

Improving Decision Making by Reducing Uncertainty in Complex Systems of Systems

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ABSTRACT

This paper will discuss techniques for improving campaign planning involving complex systems of systems (SoS) to quickly: understand the operational environment; define the problem; visualize the military end-state; and intervene with optimal operational approach (ways/means) to achieve military end state.

This paper will focus on the integration of Modeling-Simulation-Analytics-Looping (MSAL), Big Data Analytics, cognitive, and graph computing components into a framework that enables the modeling and simulation (M&S) of complex systems of systems (SoS). The framework applies Big Data technology to collect open source data; natural language processing (NLP) to automatically extract entities and relationships; analytics to model values, behaviors, patterns of life; and graph computing to graphically depict a Common Operating Picture (COP) that represents the real-world (mission environment). In the Model Analysis Looping (MAL) process, the mission environment is translated into static models (mission model) as a set of inter-connected graphical paths, capabilities, and behaviors that describe relationships between systems of the mission environment under test. Decision-makers define the goals and supporting mission threads (sequence of nodes and events) to achieve the goals. The Simulation-Analysis-Loop (SAL) tests the dynamic behavior of a model along a goal-based, mission thread via simulation to quantify both performance, sensitivity, and uncertainty (i.e., the random nature of MSAL data will vary as the epistemic framework evolves). Through SAL, decision-makers can understand the impact of local/macro uncertainty and performance – weigh/make trade-offs to derive optimal operational approaches that achieve mission goals.

1.0 INTRODUCTION

The world has seen an unprecedented acceleration in population growth, industrialization, urbanization, and economic growth along with a large increase in production and consumption. This has generated competition between states, driving up the demand for resources. The globalization of economic prosperity has been distributed unequally leaving 2.8 billion people living below the poverty level, which has intensified tensions between the haves and have-nots [1]. The population growth is occurring mostly in developing countries in areas such as Africa, the Middle East, and South Asia. The majority of these people live in high population urban areas where local and state governments have failed to provide basic needs (food, water, clothing, and shelter) necessary for physical and social well-being. These pressures have led to population dissatisfaction and increased opportunities for instability, radicalism, and extremism [1].

These drivers of globalization, adversaries' rapid adaption of innovative technologies; demographic changes coupled with increasing urbanization; rising resource demands; climate change and natural disasters diminishing available resources; proliferation of weapons of mass destruction; and the consequences of failed or failing states have destabilized regional societies and created an era of persistent conflict. These events have led to an increase in political, economic, and ethnic divisions/diffusion of power thus creating a complex hybrid warfare environment. Extremist adversaries will use unconventional, asymmetric, immoral warfare tactics and means to achieve their ends [3]. This hybrid warfare environment is creating a complex security environment characterized by several persistent trends: the proliferation of weapons of mass destruction, the rise of modern competitor states, violent extremism, regional instability, transnational criminal activity, and competition for dwindling resources [4].

The range of contingencies in today's hybrid warfare environment requires a wide Range Of Military Operations (ROMO) from crisis and disaster recovery to major operations and campaigns. These military operations present challenges for NATO in understanding the composition of the entities, conditions, circumstances and influences that makeup the operation environment. The hybrid warfare environment is becoming more complex and more unpredictable due to the multiple factors, feedback loops and inter-correlated effects such as enemy, friendly, and neutral entities (systems) across the spectrum of conflict. They also include an understanding of the physical environment, the state of governance, technology, local resources, grievances and the culture of the local population across space and time. NATO commanders will need to develop new model and simulation capabilities to better understand today's complex operating environment (OE).

The complexity of a hybrid warfare environment can be described by McCabe's cyclomatic complexity number¹ – where complexity in the real-world environment increases as the number of entities (nodes), connected edges (relationships and inter-correlated effects) and active paths (feedback loops) increases. This complexity and uncertainty in modeling and simulation (M&S) of hybrid warfare environments and non-traditional security threats can produce a wide range of variations in predicted results due to: 1) the lack of data; 2) challenges of processing and analyzing Big Data; and 3) challenges in modeling human, cultural and organizational behavior that contribute to uncertainty.

In M&S hybrid warfare environments, the goal is to identify each important source of uncertainty, and then quantify its magnitude, risk, and impact in decision making. Uncertainty Quantification (UQ) involves the identification, characterization, propagation, analysis and reduction of all uncertainties in M&S [6]. Various types of uncertainties need to be considered including: parameter uncertainty, parametric variability, structural uncertainty, algorithmic uncertainty, experimental uncertainty, and interpolation uncertainty. This

¹ Complexity is being defined as a function of the number of entities and entity interaction/relationships in a manner in kind with McCabe's Cyclomatic number (McCabe 1976) used in the software community.

paper will present techniques to collect, model, simulate, and analyse data in iterative loops to reduce unknown uncertainty in M&S. The authors will also describe stochastic capabilities that augment commanders' decision making, to help them better understand the current and forecasted problems, risks, impacts, and resource dependencies. The combination of these capabilities with a set of supporting technologies (MSAL, Big Data Analytics, cognitive, and graph computing components) integrated into a common framework will enable better 1) simulations of optimal operation approaches; 2) deployment of resources; and 3) understanding of risks within an OE to achieve the end state.

2.0 CHALLENGES OF MODELING AND SIMULATING HYBRID WARFARE ENVIRONMENTS

In Hybrid warfare, insurgents combine traditional, disruptive, catastrophic, and irregular capabilities to then create advantageous conditions, quickly changing the nature of the conflict and moving to employ capabilities for which the NATO allied forces are least prepared. In hybrid warfare, the enemy uses small groups to engage in complex terrain and urban environments, where they hide and fight among the people to offset allied forces [1]. These tactics used by insurgents in hybrid warfare try to exhaust/defeat allied forces by creating grey zones. These grey zones create a challenge for allied forces because they have to develop capabilities to understand human aspects of the operational environment through these operational environment variables: political, military, economic, social, information, infrastructure, physical environment, and time (known as PMESII-PT).

Applying the PMESII-PT framework to understand human and organizational behaviour is a challenge because there is a high degree of uncertainty in the variables discussed above, and risk inherent in understanding how humans will behave and react to traditional, disruptive, catastrophic, irregular, climate change, and non-traditional threats (water, food, and energy insecurities) [1]. In addition, modeling the PMESII-PT operating environment variables are a challenge because they introduce complex cultural, demographic, and physical environmental factors to the model. These factors add to the uncertainty and risk in understanding and making decisions on how to intervene in an operational environment. Also, NATO forces are potentially challenged to keep pace with the current/future situation and problems in the dynamics, interconnectedness, and extreme volatility of a hybrid warfare operating environment.

Leveraging defense information such as “all source, multi-INT” for PMESII-PT data has its challenges. Difficulties in collection, processing, analyzing, and visualizing of the associated Big Data (using traditional methods) contribute to the challenges in understanding the PMESII-PT variables. Traditional M&S technologies have challenges in processing the large volumes, variety, veracity and velocity associated with multi-INT Big Data, e.g., exploring and discovering the nth interrelationships between indirect variables within and across networks needed to model real-world hybrid warfare environments. These challenges lead to the inability to accurately: 1) Model strategy—matching the problem to the real world; 2) Model tactics—designing the internal structure of a model; and 3) Model physical phenomena and human behavior —dealing with uncertainty and adaptation.

New Capabilities to Understand Hybrid Warfare Environment This work will apply concepts of system dynamics and cybernetics supported by an integrated set of technologies like Big Data (information extraction), graph computing, cognitive computing and IoT to help decision makers understand the complexities of the entities, drivers, relationships, and feedback loops that exist in the hybrid warfare operating environment. This paper will discuss how the use of cybernetics will better enable the understanding of the PMESII-PT variables in an operating environment for planning mission operations. The concepts and technologies presented in this paper will provide decision makers the capabilities to capture factors that are critical in the urban battlespace.

Cybernetic capabilities are important for decision makers to understand how human and organizational behaviors play across the full spectrum of operations, particularly during urban operations. As stated by the Joint Urban Operations Workshop: “Employ high-resolution modeling, simulations, and other decision support tools that incorporate friendly, enemy, and neutral forces, plus the urban population in order to conduct rehearsals, assess courses of action, and make better decisions faster than the enemy in an urban operation” (Mahoney, 2005). A platform containing these concepts and technologies will enable decision makers to:

- 1) Semi-automate the process of data collection and graphically depicting the entities, relationships, and feedback loops into an environment model as they exist in the real world;
- 2) Understand regional physical and human behaviour problems; perform abductive reasoning; predict future impacts on regional socio-economic and environment stability;
- 3) Predict future possible outcomes of conflicts;
- 4) Better visualize the end-state;
- 5) Understand human and organization behaviours – dealing with uncertainty and adaptation;
- 6) Derive M&S optimal solutions with known probabilities of success, performance, and uncertainty (aleatoric/epistemic) to achieve mission goals.
- 7) Combine components and federating models to span multiple levels of the M&S pyramid of strategy and tactics by linking and traversing a set of graph models.

