SANDIA REPORT

SAND2004-0768
Unlimited Release
Printed March 2004

A Development Environment for Operational Concepts and Systems Engineering Analysis

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A Development Environment for Operational Concepts and Systems Engineering Analysis

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Abstract

The work reported in this document involves a development effort to provide combat commanders and systems engineers with a capability to explore and optimize system concepts that include operational concepts as part of the design effort. An infrastructure and analytic framework has been designed and partially developed that meets a gap in systems engineering design for combat related complex systems. The system consists of three major components: The first component consists of a design environment that permits the combat commander to perform "what-if" types of analyses in which parts of a course of action (COA) can be automated by generic system constructs. The second component consists of suites of optimization tools designed to integrate into the analytical architecture to explore the massive design space of an integrated design and operational space. These optimization tools have been selected for their utility in requirements development and operational concept development. The third component involves the design of a modeling paradigm for the complex system that takes advantage of functional definitions and the coupled state space representations, generic measures of effectiveness and performance, and a number of modeling constructs to maximize the efficiency of computer simulations. The system architecture has been developed to allow for a future extension in which the operational concept development aspects can be performed in a co-evolutionary process to ensure the most robust designs may be gleaned from the design space(s).

Acknowledgements

This work was performed at Sandia National Laboratories. Sandia is a multiprogram laboratory operated by Sandia Corporation, a Lockheed-Martin Company, for the United States Department of Energy under Contract DE-AC04-94AL85000.

1 Introduction

The Objective Force (now the Future Force) is the future full spectrum force of the US Army enabled by technology intended to respond more strategically across a spectrum of military operations from Major Theater War to Homeland Security [1]. Several requirements must be met in order for today's U.S. Army to transition to the Future Force.

- First, there is a need to enable leaders, soldiers, and units to *train effectively* for FCS (Future Combat Systems) even if they do not have frequent opportunities to participate in high fidelity field training exercises. This requirement places a very high priority on embedded training, or training with desktop and mobile tools that can easily be deployed in the field.
- Second, *innovative mission planning tools are needed* that prepare leaders, soldiers, and units for specific combat missions in all types of terrain, and with such technologies as semi-autonomous, or autonomous entities. This requirement emphasizes the challenge of mission planning under asymmetric and ambiguous circumstances coupled with the need to understand the effects of technology insertion on mission effectiveness in the battlefield.
- Third, inexpensive and high fidelity *prototyping and testing systems are needed* to allow FCS mission planners and decision makers to *explore concepts, analyze strategies, and evaluate changes* in doctrine, organizations, logistics, equipment, and soldier training characteristics.
- Finally, these requirements are indicative of a growing desire to *manage change*, as new missions in new battlefields require different skills. The three needs described above are important today—and they will be even more important in the future, especially as the Future Force transitions to the insertion of more technology (including but not limited to the use of semi-autonomous or autonomous entities) in Homeland Defense and Major Theater Warfare [2].

In response to the challenges mentioned above, the present LDRD effort (1) focused on representing the tactics of autonomous forces, (2) considered the issues involved in integrating the resultant algorithms into a JCATS-like combat simulation, and (3) addressed the design of a mission planning interaction environment (interface) which can be utilized for both mission planning and training. Additionally, the doctrinal / tactical algorithms explored in this LDRD effort should interface to UMBRA and UMBRA-like analysis capabilities in order to perform the detailed analyses which comprise design validation assessments.

While the detailed modeling of the individual entities comprising next generation autonomous systems is imperative, the integrated representations of these entities, including sensors, robots, and the associated support infrastructure (such as communications) is needed to characterize performance in combat situations. These algorithms will provide mission planners with the ability to perform "what-if" decision analyses and trade studies providing a basis for the design of integrated robotic / sensor suites. Determining mission performance forces us to find the optimal deployment, utilization, and design of these systems.

With the present LDRD effort we intended to propose the initial steps to a platform for demonstrating the advantages/disadvantages of an autonomous system design in a combat environment. We believe such a platform would enable systems engineers and mission commanders alike to tailor the configurations, behaviors, and the design of autonomous systems in order to maximize the performance of an autonomous system against a mission objective. These algorithms may also provide a basis for the development of doctrine in an integrated combat force consisting of autonomous, semi-autonomous systems, and human assets. Ultimately this is the force level objective of any tactical / doctrinal tool.

The need for this type of analytical capability is recognized by military commands, in particular by STRICOM. Their interest has resulted in the formation of a STO within the Army command focused on this analytical gap.

Section I References

None

2 Background

The Development Environment for Operational Concepts and Systems Engineering Analysis (CONOPS) can be viewed as comprising four main efforts. The first was to provide a framework that is useful to both the design engineer and force commander interested in automating or acquiring new solutions to a combat problem. The second effort involved defining a generic infrastructure that can employ evolutionary optimization techniques associated neural nets, evolutionary strategies, genetic algorithms, and genetic programs in a classic single fitness optimization approach as well as in a Pareto optimization. The third effort is associated with representing systems in a manner consistent with systems engineering methodologies as well as employing state based technologies that enable a search for robust configurations and doctrine associated with the system. The fourth effort involved bringing it all together in a meaningful interaction environment, or decision support system, that concentrated on augmenting mission planners' situated problem solving, decision-making, and on training users to familiarize themselves with the capabilities offered by autonomous and semi-autonomous (robotic) entities.

The present LDRD effort also addressed the analytical and doctrinal deficiencies associated with the use of autonomous systems in combat situations. Conventional combat analysis with battle simulations utilizes extensive and detailed combat doctrine. Doctrine provides guidance in terms of structure, control hierarchies, force mix, and tactics in order to determine the optimal utilization of a force in a combat environment. Doctrine impacts the training of the organic elements of a force as well as affecting the requirements of the systems that support the organic components. The environments likely to be faced by future combat forces include an asymmetric threat, urban warfare, and on the other extreme, humanitarian assistance. These drivers result in a trend toward autonomous and semi-autonomous forces (robotics, FCS, DD-21, UAV's etc.) on future battlefields. Unfortunately, the current suite of analysis tools lack the computational capabilities to assess the impact of these forces in future conflicts or develop doctrine for these new force structures. The current approaches to assessing the capabilities of autonomous forces are to envision these systems as conventional "static systems" and to represent these autonomous force capabilities in classic combat simulations such as JCATS or other less sophisticated algorithms. These approaches, while reasonable given the current state-of-the-art, fail to capture the unique capabilities and constraints of autonomous forces. The more important shortcoming of this approximate approach is the failure to provide a full, dynamic integration of the functions associated with autonomous forces. We define a system as a composite of multiple platforms, sensors, information architecture and protocols, decision support, control agents, information fusion algorithms, interaction environments or interfaces, and soldiers. Assessments that separate these core functions and battlefield entities are destined to miss the efficiencies and synergistic effects inherent in integrated systems.

Section II References

None

3 Simulation/Systems Engineering Analysis Architecture

The present LDRD approach uses evolutionary computational technologies to perform multi-level optimizations on a suite of integrated "fitness" functions representative of the combat system. These representations must define system behavior at multiple levels; at the entity level, the system or collective level, and at the control level. Entity level behavior, in this context, might be an entity tasked with intersecting an approaching target and fusing a weapon at lethal ranges, or searching for a target with a specific acoustic signature. This behavior might also be called functional behavior and may include the response of an entity to interactions with similar and dissimilar entities of the system. The collective behavior reflects the system's need to organize and interact with other like entities within the system to mitigate multiple targeting or search inefficiencies.

Systems perform actions to achieve some desired terminal state of the system. Integration of system engineering concepts into the architectural structure of the algorithm provides a natural transformation between function and state. The approach is then to use optimization techniques to identify transition probabilities between various states through the integrated optimization technologies, effectively aiding in the discovery of the optimal control strategies. Once a state sequence has been defined, this information could be used to train neural nets to define a collective control function. The state sequencing is a representation of the tactics / doctrine associated with the functional characteristics of the system.

The CONOPS simulation and systems engineering analysis architecture focused on separation and integration at the same time. We needed to be able to separate the collaborative interface and the combat validation from the core algorithms which are systems analysis oriented (the collaborative interface is discussed in greater detail in subsequent sections). In order to link the components in confirmatory analyses an XML infrastructure was explored and assessed for implementation. While use of XML constructs are very useful and robust after the fact, writing algorithms that automate the process proved to be labor entensive. The link to post analysis algorithms consisted of using MARRS as the final demonstration tool. MARRS is a Naval Post Graduate School (NPS) simulation visualization environment that has been the topic of a number of independent efforts and Masters theses. The following series of figures provide a view of the CONOPS simulation and systems engineering analysis architecture developed to address the problem discussed above (see Figure 3.1).

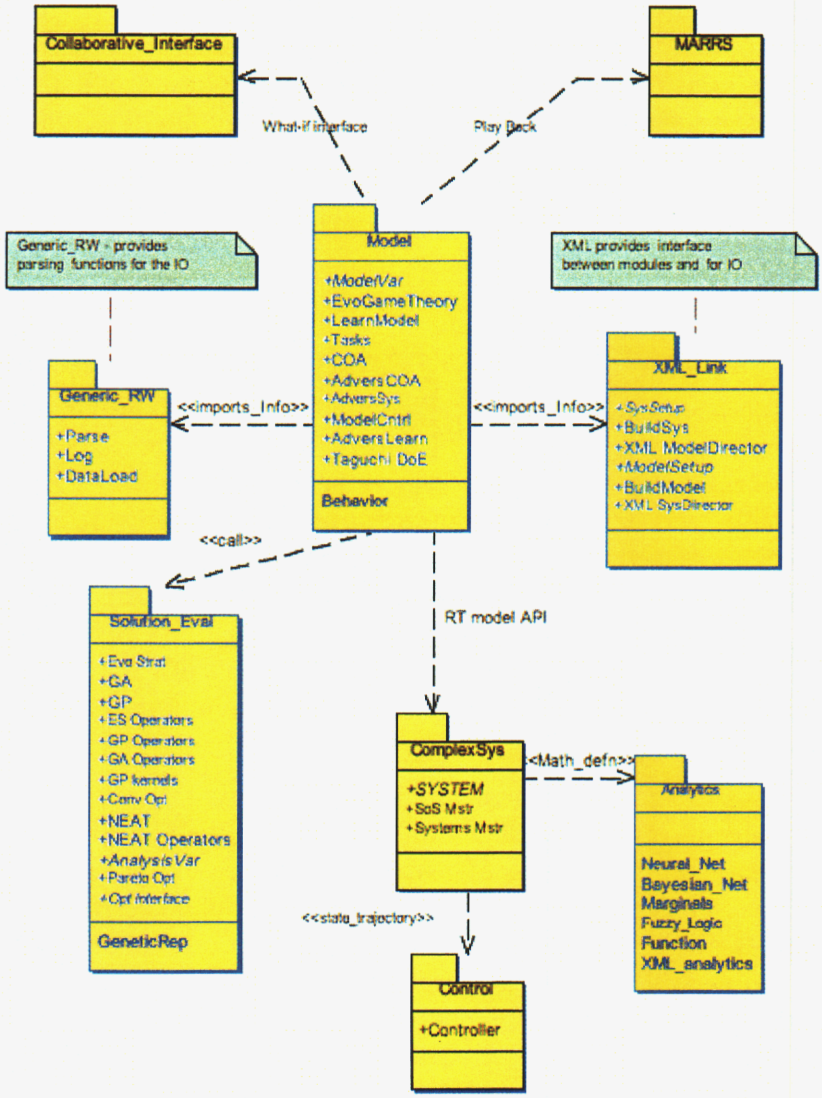

Figure 3.1 Root level algorithmic architecture.

There are 6 major components in this algorithm: the collaborative interface, the playback in MARRS, the controller or model, the XML and generic input, the optimization, and the system representation. The MARRS [1] playback was intended to provide an environment to demonstrate evolved controllers as well as provide an environment for demonstrating the results of the analyses associated with this capability. MARRS is unique in its graphics, discrete event simulation, and XML input infrastructure.

XML [2] was identified as the most effective means of linking the interface and the playback environments to the core algorithms of this approach for solving complex systems and doctrine design. In addition XML provides the ability to define flat databases of technologies, scenarios, and criteria that can be used in the analyses. These databases can be used in multiple environments to simplify working with complex and large information repositories associated with design problems of complex systems.

