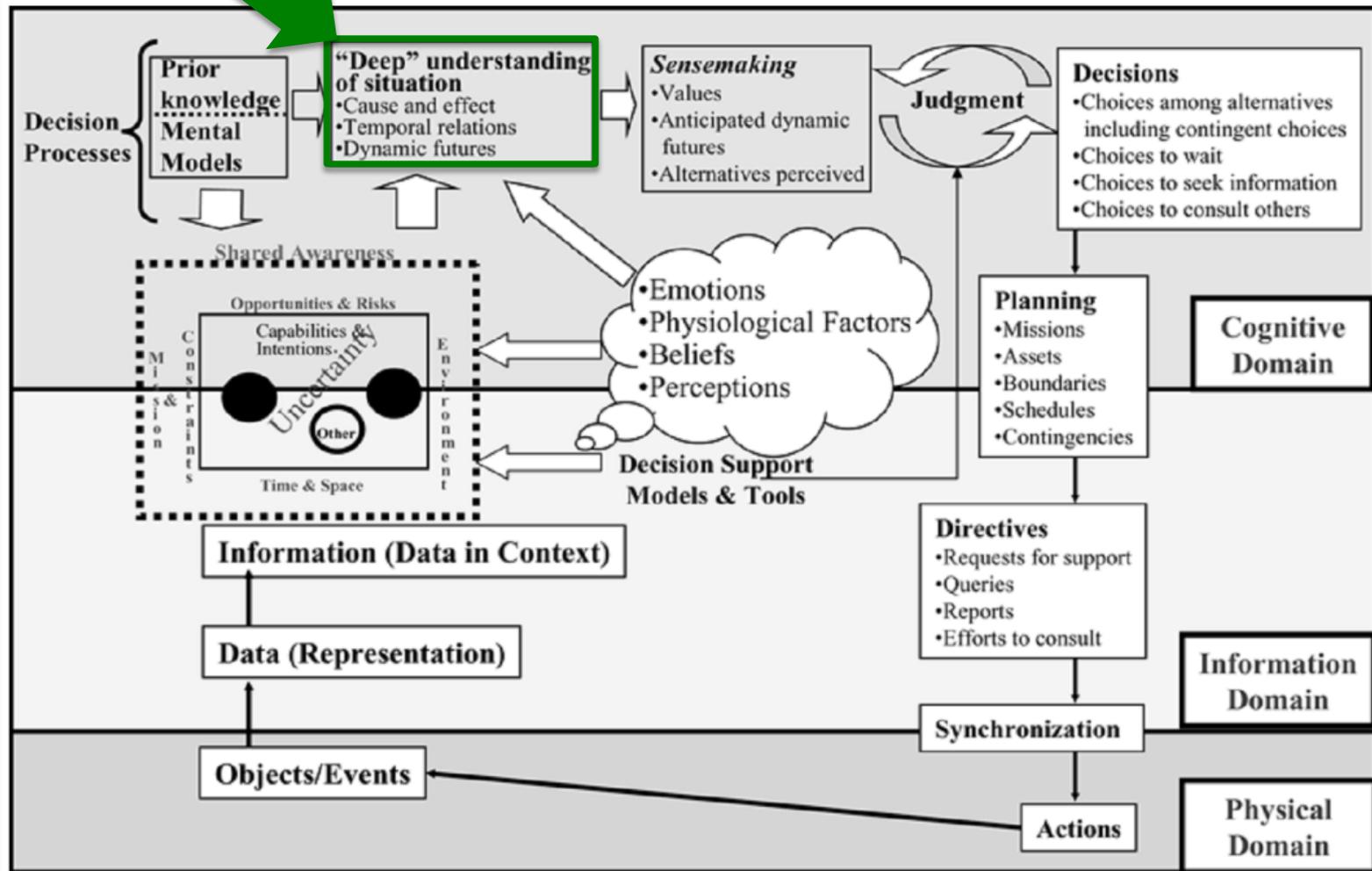
- JP 3-30 Command and Control for Joint Air Operations



Literature Review

- EBO
 - *“Coordinated sets of actions directed at shaping the behavior of friends, foes, and neutrals in peace, crisis, and war.”* (SMITH, 2002)
 - Effects
 - Occur simultaneously on all levels of a military operation
 - Are interrelated and tend to cascade into successions of indirect effects in an unpredictable way
 - Goal (of the planning)
 - To identify the most likely outcomes (effects) that are sufficient for reach the desired end state