Adopting these platform capabilities would allow NATO to develop the capability to better intervene in hybrid warfare to prevent crises, manage conflicts and stabilize post-conflict situation.

The Battle of Aleppo (2016) is an example of a complex hybrid warfare environment that contain multiple state, non-state, and foreign countries that use traditional, catastrophic, disruptive, irregular warfare tactics to impose their will on the civilians in supporting or overthrowing the local government. The military confrontation in Aleppo is mostly between the Free Syrian Army, Islamic Front, People's Defense Units and Sunni militants against the Syrian government, Hezbollah and Shiite militants. The ongoing conflict in Syria involves foreign countries like U.S., Russia, Iran, and Saudi Arabia participating in a series of overlapping proxy wars between the regional and world powers [14]. The city of Aleppo used to be Syria’s commercial capital – still mixed with multicultural groups (Kurds, Iranians, Turkmen, Armenians and Circassians) and multi-denominational churches and mosques that still share the space. Nationwide protests against the government of President Bashar al-Assad started in March 2011, as part of the “Arab Spring” movement. These protests were led by disgruntled countrymen who were forced to leave their farms and villages in Al-Bab, Marea, Azaz, Tel Rifaat and Manbi due to droughts, lack of water or food. When these people arrived in Aleppo, the Syrian government failed to provide their basic needs. Tensions between the rich and poor, different cultures, and ethnic groups broke into protests and conflicts. The Free Syrian Army, largely composed of army defectors, were able to provide Aleppo countryside men with their basic needs. In turn the Free Syrian Army won their loyalty and were able to recruit many to join their army, support their ideology, and attempt to overthrow the Syrian government [8].

The war in Aleppo is composed of complex and uncertain interconnected parts and behaviors. This work will discuss how system dynamics and cybernetic concepts supported by MSAL, Big Data, IoT, Cloud, and cognitive computing enables decision makers to model and simulate complex and unpredictable systems-- combining components and federating models from the conceptual (strategic) to the tactical model in the M&S pyramid. The cybernetics cognitive and social systems technologies will be applied to help decision makers understand “circular causal” relationships and interplays of the PMESII-PT variables influencing and triggering change in Aleppo’s OE. These capabilities will help decision makers understand the current and predicted situational awareness, visualize the end state and goals, and derive optimal alternative mission approaches through iterative MSALs to answer these questions:

1. What groups make up the rebel forces? What are their Ends, Ways, and Means?
2. What groups make up the established government/ military forces?
3. Who are the most influential people/organizations/outlets?
4. What are the social culture impacts caused by the conflict? What's the current refugee situation?
5. How does water/farming play a vital role in Aleppo's sustainable development that include human health, food and energy security, urbanization, and industrial growth?
6. How does economics play into the conflict? What's the impact to cost of living? What business benefit, what businesses are destroyed by the conflict?

3.0 SYSTEM DYNAMICS ENABLING THE M&S OF COMPLEX ENVIRONMENTS

System dynamics modeling is a method of modeling the dynamic behavior of complex systems by breaking down these systems into simpler interconnected components ("blocks") which are connected together via links that as a whole exhibit one or more properties (i.e. behaviors) not obvious from the properties of the individual parts. This method can allow decision makers to model and simulate hybrid warfare Operational Environments (OEs) like Aleppo's complex social, warfighting, economic, political, and ecological systems. Applying system dynamics enables M&S of complex interdependencies in the Aleppo operating environment.

The Aleppo entities representing disorganized complexity are treated using probability theory and statistical mechanics. System dynamics enable the M&S of the many complex systems represented in Aleppo's operating environment and capture 1) the large number of entities, with 2) non-trivial interaction networks, whose 3) impacts on one another are non-linear, and whose overall behaviour tends to display emergent characteristics.

3.1 Modeling and Simulation of Complex Environments

The Observe-Orient-Decide-Act (OODA) loop is a good way to represent the decision-making behavior in a SoS simulation as shown in Figure 1. The idea behind OODA is that decision-making occurs in quick recurring cycles while observing and reacting to unfolding events rapidly [7]. The four interrelated and overlapping OODA processes are listed below.

- **Observe:** the collection of data by means of sensing. Enhance **understanding** of operating environment PMESII-PT variables. Big Data, IoT, NLP, and advanced analytics enable the collection, fusion, and analysis of multi-INT data. The NLP and information extraction enables automated extraction of entities, relations, and co-references between entities into structured databases like SOLR. Applying graph computing enables an automated graphical depiction of a Common Operating Picture (COP) in the form of a Knowledge Graph representing the real-world (SoS). This will enhance current **understanding** of the forces driving regional violence and instability. This will improve the decision maker's abilities to identify non-obvious relationships that may be causing problems in the region. Graph computing algorithms like graph database, network topological, graph matching and search, and probabilistic graphical model will enable defining the mission model under test and possible mission threads to achieve the mission goals.

- **Orient:** the analysis and synthesis of data to form one’s current mental perspective. The use of agent based models, cognitive models, expert systems, dynamical systems, cybernetics, and input-output models, descriptive, and predictive analytics provide capabilities to create an abstract model of the real-world. These technologies will help model and visualize the current situation and predict the impacts of hybrid warfare.
- **Decide:** the determination of a course of action based on one’s current mental perspective. Cognitive computing will augment human thinking in understanding information extracted from human text and perform reasoning to test multiple complementary, contradicting, and competing ideas that will help decision makers establish connections and potential connections between stakeholders, organizations, and other factors, and dynamics that we simply would not discern using our human intuition or common sense alone.
- **Act:** the mission thread represents the operations and technical entities and inter-entity behaviors of the end-to-end activities to meet a goal. Simulation is a dynamic representation of traversing the mission model (graph model) in analyzing the entities inter-behaviors to best achieve the end state. Agent-based simulation techniques are preferred because they are inherently graph-based, explicitly address relationships, and lend themselves to discovering emergent behaviors [8].

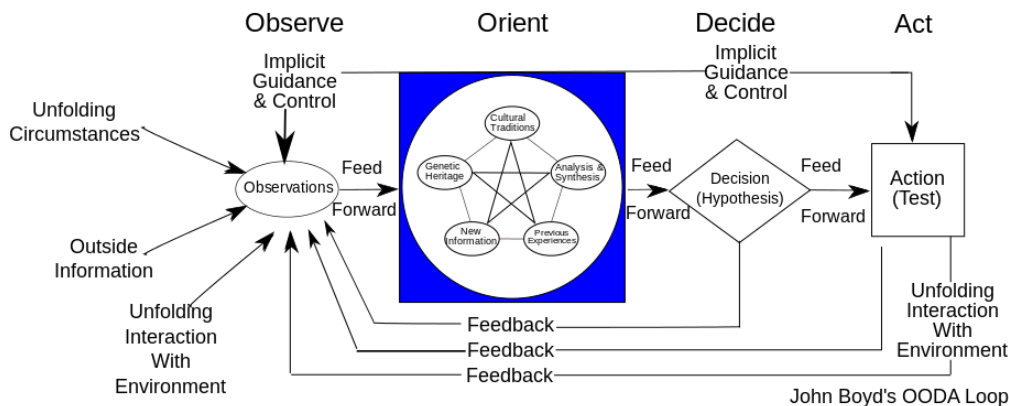


Figure 1 – The OODA Loop

3.2 Modeling-Simulation-Analytics-Looping (MSAL)

Modeling-Simulation-Analytics-Looping (MSAL) provides a framework to model systems of systems (SoS) that enables decision-makers to apply systems thinking in understanding complex and uncertain behavior patterns in real-world environments [9]. The MSAL framework naturally aligns military planning, training, and employment processes used to intervene in hybrid warfare environments like Aleppo. The MSAL architecture illustrated in Figure 2 provides modelers/analysts with a method to create a mission environment model that graphically depicts the PMESII variables and the relationships between them as they exist in the Operating Environment (OE). MSAL is based on iterative looping between modeling, simulation and Big Data and advanced analytics. It applies mathematical architecture techniques that focus on the mission environment and goal-based mission threads (plausible outcomes) to answer key questions about optimal alternative approaches to achieve desired mission goals. The goal-based mission threads are based on the underlying combinatory effects to quantitatively answer key questions about drivers and pressures effecting PMESII-PT variables, relationships, and feedback loop interactions that makeup the OE [7].