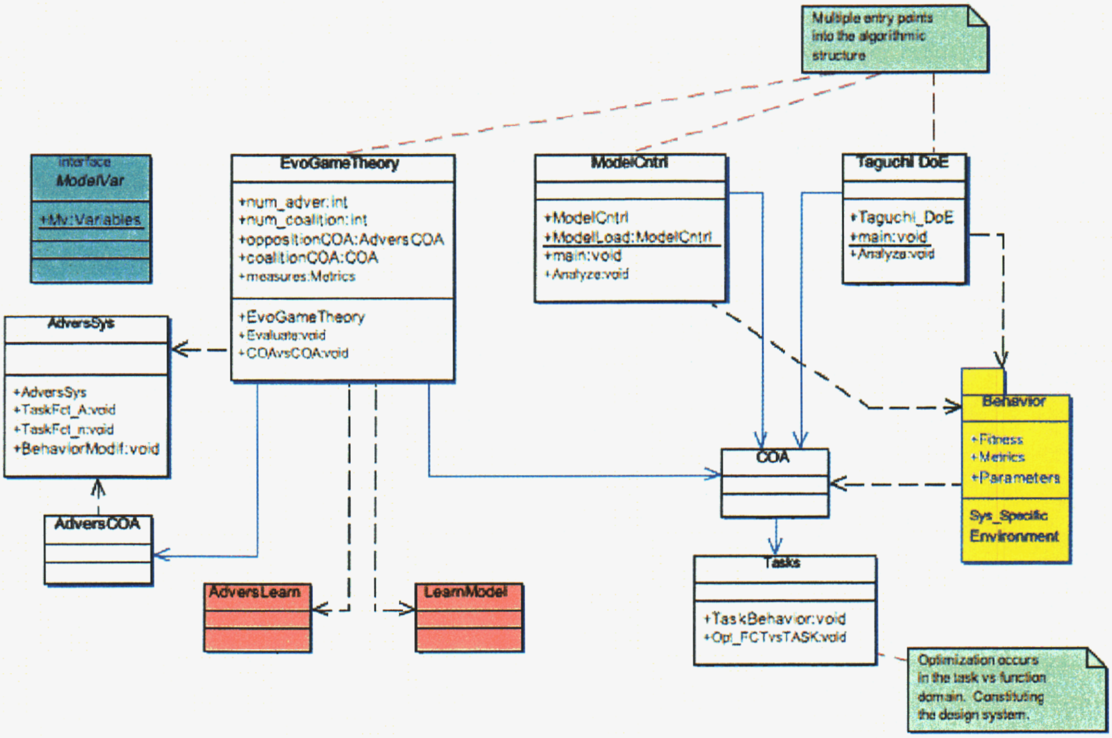

Figure 3.2 Analysis control architecture.

The nature of the problems encountered and issues to be addressed required the design of a robust control structure. The focuses of the CONOPS simulation/systems engineering analysis engine effort were the "ModelCntrl" and the "Taguchi_DoE" classes (see Figure 3.2). The evolutionary game theory is a component that needs to be developed in order to optimize designs and doctrine in a dynamic environment in which the opponents can also learn or adjust to the behaviors of the system being considered. The design of experiment component was simply an automated methodology for assessing trends and sensitivities of the independent variables (and noise variables) associated with the problem space.

Finally, there is further need to develop the characterization and design of the learning models that are integral to the evolutionary game theoretic sub-control. Information from the fields of economic theory, robotic learning, as well as philosophy of science and psychology need to be gleaned to further develop a more definitive model. The strength in these cases is that any learning model, no mater how primitive, could potentially enhance the approaches currently implemented.

Section III References.

[1] Capt. Alistair Dickie, "Modeling Robot Swarms using Agent-Based Simulation" Naval Post Graduate School Masters Thesis, June 2002.

[2] http://www.w3schools.com/ , W3 Schools – Full Web Building Tutorials: XML Tutorials.

4 Collaborative Mission Planning Interface

A collaborative mission planning interface provides the setting within which the user engages the CONOPS simulation/systems engineering analysis engine, accesses and manages data, problem solves and designs plans, and is trained for incorporating autonomous and semi-autonomous entities in future missions. The collaborative interface was designed by the second author while she was a ERCIM (European Research Consortium in Informatics and Mathematics) fellow at Fraunhofer FIT (Applied Information Technology Institute), Germany and INRIA (French National Research Institute for Computer Science and Control), France. Since the majority of the work was accomplished in overseas organizations, she designed a collaborative interface that could be used in emergency management settings as well as for military mission planning. The emergency management scenario chosen for describing the CONOPS interface was the natural disaster Hurricane Andrew, which devastated South Florida in 1992 causing millions of dollars of damage. Forcing herself to design an interface for emergency management proved to be a very valuable exercise. Utilizing this approach, the CONOPS collaborative mission planning interface builds upon innovative European research in the areas of cognition, cooperative design, and collaborative virtual environments. A stand-alone demonstration of the user interaction with the CONOPS Development Environment for Operational Concepts and Systems Engineering Analysis can be shown upon request.

Much like their European counterparts, the U.S. Military and Department of Homeland Defense are among the growing number of organizations facing the reality of increased distributed, technology-mediated communication, interoperability, and need to facilitate joint decision-making that spans geographic, temporal, and cultural boundaries. For example, the U.S. Army provides headquarters that serve as integrating agents for the Joint Task Force (JTF), Joint Force Land Component Commands (JFLCC), and Army Service Commands (ASC). It has been predicted that the reality of technologically mediated (joint) decision-making will become even more evident as we move toward the Future (formerly the Objective) Force [1].

The collaborative interface to the Development Environment for Operational Concepts and Systems Engineering Analysis (CONOPS) enables mission planners and systems engineers to have access to knowledge that is distributed across different individuals and teams of several multinational organizations such as those mentioned above. Specifically, a mission planner could interact with the CONOPS environment to engage in the design of scenario-driven concepts of operation that includes semi-autonomous entities in roles that are optimized by forward simulation. The CONOPS mission planning interface, trains the mission planner in becoming more familiar with the capabilities of semi-autonomous entities and in designing forward simulations by providing him/her with the ability to reuse past mission designs and simulations, and gain access to other's designs within a community. The collaborative CONOPS mission planning & training environment could also offer asynchronous data management support via the virtual collaborative workspace called BSCW (Basic Support for Collaborative Work) [2]. Military and emergency management mission planners could use the simulation environment in embedded training systems or as a design tool when preparing planning scenarios that utilize semi-autonomous entities.

Why is it important to provide mission commanders and decision-makers with a *collaborative* mission-planning interface environment? To answer this question we carefully analyzed mission planners' current context of work. We designed an interaction environment that is situated in their work context, and is an innovative approach that provides access to forward simulations generated in the past, and the relevant past mission-planning designs of others. Mission-planning tools have been developed for planning and analysis (e.g. [3], [4]) although few offer support for the hypothesis generation or "what-if?" exploration stages of mission planning concept of operations design (See Figure 4.1).

Several modeling & simulation application approaches used today illustrate the capabilities of semi-autonomous and autonomous forces by using conventional simulation platforms such as JCATS to represent autonomous forces in classic combat simulations. Although state-of-the-art, these approaches may fail to provide a full, dynamic integration of the functions associated with autonomous forces. Functions that comprise an autonomous forces system include multiple robotic elements, sensors, communications architecture and protocols, as well as the decision support infrastructure and information fusion algorithms. The interfaces or interaction environments associated with these platforms may also fail to capture the users' or commanders' intent for actions taken during military simulation games or mission planning.

In some cases, a fundamental lack of knowledge of doctrine and tactics associated with the integration of autonomous forces into a combat organization may also contribute to less accurate models and representations. Manufacturers of semi-autonomous entities are often unfamiliar with the doctrinal aspects of combat, and mission planners are unfamiliar with the capabilities of semi-autonomous entities. Neither group may know with a comfortable degree of certainty how semi-autonomous entities can be successfully applied to mission planning and doctrine. A misalignment of goals in planning stages, or lack of common ground can become a severe limitation if not dealt with through planning and re-planning stages [5]. This lack of common ground among manufacturers of autonomous entities, simulation designers, and mission planners could translate into potential failures in the logistic stream, system design, acquisition planning, and combat tactics or training.

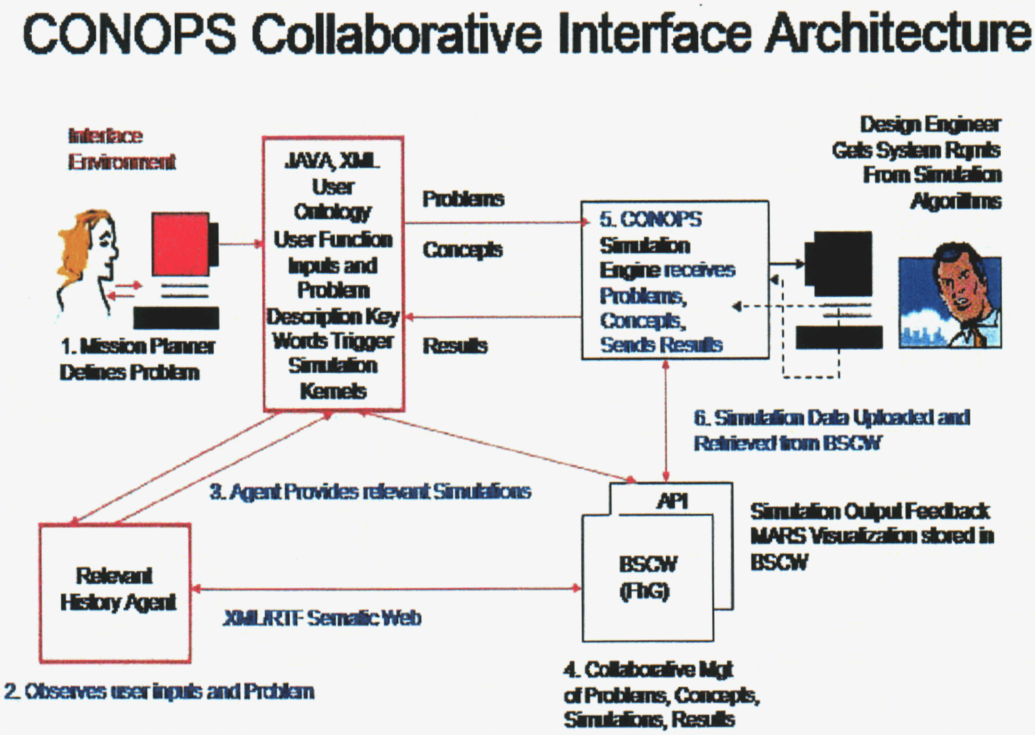

Figure 4.1 CONOPS Collaborative Interface Architecture

4.i Collaborative Mission-Planning Interaction Architecture

The following sections discuss the collaborative interface architecture shown in Figure 4.1 in greater detail. The main components of the collaborative interface include the CONOPS simulation/systems engineering engine, a collaborative virtual information management system (manages mission plans, problems, concepts, simulations, results, etc.), a history agent that finds relevant documents based on similarity algorithms, and the domain ontology (for an example see the Battle Management Language [6] in reference section).

Scenario/Storyboards Interaction Environment

Currently, mission planning is largely conducted in groups in the face-to-face context. Mission planners receive directives that illustrate commanders' intent, and later meet together to devise the Concept of Operation (CONOPS) and Course of Action (COA).

Military planners use a *Course of Action sketch* (COA sketch) when planning operations [7].

> According to [7, pg. 77-8], "COA sketches express the gist of a plan, before many details, such as timing, have been worked out. Traditionally such sketches are created using acetate overlays on maps, or on paper starting with hand-drawn abstractions of critical terrain features. A well-worked out vocabulary of visual symbol is used to represent terrain features, military units, and tasks assigned to units."

Transferring the intellectual capital about commanders' intent and the related mission planning design tasks that are generated in the course of face-to-face communication to the electronic environment is challenging. There is a specific need to capture an individual as well as a group's tacit and explicit knowledge [8-9] and decision-making. Explicit knowledge is that which is easily formalized, articulated, and coded. Tacit knowledge, on the other hand, is often derived from individual experiences and is often not formalized. For example, commanders' intent may be both explicit and tacit. Both explicit and tacit knowledge are integral to successfully making sense of commanders' intent in an electronic environment.