Literature Review



The Three Domains in EBO (SMITH, 2002)

Literature Review

- Probabilistic Ontologies (Costa, 2005)

"A probabilistic ontology is an explicit, formal knowledge representation that expresses knowledge about a domain of application. This includes:

- *Types of entities that exist in the domain;*
- *Properties of those entities;*
- *Relationships among entities;*
- *Processes and events that happen with those entities;*
- *Statistical regularities that characterize the domain;*
- *Inconclusive, ambiguous, incomplete, unreliable, and dissonant knowledge related to entities of the domain;*
- *Uncertainty about all the above forms of knowledge;*

where the term entity refers to any concept (real or fictitious, concrete or abstract) that can be described and reasoned about within the domain of application.^[7]

Probabilistic Ontologies

- Traditional ontologies lack built-in mechanisms for representing or inferring with uncertainty
- Require ad-hoc extensions, resulting in many different approaches in the last 10 years
- PR-OWL, PR-OWL 2 (COSTA 2005, CARVALHO 2008)
 - Extends W₃C's OWL
 - Based on Multi-Entity Bayesian Network – MEBN (LASKEY 2008)

MEBN

- MEBN represents domain information as a collection of inter-related entities and their respective attributes;
- Knowledge about attributes of entities and their relationships is represented as a collection of repeatable patterns, known as MEBN Fragments (MFrag);
- A set of MFrag that collectively satisfies first-order logical constraints ensuring a unique joint probability distribution is a MEBN Theory (MTheory);
- An MFrag can be seen as a “chunk of domain knowledge” that encapsulates a pattern that can be instantiated as many times as needed to represent a specific situation.

UnBBayes

File View Window Help Plugins

EBO [ebobkp.ubf]

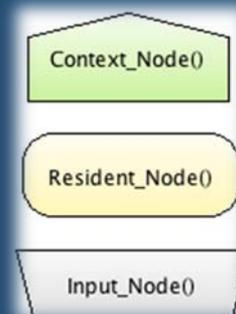
MTheory

MTheory Tree

- EBO
 - Effect_MFrag
 - AccumulatedEffect
 - IsRequestedAction
 - IsActivityToObject(act,obj)
 - Phase_MFrag
 - hasAccomplishedPhaseGoal
 - AccumulatedEffect
 - (rgn = Location(obj,t))
 - IsEffectFromPhase(act,obj,rpt,pha)
 - Reference_MFrag
 - IsEffectFromPhase
 - IsPhaseFromCOA
 - IsReportedEffect
 - Location
 - IsActivityToObject
 - Activity_MFrag
 - Action
 - IsRequestedAction

Description:

Ready



Related Work

- Addressed EBO's concepts
 1. *Model effects that are cumulative over time*
 2. *Identify the most likely outcomes that are sufficient to reach the desired end state*
 3. *Implement a process that incorporates accruing information during the decision cycle*
 4. *Develop an implementation that captures how uncertainty of the shared awareness and cognitive aspects impact the cause and effect relations, temporal relations and dynamic futures of a situation*

Related Work

Work	EBO Concept			
	1	2	3	4
HAIDER; LEVIS, 2007	X		X	X
DARR; BENJAMIN; MAYER, 2009		X	X	X
MOFFAT; FELLOWS, 2010		X	X	X
BÉLANGER; GUITOUNI; PAGEAU, 2009		X	X	X
WAGENHALS; HAIDER; LEVIS, 2006	X		X	X
MATHEUS et al, 2009			X	X
BOURY, 2007			X	X

Related Work Summary Based on the Four Addressed EBO Concepts

Proposed Approach

- Aims to support the Joint Operation Planning Process (JOPP) at the Joint Force Component Command level

	1	2	3	4	5	6	
J O P P	Warning Order/ Planning Directive ↓ Command Initiation	Mission Analysis	COA Development	COA Analysis/ Wargaming	COA Comparison	COA Approval	Supporting Plan/Order
	•Command Intent	• Understand Intent and scenario • Reason about situation	• COA determination	• COA alternative evaluation	• Choose the best available COA	• Track changes in scenario	
R o l e							
T a s k	• Represent Intent	• Generate causal relations	• Generate space states •Generate probabilities •Generate constraints •Problem solving methods	• Establish a war-game environment • Generate different scenarios • Compare results • Generate a scored list based on the established metrics for comparison	•Decision	•Update COA	