MSAL is a set of three nested loops about a common Mission Model. The Uber Loop is the intersection of the real or tactical world with the virtual run-time environment. The Uber Loop is a process where modelers use a construct called the **mission environment** to create a real-world system thinking model of the OE. The mission environment model allows decision-makers to visualize the real-world environments (entities, behaviors and interconnections) as a set of nodes, edges and paths/walks in the graph. The Model-Analysis-Loop (MAL) creates the static models (**mission model**) that are abstractions of the real world mission environment model that is under test. In the MAL process, decision-makers define the **goals** and supporting **mission threads** (sequence of nodes and events/stimulus) to achieve the goals. The **Simulation-Analysis-Loop** (SAL) tests the dynamic behavior of a model along a goal-based, mission thread via simulation to quantify both performance and uncertainty. The MSAL determines optimal alternative approaches using quantitative risk models that calculate the impact of the uncertain parameters and decisions through continuous MSAL processing of past and current data. [9].

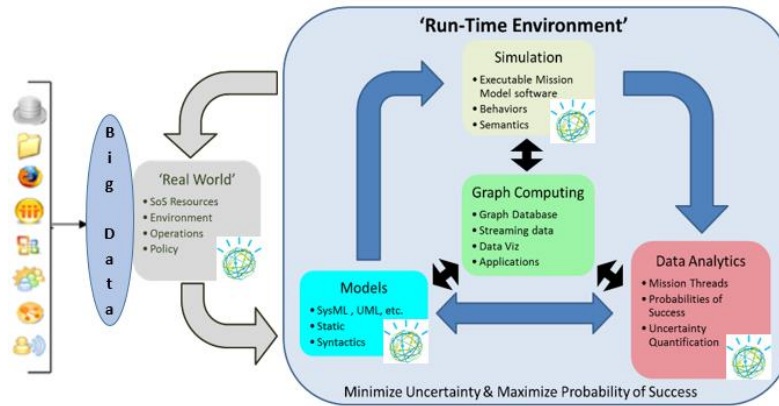


Figure 2 – Model-Simulation-Analysis-Looping Architecture

3.3 Modeling the Real-World Environment

The MSAL architecture provides graph analytics to create an abstract model that represents the complexities and uncertainties of the real-world situation(s). The mission environment is a SoS representing the entities, structures, and interconnections. The mission environment models are represented as graphs, enabling the ability to capture and represent complex relationships in systems. In a hybrid warfare environment – the mission environment represents the PMESII-PT OE variables, relations, and feedback loops as they exist in the real-world. Big Data technologies, Natural Language Processing (NLP), contextual analytics, and graph computing enables the collection of structured/unstructured data. A Common Operating Picture (COP) can be constructed that represents the complexities and uncertainties of the population, human and organizational behaviours, and their inner connections to real-world situations.

IoT (Internet of Things) is a key technology to collect environment data from the entities/systems represented in your mission environment (real-world), as illustrated in figure 3. For example, in the Aleppo OE battlefield – IoT enables things to be instrumented, interconnected, and intelligent. These capabilities plus Big Data technologies (Streams, Cloudant DB, Apache Spark) enables the capture of data sources in real-time.

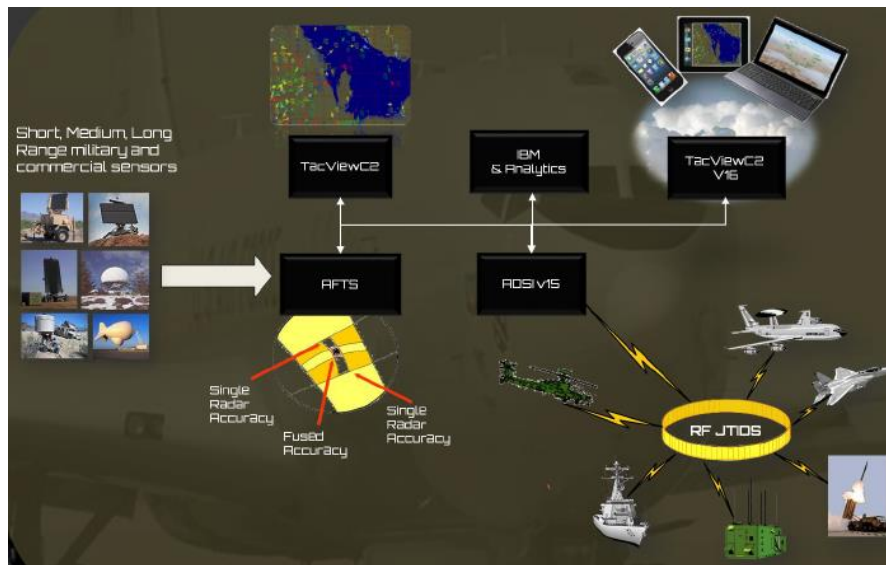


Figure 3 – Capturing Battlefield Environment Structured Data

3.4 Modeling an Environment’s Human, Organizational, and Societal Behaviours

When extreme weather events hit a region or basic needs for citizens are not met, like in Aleppo – extremists seize opportunities to use unconventional, irregular, and criminal tactics to create conditions of instability in regions. The threat actors in Aleppo use irregular warfare tactics like blending with civilians to protect themselves against allied strikes. NATO can improve their situational understanding of who are these Syrian government’s opposition like Syrian National Coalition; and what foreign involvement are they receiving (military, financial, logistical, and political); and how do their actions favor/conflict with NATO’s overall strategy. Also, understand who are the Syrian government’s opposition forces (Islamic State (ISIL)) opposing NATO’s strategic mission goals and who (U.S., Russia, and France) are participating in direct military action against ISIL in the territory of Syria. In order to better understand the current PMESII-PT variables, relationships, and feedback loops in the Aleppo OE – NATO could adopt techniques such as web crawlers, NLP, information extraction, contextual analytics, and graph computing to automate the collection of unstructured data (text, voice, and video) and extraction of an ontology’s entity types (people, places, resources, organizations, etc.) and their relations and co-references; store the data in a structured format (SOLR/Cloudant DB); and dynamically create a COP of the real-world. These capabilities will enable continuous collection of unstructured data and extraction of tacit knowledge from the unstructured data into implicit knowledge for intelligence analysis.

A widely used classification framework for mention detection is the Maximum Entropy classifier, which integrates arbitrary types of information and makes a classification decision by aggregating all information available for a given classification [9]. Figure 4 illustrates how the Maximum Entropy classifier (statistic machine translation) enables computers to extract and understand important entities mentioned in textual data and relationships between them (like terrorist and insurgent networks and organizational structures and events) where modelers can ingest the unstructured data into their mission environment models and apply graph computing techniques (relation graphs, multivariate graphs, etc.) that can be used to dynamically depict COP

of the OE.