As distributed teams and distributed cognitive contexts become more of a reality, there is a need to create team or group awareness systems that emulate or closely replicate the experience of a face-to-face mission planning session while capturing the collective design iterations and decision-making of mission planners. The interaction technology should be seamless, and the context-aware architecture should assist the users' decision-making and reasoning instead of hindering their creative processes. Since mission planning is an activity that involves many contributors, the CONOPS mission planning and training interface supports asynchronous and synchronous group cognition, learning, and cooperative design. Although the use case is written from the perspective of the single user, it is useful for the reader to imagine several users connected to the CONOPS Development Environment for Operational Concepts and Systems Engineering Analysis in which they have access to past scenario designs, simulation subtasks, past performance metrics, and general user input.

4.ii CONOPS Collaborative Interface Use Case Scenario

Use Cases are written from the perspective of the user. The user in this case is the military mission planner. The user's task is the design of a scenario-driven concept of operation that includes semi-autonomous entities in roles that are later optimized by forward simulation.

Consider the following scenario as an example of a use case in which mission planning is conducted in near real-time by the U.S. Army at three locations: Ft. Benning, Georgia, Ft. Knox, Kentucky, and the 409th Army base at Vilseck, Germany. In this example, groups of mission planners at each of the three Army bases meet in face-to-face settings to discuss the directives they have received. During the design of the COA and CONOPS, the mission planner may have "what-if?" questions about the use of semi-autonomous entities in the mission. For example, the user may ask himself, "how many semi-autonomous entities will I need if I am to employ them in a fall back role for this particular mission?" (See Figure 4.1, No.1.).

There are several reasons why the mission planner will elect to use the CONOPS mission planning and training environment. First, the CONOPS collaborative interface integrates the history of past semi-autonomous entity performance in previously explored CONOPS simulations that have been collected from previous "what-if?" concepts of operations mission planning sessions (see Figure 4.1, No. 2-3). Second, each mission planner has access to every mission that was planned at each Army base participating in the CONOPS Development Environment for Operational Concepts and Systems Engineering Analysis (see Figure 4.1, No. 4-6). As the mission planners interact in the CONOPS environment, asynchronous (or real-time) awareness information is made available to each of the individual at the different sites on iterations or events generated with regard to specific mission planning activities (see Figure 4.1, No. 4). If a mission planner chooses to automate a particular function of a mission (i.e. automate the performance of ten assets with a semi-autonomous entity) and this activity has been executed in the past by another individual, then the mission planner will be asked if he would like to see the history and result of the similar iteration enacted by a different user [10,11].

4.iii CONOPS GUI Use Case

In order to answer questions such as "How many semi-autonomous entities will I need if I am to employ them in a fall back role for this particular mission?" the user accesses (logs on to) the CONOPS interface. The user selects icons (symbols) that depict terrain, communications, sensors, units, tasks, and semi-autonomous entities. The user indicates entry and egress points, and weather conditions, time of day, etc. The user plans a route by dragging and dropping icons into the active window. As the user designs the scenario, he uses patterns of icons, or symbols. Figure 4. provides a screen capture of the interface when the user has engaged information providing situational awareness of an emergency management problem after Hurricane Andrew in 1992: search and rescue survivors in a 4 km area in the suburbs of Cutler Ridge, Florida. The mission is to be completed in 12 hours using 6 human assets and two robotic vehicles. A distance of 15 km must be covered before entering the SAR zone.

Figure 4.2 Screen Capture: User Problem Definition Phase.

In the course of planning the mission, the user may decide to interact with documents, simulations, videos empirical results, etc. directly. By clicking on the BSCW icon, the user engages the collaborative management system (see Figure 4.3). The interface provides the flexibility to switch among diverse media (maps, situational awareness content, video, audio, simulations, etc.) without losing the view of the mission planning interaction area.

When the user has selected the autonomous or semi-autonomous entities (in this case robotic vehicles) and indicated by drawing a square around the coordinates of the mission space, the context-aware interface recognizes the patterns of sequential subtasks, key words, interface events, and prompts the user to view a history (stored in the BSCS database) of related subtasks that have been submitted in prior mission planning sessions, either by the same user or different users (see Figure 4.4 and recall Figure 4.1).

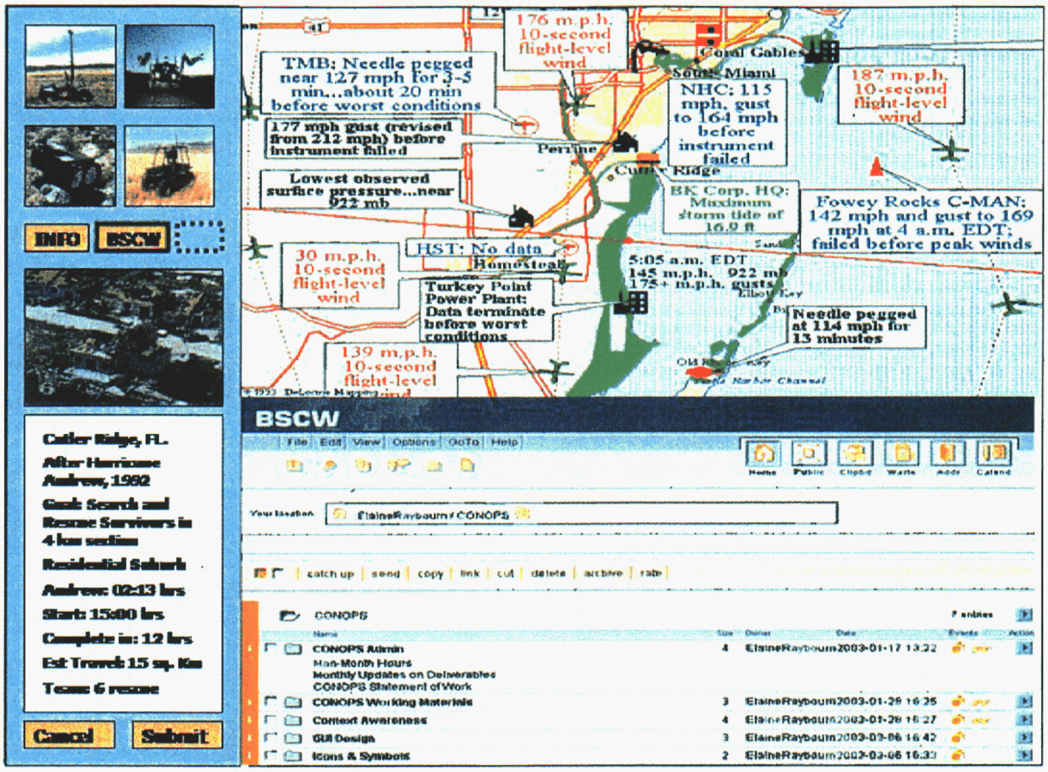

Figure 4.3 Screen Capture: Engage the Collaborative Management System.

Figure 4.4 Screen Capture: Engage History Agent to call previously generated analyses.

Having access to a collaborative management system of previous missions planned by different users provides asynchronous group decision-making support; that is, all users have access to prior lessons learned from previous missions. The users can then decide to make changes to their CONOPS or COA *at the interface* before they hit the submit button to trigger the simulation run, since the simulation run will provide an output approximately 24 hours later. If needed, the user may view a forward simulation of a mission planned in the past, interact with documentation associated with the simulation, or contact the mission planner or emergency management coordinator who engaged the CONOPS system about a similar mission (see Figure 4.5). After the user hits the submit button, he has completed an interaction session (see Figure 4.6). When the simulation results have been generated, the simulation engine issues a notification in the form of an email to the user to indicate that the simulation is ready to be viewed in a subsequent interaction session.

Figure 4.5 Screen Capture of CONOPS Collaborative Interface: Contact Individual.

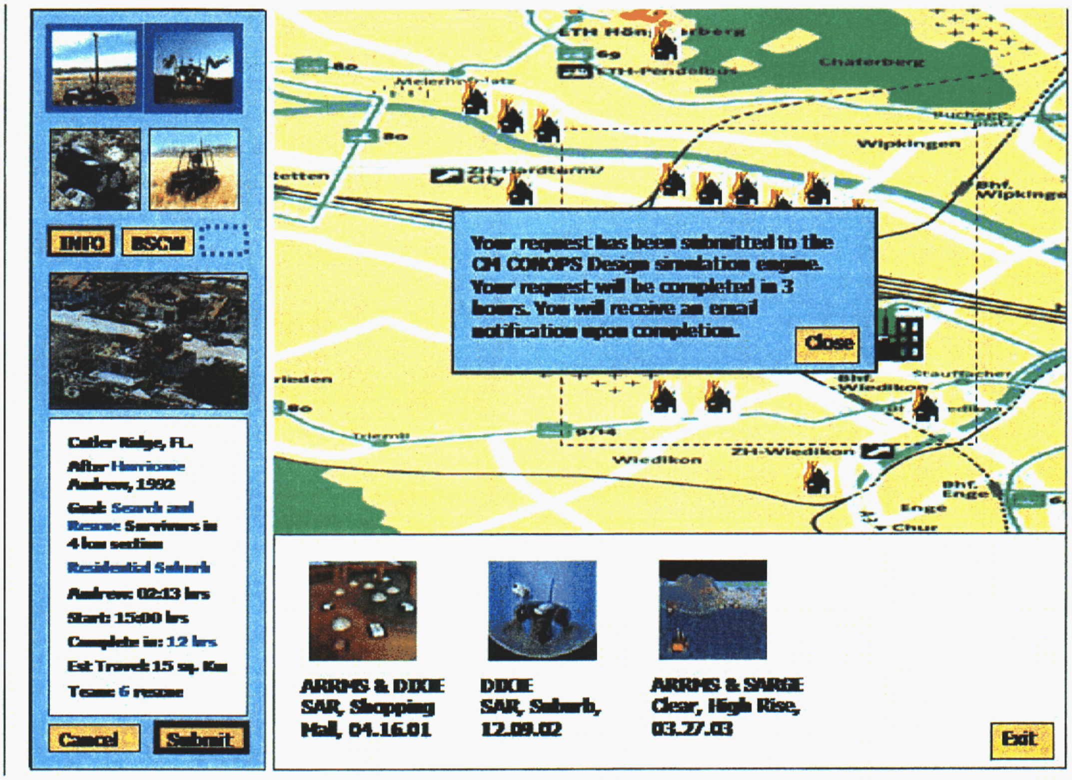

Figure 4.6 Screen Capture of CONOPS Collaborative Interface: System Feedback.

4.iv Cognition and Cooperative Design Theoretics

Cognitive psychologists often refer to design problems as "ill-defined" [12]; that is, the specifications provided are never completely defined or unambiguous. Resolving conflicting constraints is often necessary. There may be few definite criteria for testing proposed solutions, and numerous design solutions may be acceptable—that is, there is seldom one particular route to achieve a desired outcome [13]. Ill-defined design problems are present in many domains including but not limited to software engineering, health sciences, and military or emergency management mission planning.

In dealing with complex design problems, designers evoke or elaborate solutions that may have been used before, are completely new, or a combination. Evoking a solution may involve mentally simulating the evaluation of a solution such that it is recalled in a schema. Schemas have instances of episodes that represent general cases—such as an individual occurrence of something located in time and space. Schemas may be described as static representations of problem components, as in the case of plug-n-play components. Elaboration occurs when designers reframe the problem in order to call to mind new schemas, or new decision heuristics [14, 15]. Elaboration may manifest in several forms, including brainstorming, analogical reasoning, and simulation [14]. In the case of analogical reasoning, designers use episodic knowledge of an analogous design situation dealt with in the past in order to accomplish their tasks. Related reasoning strategies include problem decomposition, simulation, reuse, and global and local plans [12]. These problem solving methods are often used in combination and may be employed by mission planners at different stages of the planning and design activity.

Non-routine design is also known as creating novel solutions. When planning the use of autonomous or semi-autonomous entities in new missions, the mission planner engages in non-routine design. Research has shown that case-based reasoning, or episode-based reasoning, is particularly well-suited for non-routine design activities [16, 17]. For instance, Wharton & Lange's REMIND system creates inferences from textual cues and is capable of cross-contextual reminding [18]. Experts involved in non-routine design activities often mentally simulate more or less complete solutions [19, 20]. Mental simulation is the elaboration of a dynamic enactment of a mental model, whereas the evocation of a schema involves the recall of a static mental representation [14]. When one recalls components of or entire past solutions, this process is referred to as reuse.

Reuse, then, refers to the retrieval and usage of previous solutions [19]. Reuse of past designs and schemas can be helpful as reusing past designs can aid the mission planner in both routine and non-routine design tasks, as well in deriving novel solutions [21]. The designer consciously or unconsciously performs a cognitive-cost evaluation before deciding to design from scratch or to reuse components of past designs [22]. Mission planners and emergency management planners also perform cognitive-cost analyses. Often, both planners and designers prefer to reuse components whenever possible.