Six steps for the Joint Operations Planning Process

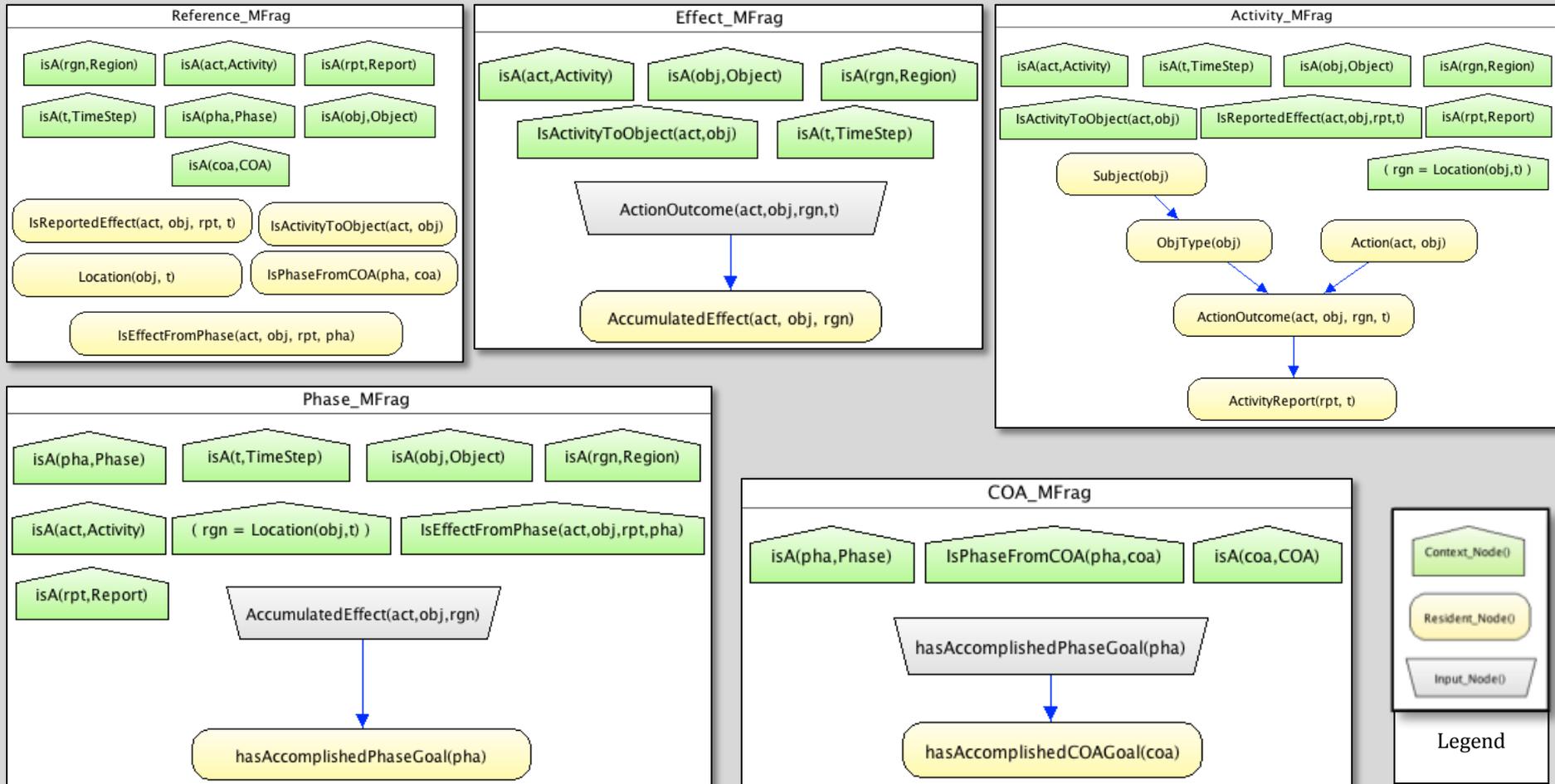
COA Determination

- MTheory will help COA determination by answering queries;
- The probabilistic part of the KB was modeled with seven classes;

Class	Description	Individuals
Activity	The possible type of missions during an operation	Air_defense_Supression, Attack_Bridge, Attack_Runway, Reconnaissance
COA	The course of action we are interested in	AirSuperiorityCampaign,
Object	The subject of the action	Target1 Bridge, Target2 AAA
Phase	The phases within a COA	AirStrike
Region	The region where the subject is	Sector ALFA1, Sector GAMA2
Report	The evidence with the information about the Object, Activity, Phase, Region and TimeStep.	Rpt0,Rpt1, Rpt2
TimeStep	The time when activities should occur (time is considered discrete)	T0,T1,T2