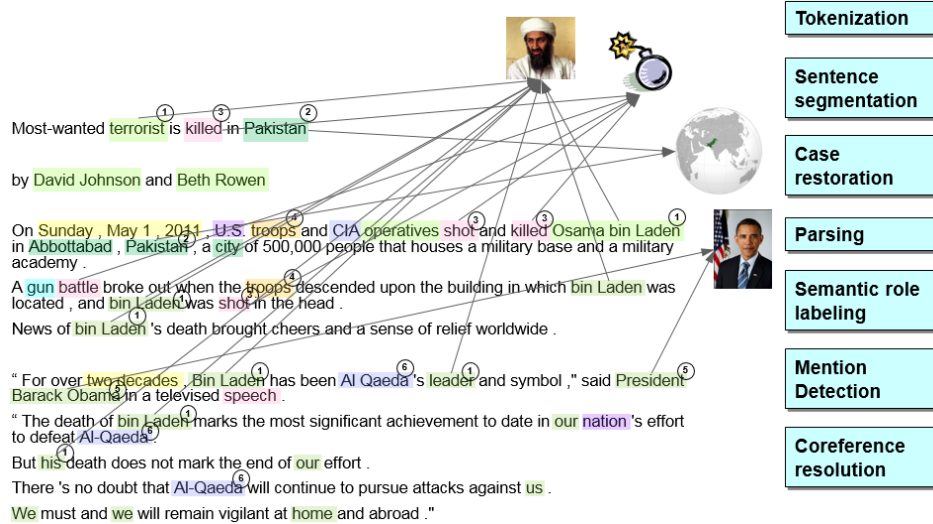


Figure 4 – Information Extraction

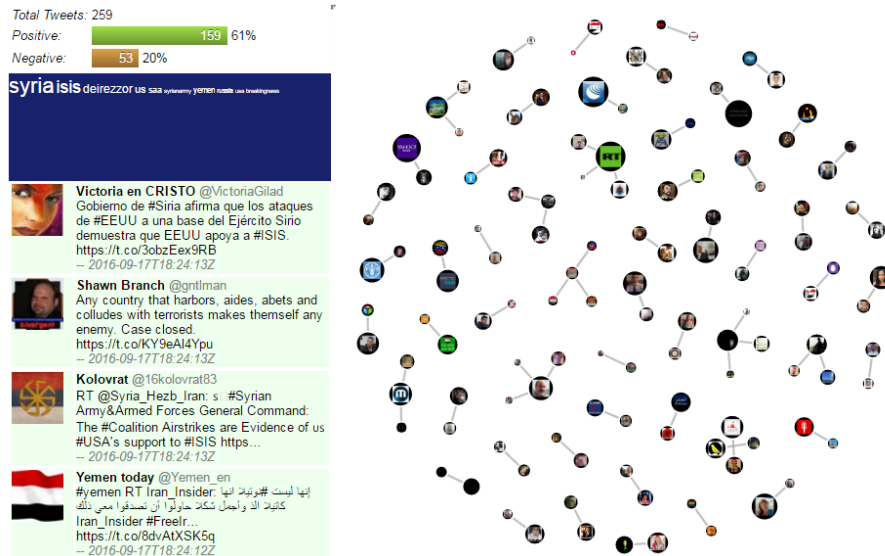


Figure 5 – Real-time COP of an OE's Entities and Relations and Sentiment

The mission environment provides decision makers a current understanding the entities, relationships, and feedback loops within the OE. For example in the Aleppo, Syrian conflict – decision makers will have an understanding of the insurgents, counter-insurgents, and terrorist groups; lethal events of asymmetric unconventional warfare tactics; social networks and influencers; who's receiving support from foreign nations/criminal organizations; what support is being provided (financial, military, logistical, etc.); and events of

civil war, state-on-state, insurgency, mass migration, competition for resources occurring in the OE, as illustrated in figure 5.

3.5 Abstracting the Real World - Understanding, Projecting, and Forming Societal Behavior

As stated above, hybrid threats will require NATO to support a wide ROMO from peace keeping, crisis management, and military operations. The military leaders know these future engagements will be mostly influenced by society: political and military organizations, ethnic groups, national cultures, and transnational religious organizations [15]. It will be important for decision makers to model the individual, organization behaviors of the PMESII-PT OE variables. The mission environment provides decision makers a common visualization and assessment of the real-world OE. The MAL framework provides the capabilities to leverage models to developed tactical, operational, and strategic missions.

MAL enables leaders to create the static models (**mission model**) that are abstractions of the real world (mission environment model) that is under test. MAL provides an operational design approach to help decision makers link ends, ways, and means to achieve the desired end state (see figure 6). The mission model is a set of scenarios that identify the major systems/actors that must be represented by the simulation, a conceptual description of the capabilities, behaviors, and relationships (interactions) between these major systems/actors over time. The decision makers will use the MAL framework to:

1. **Understand the Problem** – using human, organizational, and societal behavioral models, leaders are able to identify the current and predicted set of obstacles the commander needs to overcome to achieve the end-state.
2. **Visualize the End-State** – decision makers define the military end state that must be achieved, how is it related to the strategic end state, and what objectives must be achieved to enable that end state. This step defines the model under test.
3. **Design the Operational Approach** – in this step, decision makers define sequence of actions and critical capabilities (*mission threads*) which are most likely to achieve those objectives and the end state (*Ways*). They need to determine the required resources to accomplish that sequence of actions within given or requested resources (*Means*). In the MAL, the **mission threads** (plausible outcomes) are based on the underlying combinatorics of everything in the mission environment model (real-world). The Simulation Analytics Looping (SAL) will simulate the performance, probability of success, unacceptable consequences, and uncertainty in performing that sequence of actions (*Risk*). Dynamically simulating the mission threads will determine optimal alternative approaches that are the most probable and provide insight into the general order of actions. See section 3.9 on “Simulating the Optimal Goal-Based Mission Threads” for an explanation of the SAL process.

During the MAL process, modelers can use graph computing, Social Network Analysis (SNA), link analysis, and agent based models (ABMs) to understand, project, form, and intervene in urban situations. These models and technologies will help modelers understand and project: 1) overlapping society networks; 2) local cultures and ethnic groups; 3) local economies; 4) adversaries’ actions, and individual and collective behaviors. These models combine elements of voting, game theory, preference, complex systems, emergence, computational sociology, multi-agent systems, operational/managerial independence, evolutionary programming [10]. Applying these models on the unstructured data will enable decision makers to 1) plan and measure the effectiveness of PSYOPS campaigns; 2) monitor and predict regional socio-economic stability; and 3) identify who is or likely to harbor or become a terrorist.

The goal of the MAL process is to reduce the number of mission models to the ones with the most impact on the model under test to perform in the SAL. This is done by performing iterations on the mission threads in the model under test using network topological analysis to look for characteristics such as complexity, centrality, density, etc.

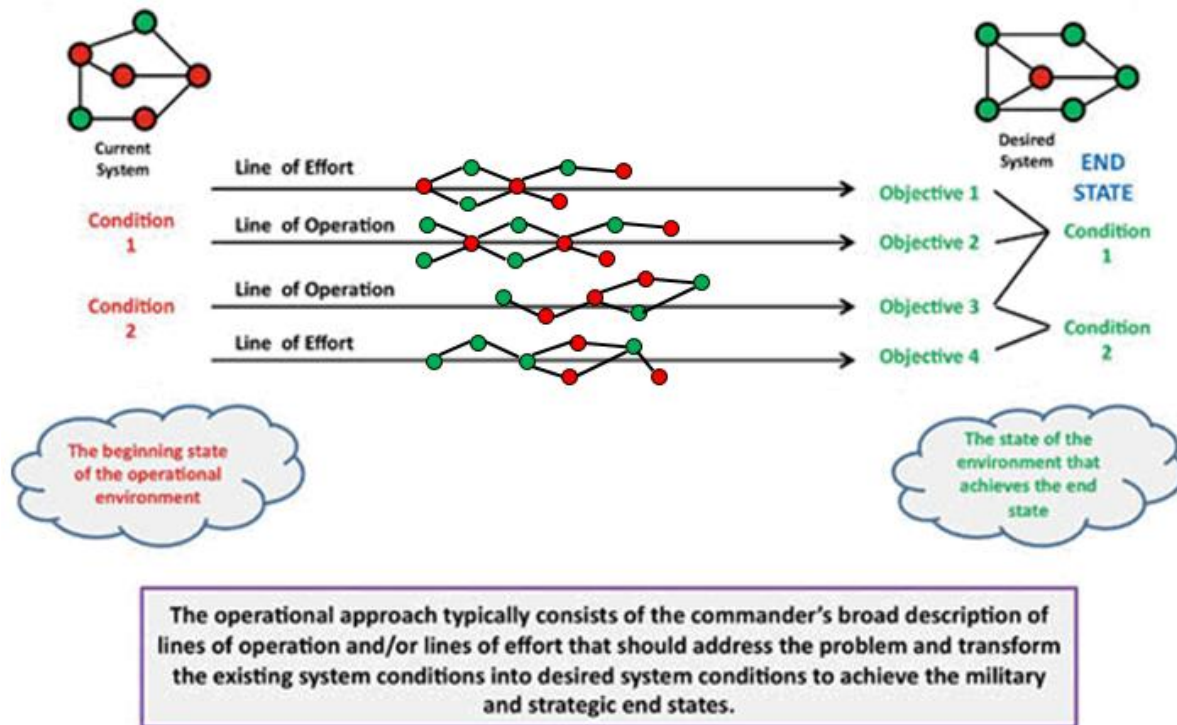


Figure 6 – MAL - Mission Goals, Mission Model, and Mission Threads

3.6 M&S Graphs and Graph Analytics

This section will explain how graph computing (database, analytics, and models) applies to M&S. Graph computing provides the definition of the execution of events to be used in a simulation (an event string is a graph path). Two fundamental components of a simulation model are a set of **state variables** and a set of **events**. The model emulates the system being studied by producing state trajectories/paths; that is, time plots of the values of the system's state variables. Measures of performance are determined as statistics of these state trajectories. In addition to graphs defining the order in which events are processed in a simulation, graphs can also be the basis for stochastic simulation, e.g., Markov chains, Bayes nets, and credal nets. For example, a Bayesian network (Bayes network or belief network) is a probabilistic graphical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph (DAG). A Bayesian network could be used to represent the probabilistic relationships between prolonged food shortages and famine. Given food shortages, the network can be used to compute the probabilities of the presence of various famine [7].