In addition to design activities being ill-defined and non-routine in which different components may be reused, design activities may also be characterized by the act of replanning. According to [5], replanning is the process of modifying pre-existing plans and procedures to meet changing goals, circumstances, and demands. When interacting with data or information, planners and designers must allow plans to be modified for new circumstances as they arise. When supporting the non-routine planning and design process with computer-based applications, it is imperative that the software environment foster a mission planner's problem solving activity in which goals are discovered and revised though the act of developing new courses of action (COA).

As described above, many studies on reasoning and problem solving in design have focused on the individual. However, an increasingly important phenomenon is the growing likelihood of more frequent interactions among planners and designers through the reuse of knowledge due to the support of technology-mediated collaborative work [23-26]. Prior research has found that it is not uncommon for teams and groups to accomplish tasks together when one or more individuals has never met the others face-to-face [27, 28, 29]. For these and a host of other reasons, supporting user electronic behavior settings in distributed environments cannot be ignored [30].

The notion of mission planning as a collaborative activity was introduced earlier in the present chapter. In addition to supporting individual cognitive tasks, the CONOPS collaborative interface addresses asynchronous supports for collective planning and design activities. Collective design is a process which may involve evaluation, review, replanning, and generation of alternative solutions [23, 24]. The CONOPS collaborative interface provides the mission planner with the opportunity to evaluate, review, replan, contact other individuals who submitted mission plans into the database, identify alternative solutions, and finally generate novel solutions with the aid of the optimizations created by the CONOPS Development Environment for Operational Concepts and Systems Engineering Analysis.

4.v Conclusions

This chapter described in detail the user interaction protocol of the CONOPS Development Environment for Operational Concepts and Systems Engineering Analysis collaborative interface environment, and discussed the cognitive underpinnings for supporting both emergency management and military mission planning activities with software tools. The CONOPS collaborative interface allows planners and designers to reuse elements of their own past designs, access others' solutions, replan solutions and problem solve at the interface while interacting with various forms of data, generate novel solutions on their own, or contact other designers in their community in order to elaborate new solutions in groups. Designers use the CONOPS collaborative interface to evoke past mission planning elements (their own and others) to create new mission plans. Resultant new solutions are stored in BSCW, a community-based information management system and repository [2] made available to all members of a particular community. Users may contact mission planners in their community in order to engage in more synchronous communication. Finally, users are able to draw upon a simulation tool to better make sense of the consequences of certain emergency management or military mission planning and design constraints. Whereas CAD tools may primarily support the organization of concrete design activities, there are fewer tools available to designers that support the design process or exploration and maturation of ideas and concepts that are integral to scenario-driven design and planning. The CONOPS collaborative interface draws on prior research in design reuse [12-15], collective design [16-18] and reasoning [19-22] as a theoretical impetus for the cognitive implications of retrieving past designs. Previous research on intelligent community-based systems [23-26], was also used to inform the design of the CONOPS collaborative interface environment functionality.

The collaborative interface to the CONOPS Development Environment for Operational Concepts and Systems Engineering Analysis is an interaction environment that enables the mission planner to

- use a familiar lexicon in planning missions, formalize commanders' intent into more explicit modes of communication,
- draw on the intellectual capital and historical database of missions planned within participating communities across the world,
- analyze the efficacy of previous plans in new contexts,
- design new plans without introducing inappropriate or substandard solutions,
- and finally through forward simulation, plan roles for, train, and optimize the performance of autonomous and semi-autonomous entities in future concepts of operations.

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5 Optimization

Multi-level optimization proved to be an interesting design problem. Not only did the optimizations need to occur at different levels, but different optimization algorithms were required. The four basic types of optimization algorithms considered included genetic algorithms (GA), genetic programs (GP), evolutionary strategies (ES), and a unique implementation of a neural net (NEAT) that was ideal for control optimization. Evolutionary strategies (ES) and neural evolution of augmenting topologies (NEAT) were coded while genetic algorithms (GA) and genetic programs (GP) were not fully coded, only the hooks being defined by the present LDRD effort. Additionally, a generic representation was defined that could be used by any of the four optimizations. It was possible to define a representation that was identical or similar for each method, the only difference being the genetic program (GP) and the neural net (NEAT) require a phenotype transformation which the GA and ES do not (See Figure 5.1).

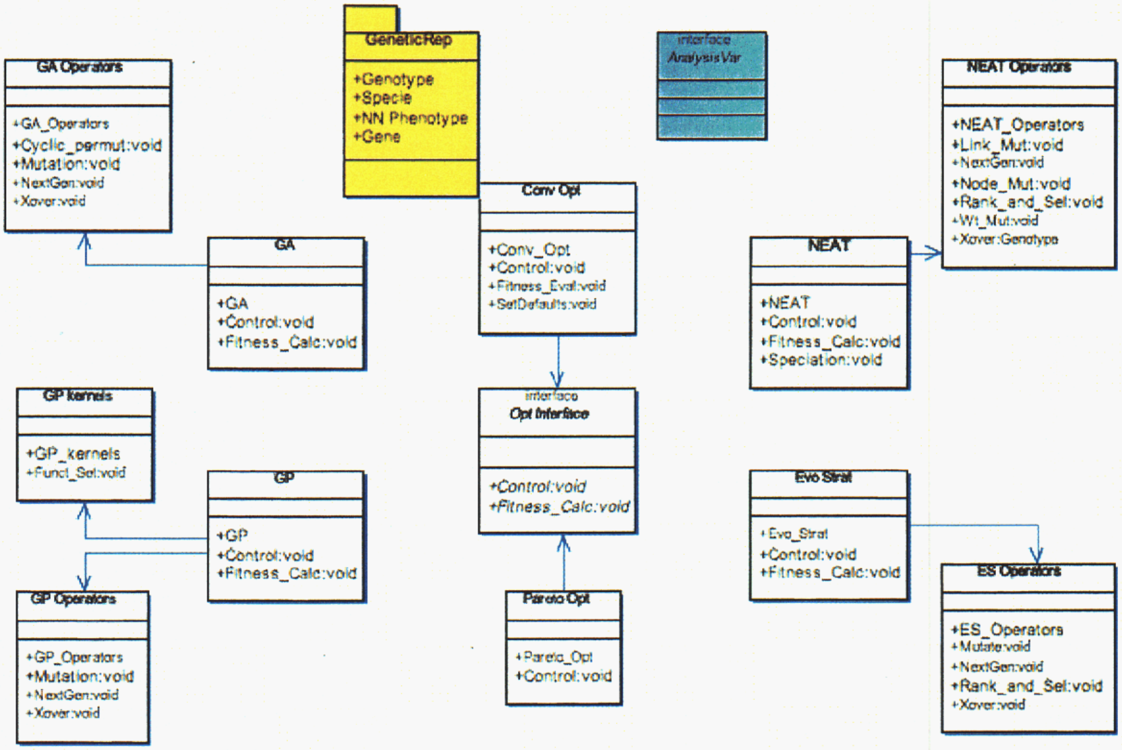

Figure 5.1 Optimization architecture.

The second aspect of the design was the desire to include conventional single fitness function optimization and a Pareto optimization capability. The Pareto optimization capability provides a unique capability for systems engineering that is far more useful than a conventional approach. Systems engineering problems are multi-criteria and multi-attribute. Under these conditions, the analyst must make assumptions with respect to the choices the decision-maker will make. This constraint leads to a situation where a complete analysis must be re-done if the assumptions were in error. The Pareto approach permits "what-if" trade studies to be performed after the analyses are complete and does not necessitate the recalculation of performance measures for the system under consideration.

The sections that follow briefly summarize the optimization methods that are the foundation of the analytic approach. Detailed information is available from the full citations in the reference section.

5.i Evolutionary Strategies (ES)

Evolutionary strategies (ES) are the workhorse of engineering optimization. This technique is statistically based and operates on real parameters, as opposed to binary representations of real numbers. It is naturally multi-dimensional and can be easily put into a constrained domain search. Like the genetic algorithm, it employs a series of genetic operators such as a mutation and cross over operator. The parameters to be optimized comprise the chromosome that represents a solution to the problem under consideration. A difference from the GA is the strategy parameter that becomes the basis for the random directed search associated with the methodology. The mathematic model is shown below.

$$\overline{P} = (c_1, c_2, \ldots, c_n)$$
$$c_i \equiv (op, sp)$$
$$\overline{OP} = (o_1, o_2, \ldots, o_m) \qquad \text{Eq. 5.1}$$
$$\overline{SP} = (s_1, s_2, \ldots, s_m)$$

$\overline{P}$ represents a vector of solutions to the problem, or the population at a stage of the evolution to a solution. c_i is a chromosome consisting of object-parameters and strategy-parameters. The object parameters represent the values assumed by the solution. The strategy parameters are used with Gausian distributions to perform mutation operations. Mutation is defined in the following set of equations.

$$\overline{OP}_{mut} = op + N_0(sp)$$
$$or \qquad \text{Eq. 5.2}$$
$$\overline{OP}_{mut} = (o_1 + N_0(s_1), o_2 + N_0(s_2), \ldots, o_m + N_0(s_m))$$

The mutation of the strategy parameter is as given below.

$$\overline{SP}_{mut} = (s_1 \cdot A_1, s_2 \cdot A_2, \ldots, s_m \cdot A_m)$$
$$A_i = \alpha \quad if\ E < 0.5 \qquad \text{Eq. 5.3}$$
$$A_i = \frac{1}{\alpha} \quad if\ E \geq 0.5$$

In this equation E represents a random number from a uniform distribution selected in the algorithm. In this way the draw from the Normal distribution, N_0, will occasionally jump across the solution space and assess the utility of a solution in that region.

One variant of the cross-over operation is represented in the equation below.

$$r_{discrete} = (c_1, c_2) \quad c \equiv (\overline{op}, \overline{sp})$$
$$with$$
$$op_i = \{op_{c1,i} \mid op_{c2,i}\} \qquad \text{Eq. 5.4}$$
$$and$$
$$sp_i = \{sp_{c1,i} \mid sp_{c2,i}\}$$

z={x|y} is a notation for z being equal to either x or y with equal probability. This provides a basis for the ES methodology. Other cross over operators and genetic operators exist. Some may be specifically designed for the problem addressed. For example, in a GA methodology a cyclic operator provides a useful permutation mechanism for dealing with "traveling salesmen" types of problems. In the current implementation only the basic operators were defined and implemented.

5.ii Neural Evolution of Augmenting Topologies (NEAT)

Neural evolution is a methodology for evolving neural networks using genetic algorithms. The bulk of the technologies in this area evolve the connection weights associated with the neural net. The issues are speed and difficulty associated with convergence when one evolves both the weights and the topology. In this case topology refers to the number of hidden layers and hidden layer nodes. One problem for the first author has always been, the number of layers and nodes needed to find the best functional approximation. Since neural nets can represent any degree of complex nonlinear functions, there is a danger that one may be introducing higher (or lower) dimensionality into the problem space. To use these techniques in an analysis effort, one may spend a good deal of time experimenting with different neural configurations to find the best solution to the problem. The work that inspired the first author to implement a neural optimizer in the algorithmic system was the work of Stanley & Miikkulainen of the University of Texas. They have developed a methodology that can efficiently evolve both the topology and weights associated with the links in the neural net. This technology seems to be well suited for problems involving control, system functional definition, and operational constructs.

NEAT was designed to address issues associated with representing topological cross-over, with a preservation mechanism for allowing new topologies to exist long enough to demonstrate clear performance capabilities, and to minimize topologies without resorting to rigged fitness functions. The genomic representation of the neural net consists of genes that are nodes and genes that are links. The link nodes are the connections in the neural net and consist of input and output nodes, weights, if they are enabled, and an innovation number which is an anthropologic index of sorts.

Mutation in this technology involves the weights as well as adding nodes and/or links. New links are formed between formerly unconnected nodes. A new node, however, disables the link on which the node is to be added and then adds two new links reflecting the changes on the old link. When new links are created the global innovation number is incremented and assigned to the new links (see Figure 5.2).