Knowledge base description for COA determination

Proposed Approach



COA MTheory

COA Determination

- The model also has the local probability distribution tables (LPD) for the resident nodes of interest;

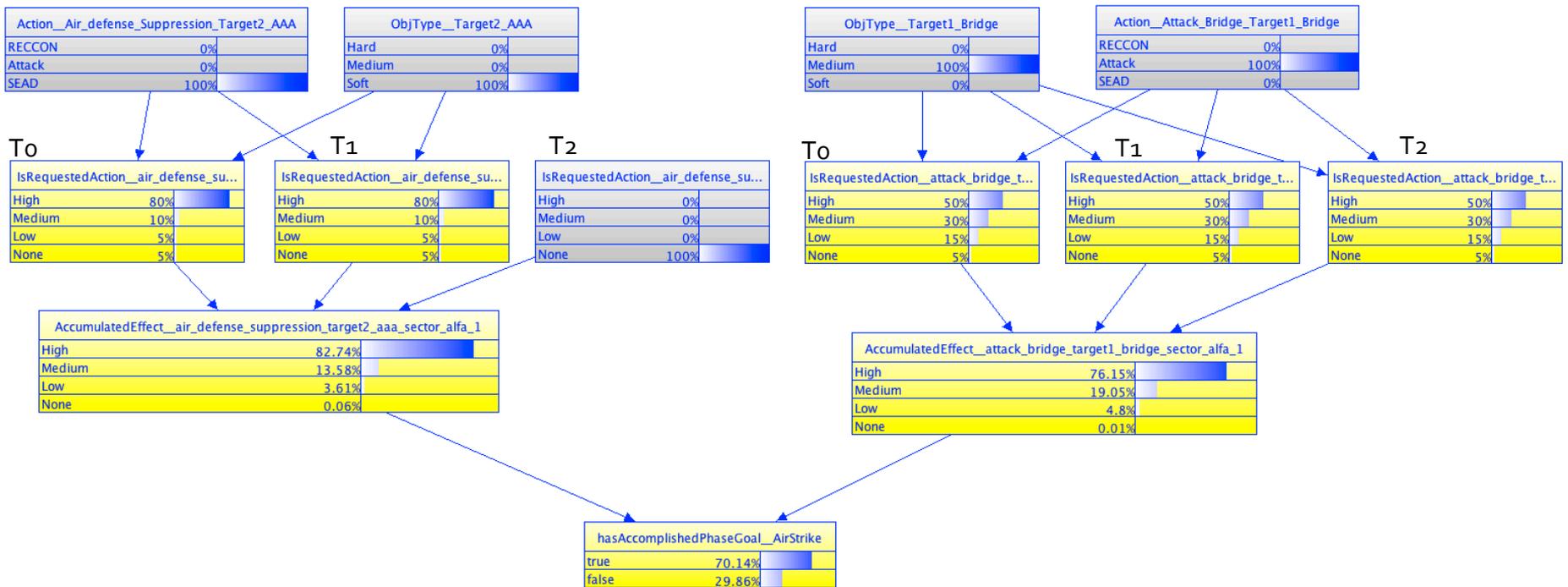
Action									
Effect	<i>Recon</i>	<i>Attack</i>	<i>SEAD</i>	<i>Recon</i>	<i>Attack</i>	<i>SEAD</i>	<i>Recon</i>	<i>Attack</i>	<i>SEAD</i>
<i>High</i>	.70	.60	.80	.60	.50	.55	.55	.20	.40
<i>Medium</i>	.20	.20	.10	.25	.30	.20	.30	.30	.35
<i>Low</i>	.05	.15	.05	.10	.15	.15	.10	.35	.20
<i>None</i>	.05	.05	.05	.05	.05	.10	.05	.15	.05
<i>Soft</i>			<i>Medium</i>			<i>Hard</i>			
ObjType									

Effect's LPD

COA Determination

- After all instances and LPDs are included in the hybrid ontology, a query can be posted to the model to assess a specific outcome;
- A Specific Situation Bayesian Network – SSBN (Laskey 2008) is the result of a query on the planned outcome of the AirStrike phase *[?hasAccomplishedPhaseGoal (?AirStrike)]*;
- In the resulting SSBN, there are planned effects accumulated from T_0 , T_1 and T_2 for the activity *Attack_Bridge* to object *Target1_Bridge* and the activity *Air_Defense_Suppression* over object *Target2_AAA*;
- The same inference process will happen to the COA evaluation.