The second way in which graphs apply to simulation is in the definition of scenarios. A scenario (or mission) is an identification of the major systems/players that must be represented by the simulation, a conceptual description of the capabilities, behavior, and relationships (interactions) between these major system/players

over time, and a specification of relevant environmental conditions (e.g., terrain, atmospheric) [16]. It is common to think of scenarios as event based and cast as a directed acyclic graph (DAG) with branches at decision points. Unlike a fault tree, scenarios are described as a *success tree* [7]. The data associated with the scenario is commonly captured in an ontology. Ontology is a model of the entity types, attributes, and relationships of the entity types that exist for a specific real-world domain. Ontology compartmentalizes the variables needed for some set of computations and establishes the relationships between them.

3.7 Understanding PMES Variables (Individual and Organizations Behaviors)

Modelers can use micro (individual), macro (organizational), and meso-level (between the micro/macro levels) models to understand individual and group interactions. These models include several social decision models, social network models, link analysis, and agent-based modeling (ABM). These models can be used to model individuals and groups’ political, social psychology, sociology, and economics behavior within an urban OE [10]. Applying these types of models on the information extracted from unstructured data, analyzed using contextual (relation graph) and cognitive analytics (Deep Learning and Emotion Analysis) and then representing the data in a graph database and spatiotemporal analytics (space/time) will enable better mapping and prediction of individuals and organizations behavior, anomalies in pattern of life, and cross person and group analysis. Applying these technologies and models will enable decision makers to understand and better predict how individuals and their group interactions will react to events in a hybrid warfare OE such as terrorism, civil war, state-on-state, insurgency, mass migration, competition for resources, and extreme weather events.

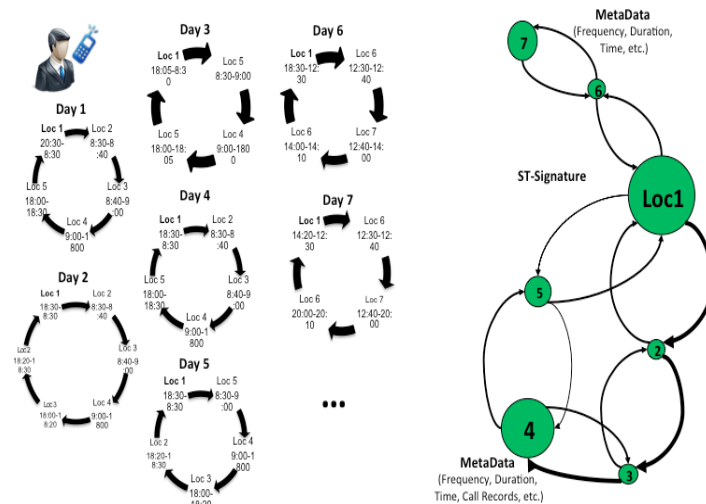


Figure 7 – Predicting Patterns of Life

In understanding how individuals and groups will react to hybrid warfare OE events, modelers need to use voting models that assume people reveal their true preferences, game theory models that assume people behave strategically in their own interest, and social psychological models that consider how individual preferences might change in group interactions. Also, cognitive models enable the modeling of both transient states and more permanent traits. Transient states are short lasting emotions, such as joy, fear, anger, and sadness, as well as longer lasting moods (e.g., fearful, happy, sad). Traits include affective personality traits, such as emotional stability and extraversion of the five-factor personality model [10].

The collection of unstructured data (such as email, text messages, tweets, forum posts, etc.) provides a natural data set for applying five-factor personality model because these social networks use similar individual,

organization, and societal models discussed in this paper. The five-factor personality model is often referred to by the five-mnemonic OCEAN, where O stands for Openness, C for Conscientiousness, E for Extraversion, A for Agreeableness, and N for Neuroticism gives the capabilities to understand individual personality characteristics, needs, and values [13]. By applying the human and organization behavioral models along with the use of information extraction, psycholinguistic dimensions, and network topological analysis (Centralities, PageRank, Communities, Neighborhood) – modelers can: 1) generate personality profiles (Human essentials - human dynamics, and info reasoning and morphing/sentiment); and 2) gain a deeper understanding of terrorist's personality characteristics, needs, and values to help intelligence analysts understand their behaviors/reactions. The five-mnemonic OCEAN personality characteristics identify an individual's preferences in making choices, as illustrated in figure 8. When linking voting models with cognitive models, the five-mnemonic OCEAN personality characteristics are importance because they enable the modeler to better understand how individuals make choices in groups where individuals can be acting rationally but as a group acting irrational.

Modelers can use these models and technologies to understand the population's society and culture elements and relationships within an OE such as: 1) organization of key groups in the society; 2) relationships and tensions among groups; ideologies and narratives that resonate with groups; 4) values of groups (including tribes), interests, and motivations; 5) means by which groups (including tribes) communicate, and 6) the society's leadership.



Figure 8 – Five-Mnemonic OCEAN Personality Characteristics

An important note, the social media services used by terrorists are based on Social Network Analysis (SNA), linked analysis, and network topological analysis techniques. Therefore, using Big Data, NLP, information extraction, and graph computing technologies on structured and unstructured data can enable modelers to accurately and dynamically depict how an adversary is organized and equipped, the threat's capabilities, and

how the threat has employed forces in the past. Modelers could use the MAL framework along with the above technologies and human, organization, societal models to design mission threads that 1) identify high-value target lists within groups; 2) exploit adversary’s weakness; and 3) employ asymmetric tactics to disrupt the adversary’s irregular warfare methods, social/culture networks, logistic/supply networks, and economic activities.

3.8 Leveraging Cognitive Assistants to Perform Mission Intelligence

In modeling and simulating complex real-world hybrid warfare OEs such as the Aleppo, Syrian conflict there are many PMESII-PT entities, behaviours and interactions to understand. When considering all the actors, cultures, religious, political, economic, policies/treaties, standard operation procedures, etc. decision makers need to remember that, when intervening in an OE, the problems, criteria and weights, and enumerations stress human rational thinking, leading to intuition thinking which causes uncertainty. Cognitive systems provide the ability to understand complex problems that involve multiple decision criteria, weights, and facts to infer the most likely answer based on the evidence. Cognitive systems are able to understand the explicit and implicit knowledge contained in human language by combining three main technologies that enable human cognitive thinking: NLP/Information Extraction, hypothesis generation and evaluation, and dynamic learning computing [1]. Cognitive systems use ontologies that represent the entities and relationships as they exist in the real world. These cognitive technologies enable cognitive solutions to ingest and extract entities and relationships from unstructured data sources and convert the data into the ontology structured model stored in a corpus. Once the unstructured data is stored in a corpus – cognitive systems like IBM Watson, illustrated in figure 9, apply: 1) questions analysis; 2) probabilistic computing (hypothesis generation and evidence scoring/ concept detection models); 3) final merge and ranking of overlapping or duplicate answers; and 4) supporting evidence merging and ranking (applies the justifying passage model to evidence) to reason/infer a ranked list of answers & evidence drawn from the system’s corpus of knowledge [1].

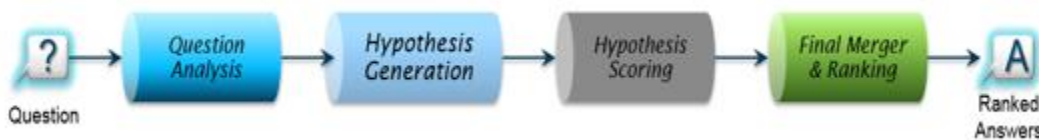


Figure 9 - IBM Watson's DeepQA Factoid Pipeline

Graph databases and models can be used to represent the cognitive system’s corpus as a knowledge graph defined by the ontology as sets of nodes (entities) that are connected by edges representing the relationships between entities. Cognitive systems, illustrated in figure 10, can apply reasoning models (Markovian & Bayesian Networks, Anomaly Detection Tools, etc.) and cognitive networks (Deep Learning/Emotion Analysis) to perform multi-inferencing that identify and computationally infer non-obvious relationships spanning over time. This capability will enable users to understand and correlate events occurring beyond one’s observation space thus reducing uncertainty and risk in decision making.