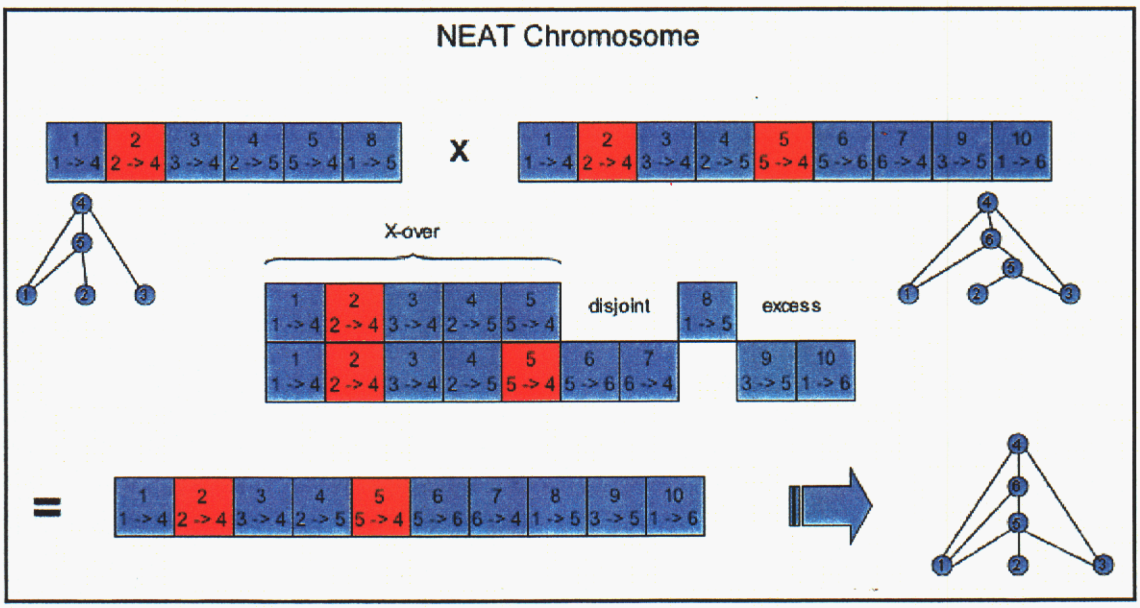

Figure 5.2 Information associated with the NEAT technology.

Cross-over is an operation that benefits from innovation number tracking in the genomes. Figure 5.2 demonstrates the mechanism of cross-over. The essence of cross-over is that offspring will possess all matching genes, all those disjoint, and excess genes from the most fit parent. This effective cross- over method builds on the "foundations" of the most historically fit, while avoiding an explosive growth in topologies.

A final feature of the NEAT technology is the speciation mechanism. Speciation is a technique for identifying similar solutions. Fitness is defined for the specie, not for each individual in the population. What this does is permit a solution to exist for a time sufficient to assess its potential for being the best solution. The combined evolution of weights and links can result in a solution being discarded before a fair assessment of its potential is determined. Speciation avoids this problem because survival is specie-dependent. The result is a very robust solution for a powerful neural net (NN) technology for use in systems analysis.

5.iii 5.3 Conventional Optimization Control

Not a lot needs to be said about conventional optimization within the context of decision support. The approach relies on the assumption that multi-criteria / multi-objective problems can be recast into a single objective or fitness function. Evolutionary optimization then proceeds classically; select a solution, assess its fitness based on the single constructed fitness function, and rank relative to the fitness values of the other solutions in the population. For simple problems this is likely to be a reasonable approach, but as the problems become complex and the number of attributes and objectives becomes large, convergence can become a significant issue. A second detractor from this approach is the difficulty of performing "what-if" analyses on the results. Establishing a single fitness function locks preferences into values associated with fitness values. The nonlinearities of complex problems make it difficult or impossible to separate some of the effects associated with a single attribute or objective.

5.iv 5.4 Pareto Optimization Control

Pareto optimization is a technology emerging from the fields of operational research (OR) and the decision sciences where problems are typically multi-attribute and multi-objective. Attributes are defined as surrogate metrics for some qualitative objective. For example, an objective to "improve a person's well being" is un-measurable in the "well being" dimension. We can identify measures that could be identified with a person's well being; wealth, number of days sick, or the number of sunny days. These attributes are somehow representative of "well being". Objectives are classic goals of a systems design problem; minimize MTTF, maximize reliability, increase performance (depending on the system function).

There are two basic approaches to multi-objective optimization using evolutionary methodologies. The first considers each objective independently, and a solution is identified. One problem with this approach is it may be impossible to design a system to those specs because they conflict in the objective dimensions, one objective drives a performance parameter in one direction while a second objective will drive the parameter in an opposite direction. This is the easiest implementation of a multi-objective optimization problem. A variant of this approach is to construct a single fitness function from the set of objectives in which the dimension of the objective space have been weighted. This approach is problematic in its inability to easily perform "what-if" types of analyses with the analysis results.

The second approach is to perform a Pareto optimization within the objective space. In this case, dominance forms the basis for fitness of the evolved solutions. The problem can be defined be the next set of equations and definitions. The goal is to find an acceptable solution in a suitably defined region. Suitability is dependant on the constraints and requirements of the design problem.

$$\text{Minimize} \quad \begin{array}{c} f(\bar{x}) = (f_1(\overline{x}), f_2(\overline{x}), \ldots, f_p(\overline{x})) \\ c_i(\bar{x}) \le 0, \quad i = 1, \ldots, r \end{array} \qquad \text{Eq. 5.5}$$

Where c_i represents the set of r constraints and the f_i are the set of p objectives and x is an n-dimensional vector. (Definitions taken from Veldhuizen's paper)

Pareto Dominance: A vector **u** is said to dominate **v** ∫ **u** is partially less than **v**.

$$\forall i \in \{1,2,\ldots,p\}, \quad u_i \le v_i$$

$$\textit{and}$$

$$\exists i \in \{1,2,\ldots,p\}: \quad u_i < v_i$$

Pareto Optimality: A solution $\mathbf{x_u} \in U$ is said to be Pareto optimal ∫ there exists no $\mathbf{x_v} \in U$ for which

$$v = f(x_v) = (v_1, v_2, \ldots, v_p)$$

$$\text{dominates}$$

$$u = f(x_u) = (u_1, u_2, \ldots, u_p)$$

The points lying on the curve in the figure represent the Pareto optimal points in the "reliability, cost" objective space (see Figure 5.3).

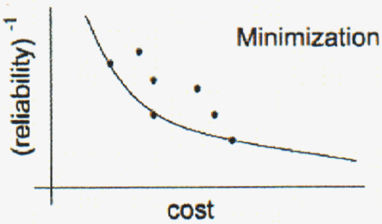

Figure 5.3 Pareto front and dominance.

An example of a fitness function for this type of problem is to rank the solutions in the population according to their degree of dominance. This ensures that the most fit solutions are those that lie on or near the Pareto front.

The final issue to be dealt with in this technology involves diversity. The statistical nature of the evolutionary optimization can result in a loss of solution diversity, and the solutions discovered may focus or evolve to a narrow portion of the Pareto front. The literature identified a number of approaches to maintain diversity. The present LDRD effort utilizes the approach in which a "distance" metric is defined between neighbors on the front. Those solutions that have close neighbors have their fitness reduced to enable solutions at other portions of the front to survive into subsequent generations.

Following the engineering analyses, the decision-maker can take the solutions lying on (or near) the Pareto front to perform meaningful "what-if" assessments. If reliability dominates the decision, the solution defined by the leftmost point on the curve is the best overall solution. If cost dominates, then the solution lying the greatest distance to the right reflects the best solution--the center point representing some form of a balance. Identifying large populations of solutions along the front gives the decision-maker a much more flexible set of solutions to identify a design solution under varying importance.

Section V References.

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6 System Modeling Requirements

Each system being analyzed must be defined functionally and architecturally by the analyst. Attempts have been made to make that job as simple as possible. A system, sub-system, or super-system is defined through the system API as shown in Figure 6.1. The behavior of the "system" level is defined by sets of functions, which are attributes of the "system" classes. The system has also defined a class structure in which a container class has been defined, which passes variables to and from the functions. This mitigates the changing argument lists that can cause problems during a design process. Input defines the independent variables that are included in the container class.

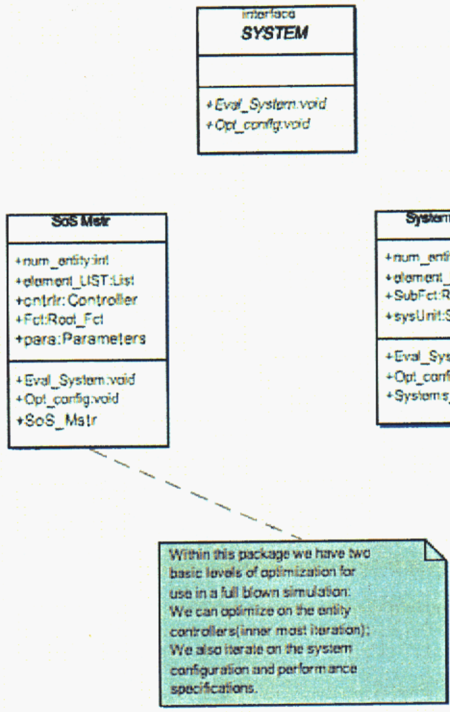

Figure 6.1 System API (proposed).

The interface between the system, the optimization routines, and the environmental interactions is identified in the next figure.

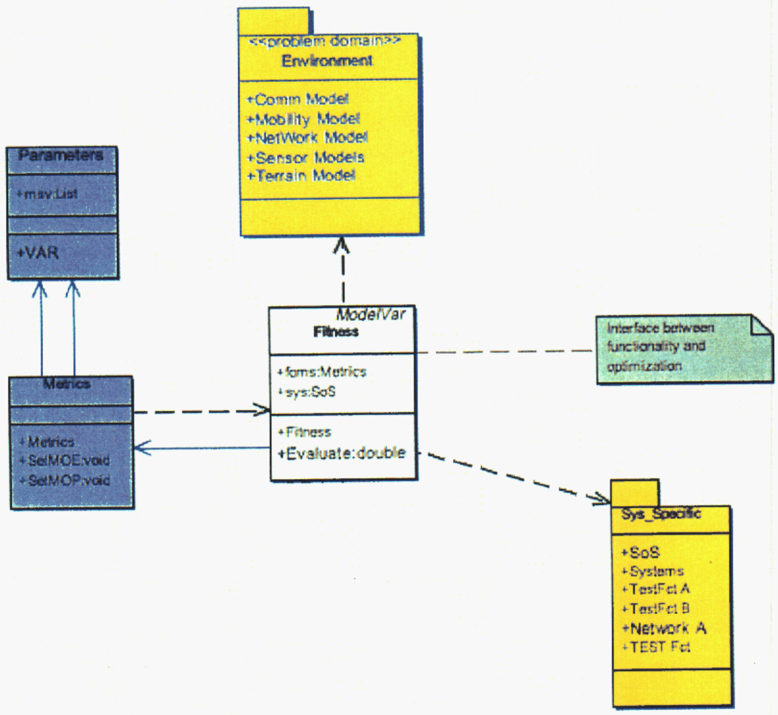

Figure 6.2 Computational interface or nexus.

"Parameters" in the figure is one of the container classes mentioned above. The package "Environment" contains functionality defining the performance and high fidelity physics interactions with the environment, in this case mobility, sensing, communications, etc. The second package is a specific implementation of a system design that utilizes the API mentioned earlier.

6.i Functional Representation

One major problem encountered in system design efforts is the ability to represent the behavior of the system. Many times that description is less than a full algorithmic representation and may consist of expert heuristics. For a systems engineer to perform the analyses needed, a quantification has to be performed to represent the dynamic behavior. A special package was defined which provides a foundation for representing a systems functionality in a number of computational dimensions. The projected set of capabilities is identified in the Figure 6.3.