COA Determination

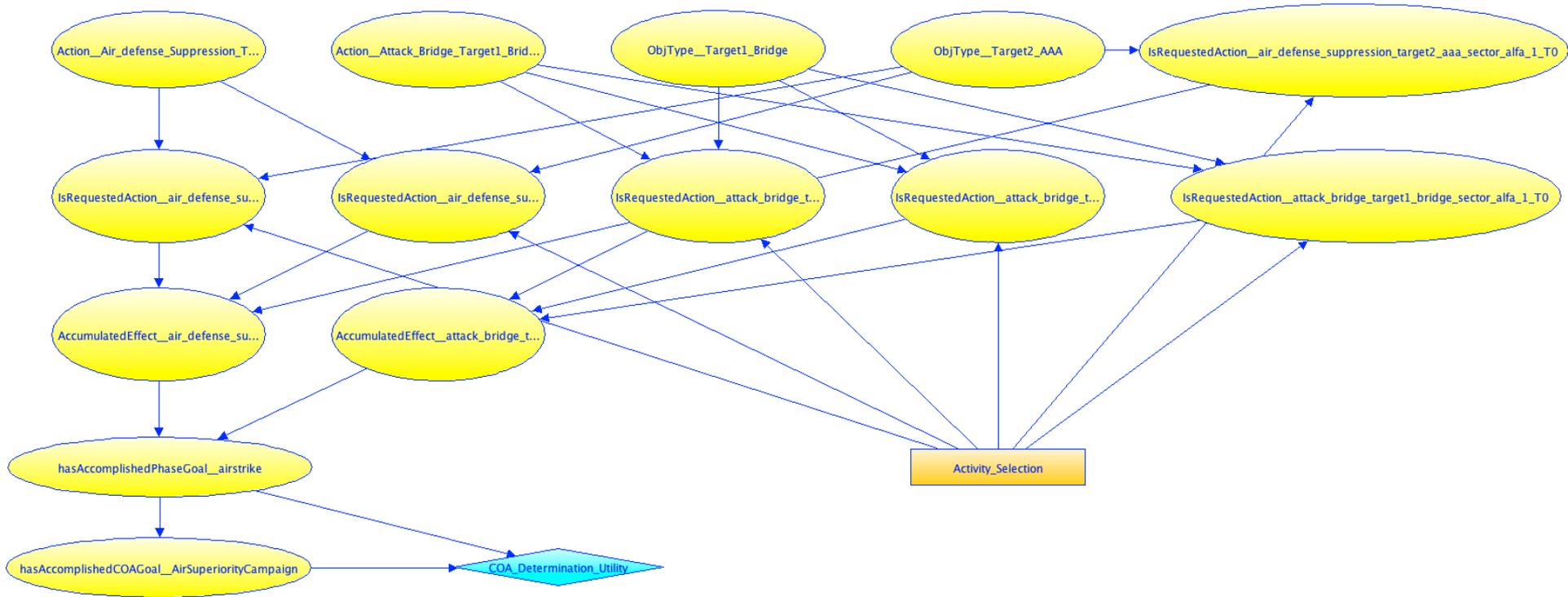


SSBN for the query *?hasAccomplishedPhaseGoal(?AirStrike)*.

COA Determination

- The SSBN does not fully support the decision process, since no information on utility and alternatives is considered;
- Thus, to provide full support to the COA determination process it is necessary to resort to Multi-Entity Decision Graphs (MEDGs) (LASKEY, 2008), which is the extension of MEBN that includes support to decision-making;
- MEDGs are for MEBNs what Influence Diagrams (ID) are for Bayesian Networks.

COA Determination



Influence Diagram for COA Determination.

Summary

- To fully support EBO it is necessary to have the ability to describe:
 - Cumulative effects
 - Temporal relations and Dynamic futures
 - The most likely outcomes that are sufficient for planning
 - Incorporate novel information during the decision cycle
- The research presented here mainly addresses the cognitive domain of the problem, attempting to improve the COA representation using a probabilistic ontology
- The model was implemented using PR-OWL (COSTA, 2005), a probabilistic ontology that is being supported by UnBBayes, a graphical modeling tool that includes a PR-OWL plugin (UNBBAYES, 2011)
- As future work, we will incorporate:
 - The planning formalism
 - Description of command intent

Questions?????

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