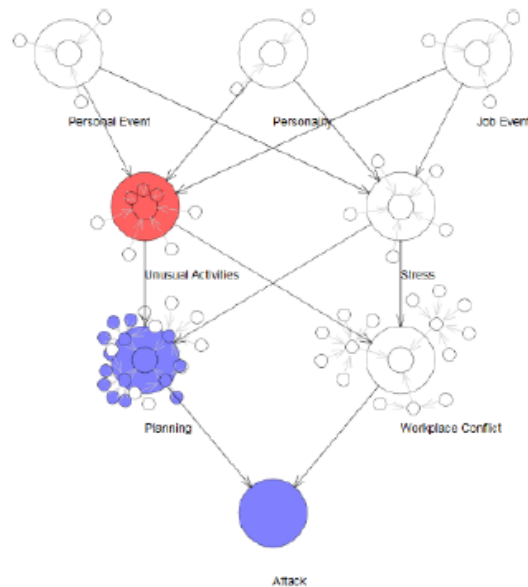


Figure 10 - Machine Learning and Deep Reasoning²

Symbiotic Cognitive Systems (Cogs) can be used to model human agents (nodes) in an abstract model. Cogs can perform abductive reasoning by applying hypotheses and evidence computing to reason about complementary, contradicting, and competing theories like grievances, greed, opportunities, and conflict cleavages (master/private cleavage (religious, north vs. south, etc.)) to reason/explain the actors, relationships and feedback loops influencing events in an OE. Cogs work together in a distributed simulated/live environment to apply probabilistic computing to every stimulus event and learn through feedback loops [17]. This will enable cognitive information to flow across a Bayes network, Markovian, and Deep Belief Networks that leverages multi-inferencing to look across entire corpora of knowledge enabling discovery of unknowns. Cogs will enable self-learning agents based on simulation runs that will be able to perform complex data-driven decision-making.

3.9 Simulating the Optimal Goal-Based Mission Threads

The Simulation-Analysis-Loop (SAL) is a simulation and analytics framework that enables decision makers to test the dynamic behaviour of a hybrid warfare model along with a goal-based, mission thread via simulation to quantify both performance and uncertainty [7]. As discussed above, hybrid warfare environments are complex OEs involving many entities, events, relations, and feedback loops such as transnational criminal/terrorist activities, insurgents, civil war, and competition for resources. The MSAL framework will enable modelers to M&S these classes of SoS that make up the hybrid warfare OE: collaborative systems, directed systems, virtual systems, and knowledge systems. The decision makers' decisions will be stochastic in nature – based on the M&S and cognitive processes to make the decision. The graph computing technology used in the MSAL framework enables the basis for stochastic simulation, e.g., Bayesian networks, Markov chains, credal nets – to M&S the hybrid warfare OEs.

² Source: 2016 IBM Corporation System G - Graph Computing as an Intelligence Machine

Once the mission goals, mission model, and possible mission threads have been developed for a hybrid warfare environment that represents the complex entities, events, relations, and feedback loops, the next step of the MSAL iterative loop process is to simulate the dynamic behavior of the model to determine optimal alternative approaches based on performance and uncertainty quantification calculations of Areas of Noteworthy Performance (ANPs). The SAL simulation process is initially driven by one-at-a-time parameter sensitivity studies to understand how the uncertainty in the output of the models or system can be apportioned to different sources of uncertainty in its inputs. The sensitivity analysis helps to increase the understanding of the relationships between input and output variables in a system or model. This also helps with uncertainty reduction by identifying model inputs that cause significant uncertainty in the output. This helps modelers focus on those input variables causing significant uncertainty and to work through the initial approach to bounding objective functions with uncertainty. The key PMESII variables that identify the mission model's entities, behaviors, and relations are binned to run optimization campaigns and calculate local uncertainty for ANP.

The next step is to conduct uncertainty quantification to identify noteworthy performance, global maximums and minimums, and those areas within which the model may want to be optimized. Uncertainty quantification aims to reduce uncertainties in the real-world application mission environment and simulation models by running simulations to determine how likely certain outcomes are if some aspects of the system are not exactly known. M&S uncertainty in complex hybrid threats OEs can be represented as aleatoric and epistemic uncertainties (vernacularly distinguished as “known unknowns” and “unknown unknowns”). Aleatoric uncertainty, aka statistical uncertainty, is representative of unknowns that differ each time we run the same experiment. Aleatoric uncertainties are “irreducible” in the sense that they are always present. Epistemic uncertainty, aka systematic uncertainty, is due to things we could in principle know but don't in practice. Epistemic uncertainties are often “reducible” through investment, time or research [18]. The SAL process provides modelers the ability to use real-time streaming data or historical data collected from the mission environment model (real-world), apply analytics, and perform iterative looping and uncertainty quantification calculation to work toward reducing epistemic uncertainties to aleatoric uncertainties. Modelers can use techniques such as the Monte Carlo method, Karhunen–Loève, and/or polynomial chaos expansions to quantify aleatoric uncertainties; and they can use fuzzy logic, evidence theory and Dempster–Shafer theory to quantify epistemic uncertainties.

The MSAL process uses a quantitative risk model to calculate the impact of the uncertain parameters and the decisions actors make on outcomes that they care about. Such a model can help decision makers understand the impact of uncertainty and the consequences of different decisions. The process of risk analysis includes identifying and quantifying uncertainties, estimating their impact on outcomes that actors care about, building a risk analysis model that expresses these elements in quantitative form, exploring the model through simulation, and making risk management decisions that can help decision makers avoid, mitigate, or otherwise deal with risk.

Modelers use forward propagation to understand how the various sources of uncertainty are propagated through the model to predict the overall uncertainty in the system response [18]. Forward propagation enables modelers to focus on the causes/influence on the outputs from the parametric variability listed in the sources of uncertainty. For unknown uncertainties associated with the SoS's input sources, modelers can use inverse uncertainty assessment and parameter uncertainty to estimate the discrepancy between the experiment and the mathematical model (which is called bias correction), and estimate the values of unknown parameters in the model if there are any (which is called parameter calibration or simply calibration). Performing inverse uncertainty assessment and parameter uncertainty simultaneously enables the model parameters to be calibrated simultaneously using test data [18].

Each simulation run creates an instance of a mission thread. The integration of multiple instances of mission threads and subsequent use of Bayes (or Markov or credal) statistics create macro uncertainty about the mission thread. Bayesian networks enables the simulation model to model the mission threads as a set of random variables and their conditional dependencies via a directed acyclic graph (DAG). For example, a Bayesian network could represent the probabilistic relationships between drought, crop growth output, economic decline, and impacts on human well-being [19]. In this paper, a Bayes net can represent a military operation OODA based event trajectory. Modelers can use Markov networks to model undirected interactions of events based on random variables. Modelers can use Markov networks to model the probable outcomes of interactions between individuals participating in tribes, organization, and/or society given a stimulus within an OE. Modelers will run multiple iterative interrelated MSAL loops using real-world data collected and fused through Big Data to improve inverse uncertainty bias correction and parameter calibration. In each simulation loop, modelers calculate probability of success, P_s , for meeting mission goals and bounding macro uncertainty. The modelers can postulate new variable definitions to reduce uncertainty and new mission model to reduce uncertainty, and then iterate through the SAL. Is the probability of success P_s now acceptable? Have 'risky' ANP been reduced or eliminated? Are the macro and local uncertainty acceptable? If not, continue to iterate. After iterations of the MAL and SAL, new mission models are postulated from the SAL results. The updated mission model is returned to the Uber loop to update the mission environment and the model under test. New MAL to SAL cycle begins again [7].

Data Analytics – Simulation data is acted upon by parametric and statistical analysis tools to evaluate the performance of the multiple simulation runs. Graphical models are tested using inference testing and pattern recognition techniques. The graph computing environment provides the continuity across each of the above components in a holistic graph environment that provides the spatial and temporal continuity across multiple layers and mission threads [7].