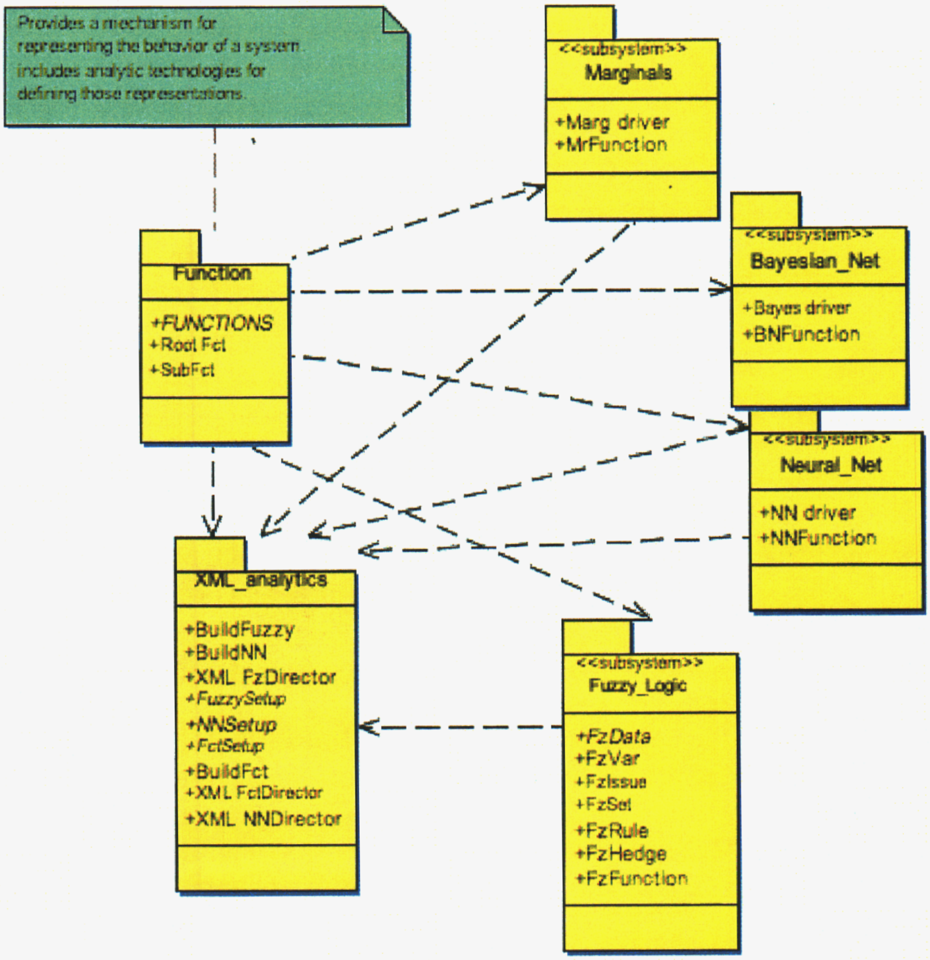

Figure 6.3 Functional representation space / technologies.

These approaches to define the behavior come from a number of technical and pseudo-technical fields, each providing a unique capability for dynamic representation. The implemented methods include "fuzzy logic", and "marginals". A Baysean capability, "JAVA_BAYES" exists in a package that has not yet been integrated into the infrastructure. It needs to have the input infrastructure replaced with an XML-type methodology. The neural net implementation (while being very robust for representing complex functions) is a known technology and was not coded into the system due to constraints of time and funding.

6.ii State / State Transition

One facet of systems design is identifying and optimizing the functional behavior and processes. While functional analysis activities associated with systems engineering are not often thought of as a state transition problem, the process of identifying functions is based on the need to move a system from one state to another. Enabling dynamic function calls in the core analytic system provides a foundation for analytically building the optimal state transition matrix and in turn identifying the critical functions of the system. The analytics can identify the most "cost" effective functionality to be identified based on the mission and the constraints associated with the problem.

Again, the complexity of the problem becomes evident when we consider the types of problems to be encountered. The first order approach is to base system functionality on a Markov type of transition, in which we can move to a new state while considering only the previous state of the system. It can be envisioned that this Markov constraint may not always be adequate and a Bayesian type approach may be required. In this situation the state being transitioned "to", may be a complex function of any subset of its prior states. This situation is expected to be important in complex highly integrated systems with many parallel functions occurring. Target detection and tracking is one that comes to mind. Tracking and targeting algorithms need to have a historical perspective in order to "remember" the target being attacked, and the sequence of controls sent, to mitigate the controller being confused as a new detection occurs within a tracking field of an earlier target.

The most interesting reason to begin using state models in the automated analytics is an approach initiated by NASA called "Model-based" programming. The systems designed and built by NASA must operate for long periods in environments that can only be guessed. Classic approaches to system control for these high reliability systems require that extensive fault tree analyses be performed and control routines be written for each contingency. This is problematic from a number of perspectives including the fact that all problems cannot be anticipated and Pareto optimality is insufficient. Additionally, even with minor design changes the fault analysis and control algorithm creation has to be re-done. Model-based programming uses a concept in which the information fed into the control system consists of the states that a system may achieve. Control is accomplished by defining desired end states with the current state defined by a kind of "state of health" capability design into the system. The control system determines its current state and attempts to find a trajectory that will ultimately transition the system to the desired end state. Knowing the states and the triggering events/functions that can transition the system between states provides a very robust mechanism for dealing with unknown or unanticipated situations.

There are also two approaches analytically to deal with building the transition matrix. The first is to use evolutionary strategies to set the probability values in the matrix. This is similar to the problem of identifying the weights in constructing a neural net. The second approach is to use the NEAT technology to select the binary transitions between states identified in the problem.

6.iii MOE's / MOP's

Measures of performance (MOP) and measures of effectiveness (MOE) are a very dynamic set and are generally defined differently under varying situations or designs. The approach developed in this effort is to dynamically define the metrics and use a special class to track and define which function will characterize the metric. In combat situations care must be taken to provide some traceability between the MOPs and the ultimate MOE which represent the dimensions in the decision domain. A roadmap (of sorts) was identified based on a number of "Netcentric warfare," FCS, Objective Force, and combat theoretic documents. A synopsis of that effort is captured in Figures 6.4 A-B.

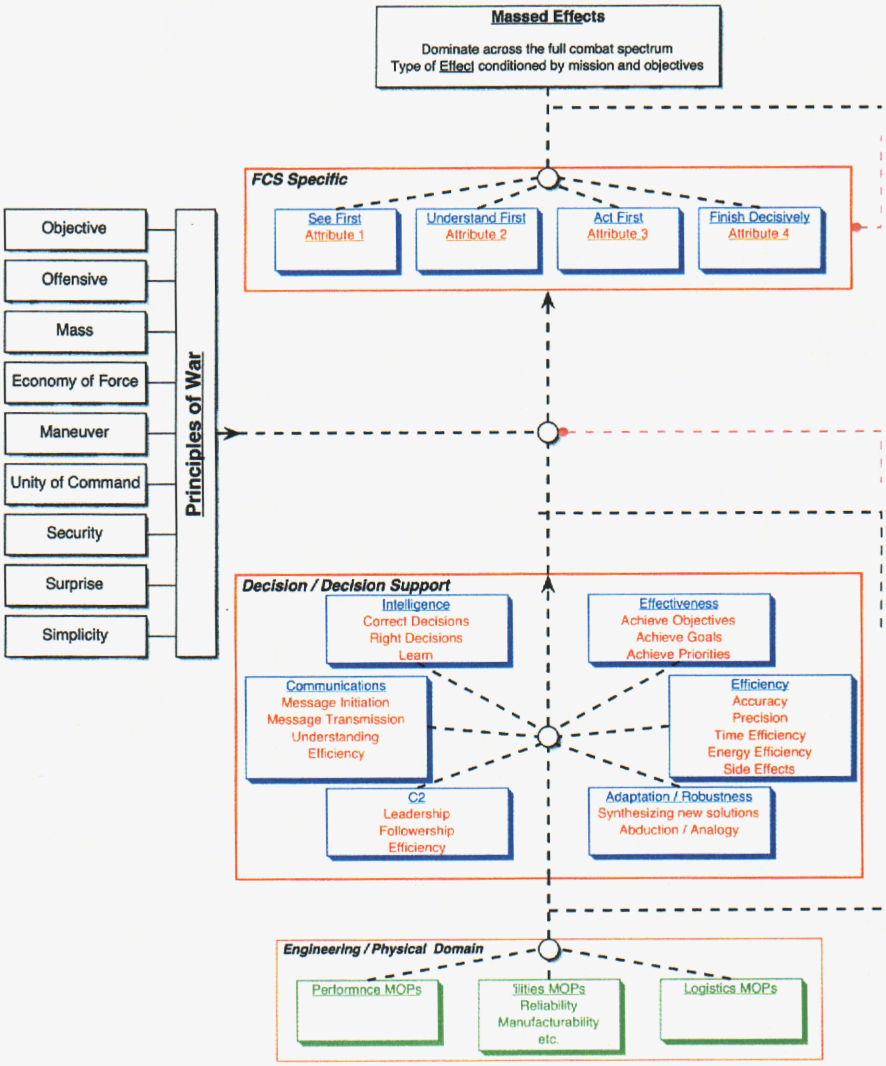

Figure 6.4A Metrics traceability guidance.

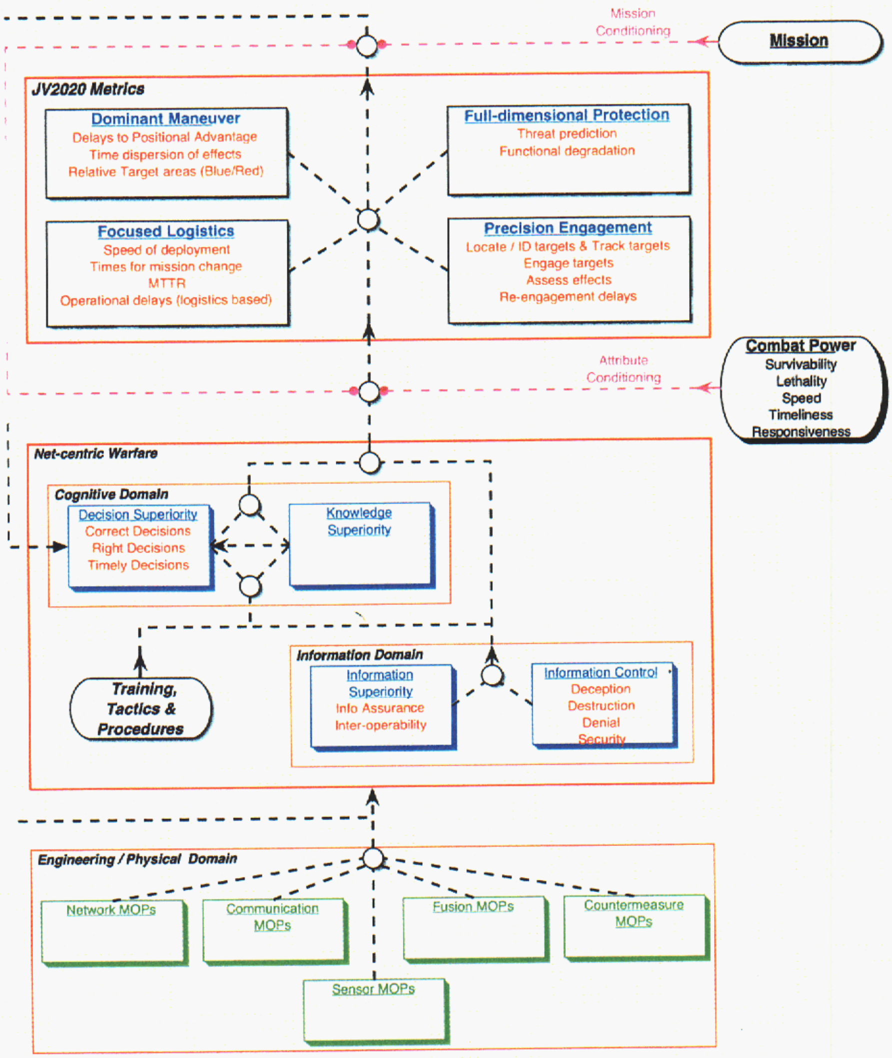

Figure 6.4B Metrics traceability guidance.

Some components in Figures 6.4 A-B are representative of filters or conditions which need to be imposed on the metrics developed. "Mission", "Combat Power", and the "Principles of War" must be considered as conditioning concepts. The block of metrics associated with decision support represents an extension of the metrics defined by Finkelstein. Finkelstein's work is the first effort that exhibits credible metrics associated with cognition / decision support systems.

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[9] JAVA Bayes URL and ref

7 Conclusions

The Development Environment for Operational Concepts and Systems Engineering Analysis (CONOPS) contributes to Sandia National Laboratories' business development efforts by providing initial steps toward the development of a high-fidelity environment for the exploration and design of Concept of Operations. Furthermore, the CONOPS Collaborative Mission Planning and Training Environment uniquely addresses 1) the goals of the U.S. Army's Future Combat Systems (FCS) embedded training requirement, 2) Objective Force Warrior mission planning under ambiguous circumstances and 3) Homeland Defense training. The CONOPS collaborative interface provides innovative mission-planning tools in a decision-support framework for exploring concepts, analyzing strategies, and evaluating and managing change.

In summary, a mission planner may use the CONOPS collaborative interface environment to engage in the design of a scenario-driven concepts of operation that includes semi-autonomous entities in roles that are optimized by forward simulation. The CONOPS collaborative interface environment offers both mission planning and training. The collaborative interface, also aids the mission planner in the design or planning activity by providing him/her with the ability to access mission designs and forward simulations generated in the past, as well as those of others within a community. The collaborative mission planning and training environment is supported asynchronously via a collaborative data management system developed by Fraunhofer FIT (formerly GMD) called BSCW (Basic Support for Collaborative Work). Military and emergency management mission planners would use the CONOPS environment in embedded training systems or as a planning/design tool when preparing concept of operations scenarios that utilize autonomous or semi-autonomous entities. Further LDRD or other investment in the CONOPS environment would strengthen the strategic positioning of Sandia National Laboratories with the U.S. Armed Forces and Homeland Defense as the collaborative interface and Development Environment for Operational Concepts and Systems Engineering Analysis described in the present LDRD report is a unique contribution to mission planning applications and tools.

7.i Next Steps

A large part of the infrastructure coding is complete, and the XML methodology was explored. The conventional evolutionary strategies methodology is in place in the CONOPS simulation engine architecture as is most of the NEAT technology. The Pareto optimization is the next step to be completed. This will consist of coding the controls and building a routine to perform the fitness ranking and evaluation.

The CID problem (or a less complex one) should be further explored. This part of the problem has to be performed every time a new problem is introduced but is familiar to any systems engineer. Systems engineers seldom have the luxury of using the same systems analysis model twice. The CONOPS approach developed in the present LDRD, in which the argument list consists of the passing of a single container function, should significantly reduce the difficulty of writing descriptive models of a system.

Finally, several steps were in progress when funding for the present LDRD effort ended. A combat ID (CID) problem was in the process of being determined in order to test parts of the architecture. The problem consisted of a combat ID system involving information flow, sensors, information database, and passive and active ID systems. The engineering of the problem began by examining the proposed use case indicated in Figure 7.1.

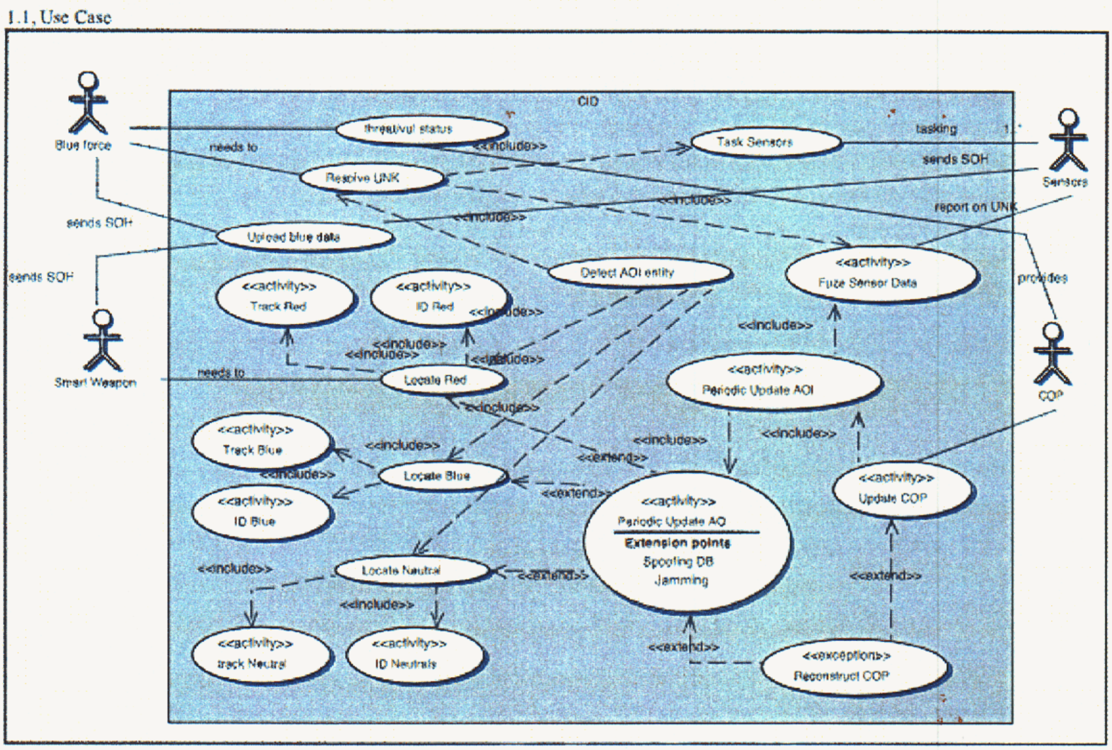


Figure 7.1 Use case diagram for a CID type system.

The use case model became the basis for a first cut at a functional model as indicated in Figure 7.2 A-B. This would have been the basis for generating a state model to take advantage of some of the computational aspects of the analytic approach. This problem is interesting since process needs to be developed simultaneously, with the hardware. It is the process aspect of the problem that requires a systems engineering approach such as outlined in this document. Although diffusion of the LDRD effort precluded a formal investigation of the integrated analytics, future steps include the instantiation of the CID problem and proposed CONOPS system as part of the first author's economics masters thesis addressing economic warfare.

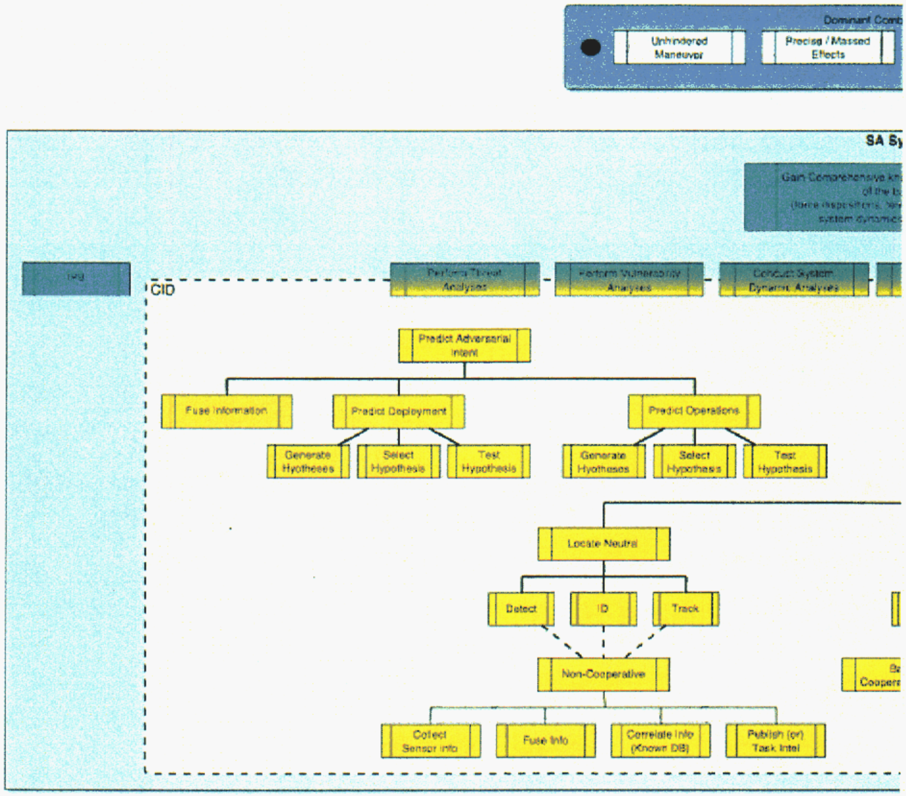


Figure 7.2 Functional model (part A).

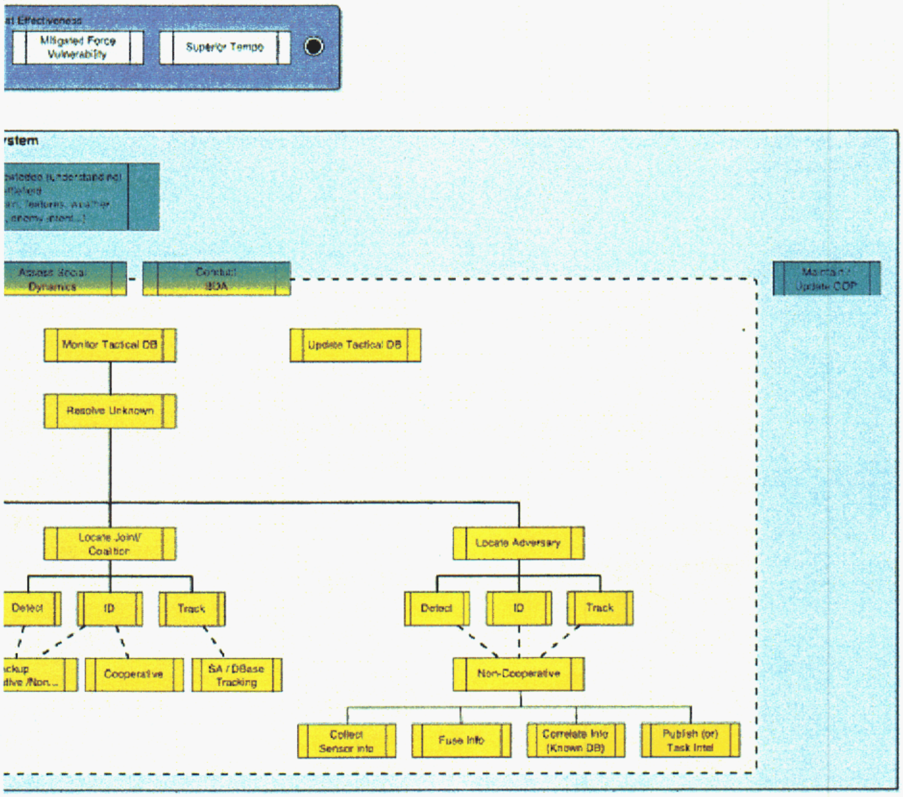


Figure 7.3 Functional model (part B).

Section VII References

None

Appendicies.

The appendices consist of information collected by SMEs in the area of mobility and communications for use in defining the physics interactions with a class of autonomous systems. We appreciate the effort expended in encapsulating that information in a form that can be readily encoded into the physics modules.

Appendix I Physics Modeling

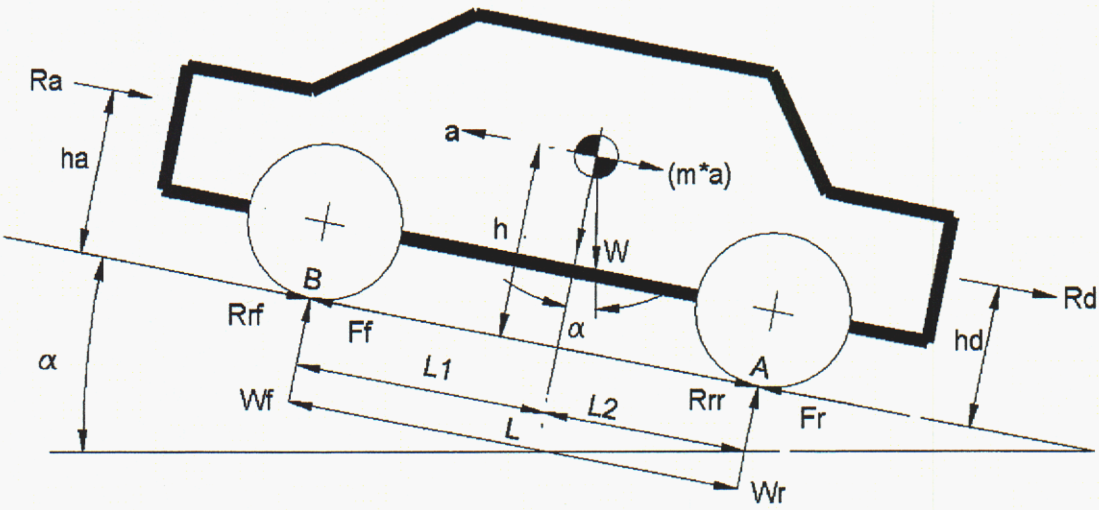
Appendix I.i Mobility (Paul Klarer; Dept 153xx SNL)

The efforts in analysis of robotic ground vehicle mobility have achieved some success in describing vehicle mobility, both against discrete obstacles and in terrain with real soil characteristics. Against discrete step obstacles, the kinematics of both wheeled vehicles and tracked vehicles have been described, as have the generic conditions of a wheeled vehicle transitioning between two planes having any assumed angle between them. To date all analysis has assumed quasi-static conditions for obstacle climbing, and true dynamic equations of motion are currently under development. The surfaces are assumed to be rigid, the wheeled vehicles are geometrically optimized for step climbing, and rigid body contacts are modeled as spring-mass-damper systems. In real terrain soils, less has been accomplished although the fundamental issues are becoming much clearer. Because operations in real terrain involve the interactions of wheels or tracks with soil, soil mechanics becomes a very important issue when attempting to describe the mobility, speed, and power consumption of a vehicle operating on a compressible soil with a limited shear strength. A simple model that accounts for two of the most important generic soil parameters for shear strength is the Mohr-Coulomb model, which is currently being investigated as a method for including soil mechanics parameters into simulations of vehicle terrain interactions. It should be noted that mobility issues involving vehicle dynamics and soil mechanics do not depend on whether the vehicle is manned or unmanned. Implications of modeling robotic control versus manned control of vehicles include varying the degree to which the vehicle can discern and avoid mobility hazards, operate at speed under adverse conditions, and react/adapt to rapidly changing conditions. These parameters will be important ones to include in any simulations of robotic or manned vehicles operating together in a battlefield environment.