The mission environment data (streaming and/or historical data) is used to run the “run-time environment.” This enables modelers to check run-time data against real world performance data and adjust both models and simulations to gain confidence in our run-time environment. Also, the ability to continuously collect real-world data and use it to drive the SAL runs and analyze the data using anomaly detection, spatiotemporal analytics, agent base models, and Bayesian Networks means that we can detect anomalies, robustness, and truthfulness of the data. This can help modelers see if there are hidden or stigmatized population, or illicit or private relations [10]. MSAL, Big Data, analytics, and the graph database enables modelers to connect the static and dynamic networks to observations and measurements and to address the scalability issues that burden algorithms that involve analyzing many links.

Figure 11 shows how modelers can use the SAL iterative looping to test the dynamic behavior of an abstract model representing the Aleppo conflict conditions. The SAL process can dynamically traverse the DAG graph (mission threads) and execute micro, macro, and meso human and organizational models to project the impacts on regional socio-economic and political stability attributes like food insecurity, increased population migration, increase social intension, etc. The graph computing enables modelers to iteratively add, update, and connect models through each looping. Each simulation looping provides better understanding of the uncertainties and accuracies of the agents, data, and interactions in the model. If the probability of success is low and ANP indicators are low, modelers can add and/or remove mission threads by connecting/disconnecting graphs. Then modelers can run another iteration of the model to determine the effects/consequence analysis such as risk to economic development, tension rising from refugees and indiscriminate bombings and deaths of children.

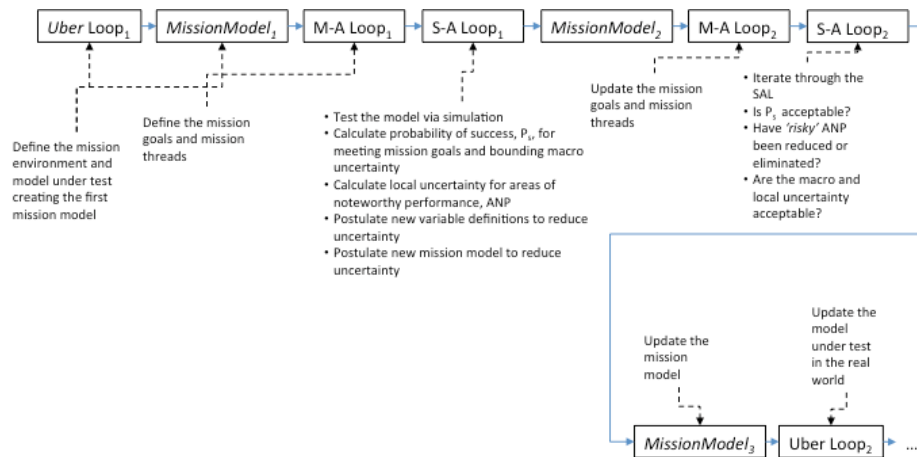


Figure 11 - MSAL Loop Timeline

Figure 12 shows how MSAL, cybernetics, system dynamics supported by Big Data, graph computing, cognitive computing, and IoT enables modelers to collect structured and unstructured data and develop a mission environment model (systems thinking model) linking the various sub-systems that represents the PMESII-PT entities, relations, and feedback loop as they exist in the real-world such as the current urban warfare situation in Aleppo, Syria. The MSAL framework enables modelers to use information extraction technologies to extract tactic knowledge from unstructured text combined with structured data in graph data and models. Modelers can apply individual, organization, and societal models like ABM to: 1) represent social groupings, people, biological entities, and physical systems; 2) understand how individual and group interactions generate macro-level outcomes. The mission model enables modelers to apply the models discussed in this paper (voting and social decision models, social network models, link analysis, multimode networks, and agent-based modeling (ABM)) to better understand and forecast the behavior and interaction of PMESII variables over space and time. This will enable decision makers to understand current and potential future problems to visualize the end-state to be achieved. The graph modeling enables decision makers to identify the set of entities (mission model) and possible mission threads to achieve the mission goals.

The SAL process enables decision makers to understand the dynamic behavior of the model under test through multiple iterative simulation runs (traversing the multi-mission threads (Bayes and/or Markov networks)) to calculate the probability of success to meet mission goals under known risk. The cogs can act as specialized domain agents that understand the cognitive concepts in the simulated data (collected from the real-world) to apply cognitive inference models that reason over multiple events, decision criteria, and weights to computational derive the optimal choices to meet mission goals. Through the multiple simulation iterations – the cogs can continuously adapt through machine learning to derive the best answers. The SAL process can use the cogs results to provide automated decision plans based on standard operating doctrine that describe the optimal alternative solutions to meet the mission goals.

Graph computing enables the combining of components and federating models. Each level in the M&S pyramid is presented as a graph – the resolution could be described as a graph, or set of graphs, which represent the system or mission of interest. Connecting strategic, operational, and tactical level missions would be a matter of traversing the pyramid - either merging graphs (going up) or extracting sub-graphs (going down). In this context, graphs would provide continuity across the M&S pyramid, allowing for data and structure connectivity [7].

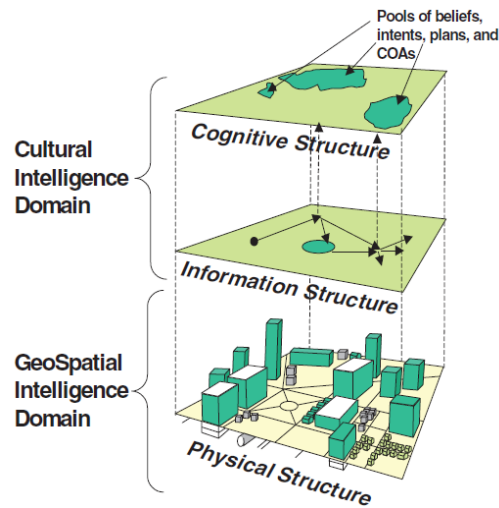


Figure 12 – Modeling the Physical and Human Behavioral Layers of an OE

Figure 13 shows a good representation of the different categories (entity types) and relationship types that the system thinking model should graphically depict as the mission environment. The MSAL framework provides a systems thinking framework that enables decision makers to graphically depict the stakeholders and the relationships between them as they exist in their OE. The system dynamics and cybernetics supported by Big Data, IoT, graph computing, and cognitive computing provide the decision makers with a platform that provides capabilities to collect MULTI-INT data from IoT and apply NLP/relationship extractions to automatically extract entities (people, places, locations, events, etc.); apply analytic models (values, beliefs, morals, expectations, values, customs, behaviors, needs, patterns of life, sociology, etc.); and graphically depict a COP that represents the mission environment. The commanders/intelligence analysts will use these different analytical models/graphical COPs to understand the dynamics related to various sub-systems within an AO and area of interest (AoI).

The platform provides military commanders/intelligence analysts with the intelligence analytical frameworks and graphical COP visualizations that enable them to analyse an aggregate (and ever-changing) system "holistically" as well as in terms of the individual forces. This systems thinking mapping allows the military to appreciate the connections between individual forces at the lowest levels and emergent effects at the aggregate level. Moreover, by depicting relationships graphically, a group of decision makers will more readily be able to imaginatively and creatively see places (both geographically, temporal, and conceptually) as windows of opportunity where the application of a commander's soldiers, resources, and unified-action relationships might influence counterinsurgent missions/activities within OE. The platform consists of Cogs that will provide the military abductive reasoning, center of gravity, and forecasting capabilities to understand what the effects of their specific missions will be once they are introduced into the environment, always appreciating that (i) their actions may not work as planned, (ii) their actions may very well generate hoped-for consequences, and (iii) their actions will also likely engender unintended and unforeseen consequences, as illustrated in Figure 13.

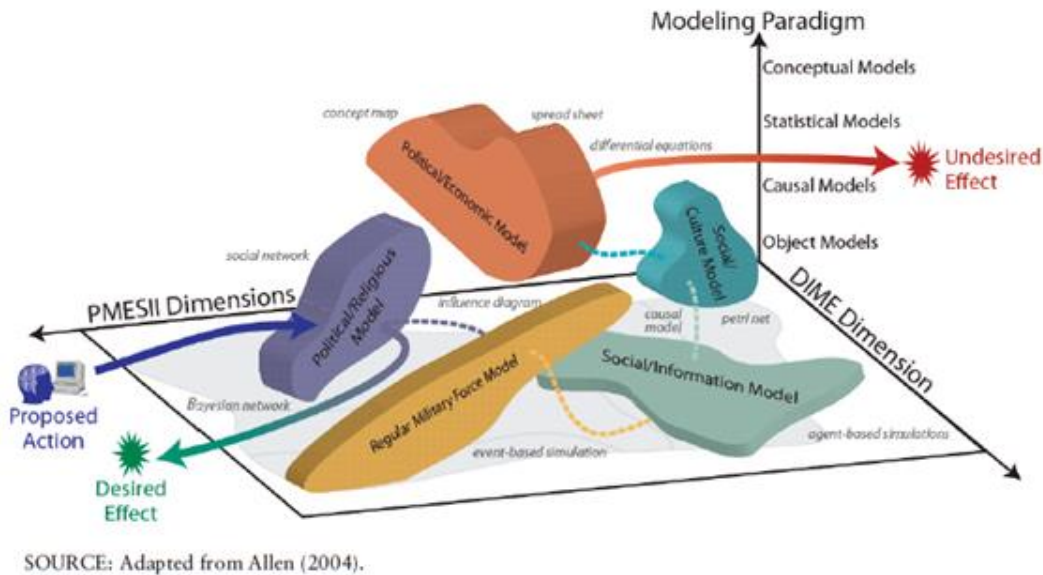


Figure 13 – Integrated Battle Command (IBC) Modeling Space

4.0 CONCLUSION

The hybrid warfare OE consists of persistent conflicts between terrorists, insurgents, established governments, and foreign countries fighting in overlapping proxy wars to pursue their own strategic interest. The adversaries will use traditional, irregular, asymmetric, immoral warfare tactics to achieve their goals. These factors and plus corruption and failed-states that cannot provide basic needs for their citizens have caused regional socio-economic instabilities. This paper has shown, to win in a complex persistent environment, decision makers can apply concepts of system dynamics and cybernetics supported by an integrated set of technologies like MSAL, Big Data, graph computing, cognitive computing and IoT to capture physical environment, cognitive, organizational, societal, and cultural factors of the PMESII’s variables over space and time that are critical in the urban battlespace. The MSAL framework supported by the above technologies enables the automation of data collection, fusion, analysis, and visualization of the mission environment (the real-world).

Once decision-makers have a common understanding of the operating environment and a clear definition of the problem – MSAL enables leaders to create the static models (**mission model**) that are abstractions of the real world (mission environment model) that is under test. Mission models (or scenario) are an identification of the major systems/actors that must be represented by the simulation, a conceptual description of the capabilities, behaviors, and relationships (interactions) between these major systems/actors over time. Decision-makers define the **goals** and supporting **mission threads** (plausible outcomes) based on the underlying combinatorics effects of everything in the real-world environment. During the MAL process, modelers can use multimode networks, social network models, link analysis, social decision models, and agent-based models (ABMs) for simulating the actions and interactions of autonomous agents (both individual, organizational, and societal) with a view to assessing their micro, macro, and meso effects on the system as a whole. It combines elements of game theory, complex systems, emergence, computational sociology, multi-agent systems, operational/managerial independence, and evolutionary programming.

Decision makers are able to use the SAL process to test the dynamic behavior of a hybrid warfare model along a goal-based, mission thread via simulation to quantify both performance and uncertainty. Modelers define

reductions and uncertainty bounds based on mission goals. Modelers perform multi-loop iterations of simulation runs on the mission model(s)' mission threads that interpolate and extrapolate real-world data (streaming/historical and structured/unstructured) from the Uber loop. For each simulation run, modelers calculate probability of success, P_s , for meeting mission goals; and apply uncertainty quantification methods (forward propagation, inverse assessment, and parameter uncertainty) to reduce epistemic and aleatoric uncertainties in ANP. By applying optimization, parametric, and uncertainty quantification sub-loops in SAL simulation runs on real-world mission threads – decision makers are able to identify optimal operational approaches that achieve end-state objectives while reducing the chance of failure or unacceptable consequences in performing that sequence of actions. Using cogs in the Uber loop and SAL provides the capabilities to apply standard operating procedures to test multiple complementary, contradicting, and competing ideas against evidence retrieved from real-world data that identifies tactical decisions and plans that best meet decision maker(s)' mission goals.

The SMAL framework supported by Big Data, graph computing, cognitive computing and IoT enables a platform that overcomes many traditional M&S problems:

- It automates the process of real-world data collection and graphically depicting COP of the OE.
- It validates the robustness of the models in the face of errors in the data. (Detection of abnormal/hidden entities (e.g., criminals, terrorists) and private relations (covert operations, political influence, etc.))
- It understands human and organization behaviours – dealing with uncertainty and adaptation;
- It enables ingesting massive amounts of data, scalable computing, and interconnecting different simulation modes across the M&S pyramid.

This paper has discussed **techniques that would allow NATO** to improve campaign planning involving complex systems of systems (SoS) to quickly understand the operational environment; define the problem; visualize the military end-state; and intervene with an optimal operational approach (ways/means) **to achieve the desired end state**.

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6.0 REFERENCES

- [1] FM 3-0. Operations. 27 February 2008
- [2] The United Nations World Water Assessment Programme (WWAP). 2015. The United Nations World Water Development Report 2015 – WWAP, 2015
- [3] 2008 Army Posture Statement. Persistent Conflict. Retrieved from https://www.army.mil/aps/08/information_papers/prepare/Persistent_Conflict.html

- [4] JC. Capstone Concept for Joint Operations 2020, 10 September 2012
- [5] NATO. North Atlantic Treaty Organization. Retrieved from http://www.nato.int/cps/en/natohq/topics_50321.htm
- [6] Adams, B.M., M.S. Ebeida, M.S. Eldred, J.D. Jakeman, L.P. Swiler, J.A. Stephens, D.M. Vigil, T.M. Wildey, W.J. Bohnhoff, K.R. Dalbey, J.P. Eddy, K.T. Hu, L.E. Bauman and P.D. Hough, DAKOTA: A Multilevel Parallel Object-Oriented Framework for Design Optimization, Parameter Estimation, Uncertainty Quantification, and Sensitivity Analysis: Version 6.2 Theory Manual, CASL Technical Report: CASL-U-2015-0090-000, May 8, 2015.
- [7] Garrett, R., & Loper, M. (2015, June 3). A Comparison of Traditional Simulation and the MSAL Approach. Georgia Tech Research Institute Information & Communications Laboratory. Retrieved from <http://www.slideshare.net/BobGarrett1/a-comparison-of-traditional-simulation-and-msal-632015>
- [8] Joseph Marvin, "System of Systems Analysis Application (SoSAA)", Prime Solutions Group, Inc.
- [9] 2014, Statistical Information and Relation Extraction (SIRE) Toolkit Dr. Mohamed N. Ahmed 2014
- [10] National Research Council. (2008). Behavioral Modeling and Simulation: From Individuals to Societies. Committee on Organizational Modeling: From Individuals to Societies, Greg L. Zacharias, Jean MacMillan, and Susan Van Hemel, editors. Board on Behavioral, Cognitive, and Sensory Sciences, Division of Behavioral and Social Sciences and Education. Washington, DC: The National Academies Press.
- [11] FM 3-24 MCWP 3-33.5 COUNTERINSURGENCY December 2006
- [12] Cluster analysis, Wikipedia, retrieved from https://en.wikipedia.org/wiki/Cluster_analysis
- [13] MARIA N. SCHWENGER, The science behind the PI service March, 9th 2015
- [14] Foreign involvement in the Syrian Civil War. retrieved from https://en.wikipedia.org/wiki/Foreign_involvement_in_the_Syrian_Civil_War
- [15] Lwin, M.R. (1997). *Great powers, weak states and asymmetric strategies*. Monterey, CA: Naval Postgraduate School. Available: <http://stinet.dtic.mil/cgi-bin/GetTRDoc?AD=ADA340989&Location=U2&doc=GetTRDoc.pdf> [accessed Feb. 2008].
- [16] MSCO DoD Modeling and Simulation (M&S) Glossary, 2011. Available at: <http://www.msco.mil/MSGlossary.html>.
- [17] IBM Research, (April 2015). *A Symbiotic Cognitive Experience Human-computer collaboration at the speed of thought*. (IBM Research) Retrieved from IBM Research: http://researcher.ibm.com/researcher/view_group.php?id=5417
- [18] Uncertainty Quantification. Retrieved from https://en.wikipedia.org/wiki/Uncertainty_quantification
- [19] Bayesian Network. Retrieved from https://en.wikipedia.org/wiki/Bayesian_network