Dynamics of Wheeled Vehicles in Terrain

This is an initial attempt to describe off-road vehicle dynamics in terms of tractive and resistive forces, and how to quantify or calculate those forces baed on limited information about the terrain and soil conditions. It begins with defining the equations of motion in classical dynamics terms and then proceeds to defining the wheel-soil interaction forces present in the dynamics in terms of terramechanics.

Rev history: 1.0 prk, 5/16/2002: original draft



Equations of Motion

The aerodynamic drag force is Ra, the drawbar load is Rd, the rolling resistances of the front and rear wheels are Rrf and Rrr, and the slope/grade resistance is Wsin(α). The tractive effort of the front and rear wheels are Ff and Fr, assuming each are driven wheels. If the wheel is not driven then its value is zero (for rear wheel drive, Ff=0).

Summing the forces along the longitudinal axis of the vehicle, the dynamic equation of motion is:

$$\Sigma F = m \cdot a$$

$$Ff + Fr - Ra - Rrf - Rrr - Rd - W \cdot \sin(\alpha) = m \cdot a \qquad \text{Eq. 1}$$

Combining the two tractive forces and combining the two rolling resistances

$$F = Fr + Ff$$

$$Rr = Rrf + Rrr$$

$$W = m \cdot g$$

Then the equation becomes:

$$F = Ra + Rr + Rd + m \cdot (g \cdot \sin(\alpha) + a) \qquad \text{Eq. 2}$$

where:

F is the total tractive force

Rr is the total rolling resistance

g is the acelleration of gravity

The tractive forces at each wheel depend on the normal forces at the point of contact, Wf and Wr. Summing the moments about A (note the last term would be positive for a 'downhill' configuration):

$$Wf = \frac{m \cdot g \cdot L2 \cdot \cos(\alpha) - Ra \cdot ha - m \cdot a \cdot h - Rd \cdot hd - m \cdot g \cdot h \cdot \sin(\alpha)}{L} \qquad \text{Eq. 3}$$

Similarly summing the moments about B (where the last term will have opposite sign than for Eq. 3):

$$Wr = \frac{m \cdot g \cdot \cos(\alpha) + Ra \cdot ha + m \cdot h \cdot a + Rd \cdot hd + m \cdot g \cdot h \cdot \sin(\alpha)}{L} \qquad \text{Eq. 4}$$

Terramechanics

Determining the tractive and resistive forces present at the wheel-soil interface is the challenge, since wheel-soil interactions are nonlinear and difficult to characterize analytically. A range of approaches have been attempted over the years by researchers, and models range from the simplest rigid wheel in a linear elastoplastic medium to flexible tires in emperically characterized nonlinear granular medium (soil) with anisotropic characteristics.

The initial formulation will proceed using a rigid wheel in an idealized, homogeneous elastoplastic soil. Future expansion of this work will extend into nonlinear soil representations.

Soil Strength Model

The Mohr-Coulomb model for soil strength (Wong, 'Theory of Ground Vehicles, 2nd Ed.', page 86):

$$\tau = c + \sigma \cdot \tan(\phi)$$

where:

τ is the soil shear strength

c is the apparent cohesion of the soil

σ is the normal stress on the sheared surface

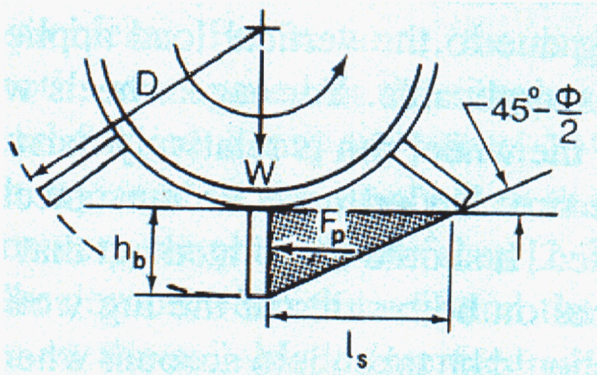
ϕ is the angle of internal shearing resistance of the material

Obtaining a value for σ is entirely dependent on the vehicle configuration chosen and what assumptions can be made about the wheel/soil interface geometry (sinkage, tire deflection, etc.). Obtaining values for *c* and ϕ are problematic, although some approximations can be made based on empirical data already tabulated by others. By way of explanation, Wong states that soil cohesion is the bond which cements particles together irrespective of the normal pressure exerted by one particle on another. In contrast, frictional masses are held together only where there is a normal pressure existing between them. Note that in an idealized fully cohesive soil such as a saturated clay ϕ can be assumed to be zero, whereas in an idealized fully frictional material like dry sand there is no cohesion and *c* can be assumed to be zero.

Tractive Effort of a Wheel With Grousers in Soil

Two basic types of soil failure can occur in a prismatic section of soil from an infinite mass under the Mohr-Coulomb model, called Rankine active (shear expansion of the prism) and Rankine passive (shear compression of the prism). Generally, vehicles acting on terrain generate the passive failure mode. For a wheel with a grouser (a tread, lug, or paddle), if the grousers are far enough apart to ensure the soil between successive grousers does not 'stick' and thereby merely increase the wheel diameter, then the tractive force generated by the grouser pushing against the soil can be approximated. It is assumed that the ratio of the grouser's width to the penetration depth into the soil is large, and that the wheel rim is narrow so that no pressure surcharge is applied to the soil via the rim itself (Wong, 'Theory of Ground Vehicles, 2nd Ed.' pp. 89- 90). The tractive force generated by the grouser in the vertical position is approximately (see figure below) where z indicates the vertical (soil depth) dimension.

$$Fp = b \cdot \int_0^{hb} \sigma p \, dz \qquad \text{Eq. 5}$$



Grouser lug in soil, from Wong, 'Theory of Ground Vehicles, 2nd Ed.' pg. 89
From the geometry of a Mohr diagram of major principal stresses in soil (Wong, 'Theory of Ground Vehicles, 2nd Ed' pg. 88), the passive earth pressure σp is given by:

$$\sigma p = \left(\gamma s \cdot z \cdot N\phi + 2 \cdot c \cdot \sqrt{N\phi}\right)$$

where $N\phi$ is defined to be:

$$N\phi = \left(\tan\left(\frac{\pi}{4} + \frac{\phi}{2}\right)\right)^2$$

Performing the substitution into Eq 5:

$$Fp = b \cdot \int_0^{hb} \left(\gamma s \cdot z \cdot N\phi + 2 \cdot c \cdot \sqrt{N\phi}\right) dz$$

and then performing the indicated integration, an expression for the tractive force Fp is obtained

$$Fp = b \cdot \left(\frac{1}{2} \cdot \gamma s \cdot hb^2 \cdot N\phi + 2 \cdot c \cdot N\phi^{\frac{1}{2}} \cdot hb\right) \qquad \text{Eq 6}$$

where:

$N\phi$ is called the "flow value"

γs is the unit weight of the soil

hb is the height of the grouser

b is the width of the grouser

Note that the above is a conservative estimate for the tractive force, since end effects of the grouser, side pressure on the soil prism, and adhesion between the soil and the grouser will tend to increase the available tractive force. Also note that the force will vary with the angle the grouser makes with the ground and that, if multiple grousers are in simultaneous contact with the soil, the total tractive force will be the sum of the forces generated by all the grousers.

An example of how to use it (see Wong, 'Theory of Ground Vehicles, pg. 91), units are SI:
Given info:

$c := 20000Pa$

$\phi := 6deg$

$\gamma s := \frac{15700N}{m^3}$

$hb := 0.15m$

$b := 0.25m$

$\phi = 0.105rad$

Check the rupture length to be sure soil won't "stick" between grouser lugs. From the geometry, the spacing between the grouser lugs at the tip is 27 cm. If spacing between the lugs is such that the tip-to-tip distance is greater than the hypotenuse of the triangle bounded by the rupture length ls and the penetration depth hb then no stick occurs.

$$ls := \frac{hb}{\tan\left(\frac{\pi}{4} + \frac{-\phi}{2}\right)}$$

$$rdist := \sqrt{\left(ls^2 + hb^2\right)}$$

$rdist = 0.224m$

is less than lug spacing (27 cm) so the soil should not stick to the wheel

Calculate the flow value

$$N\phi := \left(\tan\left(\frac{\pi}{4} + \frac{\phi}{2}\right)\right)^2$$

$N\phi = 1.233$

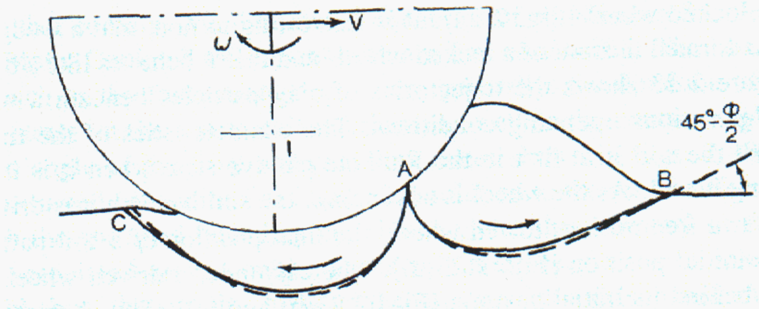
Calculate the tractive force for one wheel generated by one lug at the vertical position Result in Newtons:

$$Fp := b \cdot \left(\frac{1}{2} \cdot \gamma s \cdot hb^2 \cdot N\phi + 2 \cdot c \cdot N\phi^{\frac{1}{2}} \cdot hb\right)$$

$Fp = 1.72 \times 10^3 N$

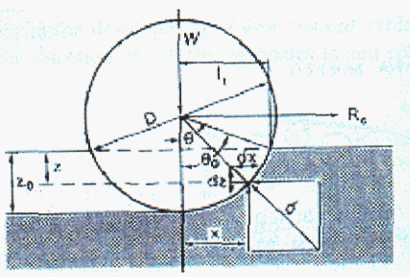
Resistance of Soil to a Rotating Wheel

The action of a wheel in soil creates a set of particle flow zones under the wheel, such that some soil is thrust behind the wheel (in the direction of wheel rotation) and some is piled up in front of the wheel (in the direction of travel). This is due to the state of shear stress in the soil and actions imparted to individual particles of soil by a variety of factors, including wheel slip, soil characteristics and whether the wheel is driven or towed. The 'bulldozing' or piling up of soil in front of the wheel effectively presents a resistance to vehicle motion, which can be characterized as a force that depends on soil characteristics and wheel geometry. Note that calculating the resistance forces due to the bulldozing effect involves a fairly involved knowledge of both soil and wheel lug surface conditions, which is highly problematic for a design problem. Therefore, the bulldozing resistance force is not treated here, but should be approximated only for very sandy soil conditions, as it is not much of a problem in clayey soils.



Flow patterns & bow wave under a driven roller in sand (from Wong, 'Theory of Ground Vehicles', 2nd Ed., page 99)

A simplified model first proposed by Bekker in 'Theory of Land Locomotion' assumes the soil is soft enough such that it compacts to a much greater extent than the wheel deflects, and so the wheel can be treated approximately as a rigid cylinder in a compressible medium (see figure below). This model can be used to estimate the compaction resistance of the soil,so long as the wheel diameter is not too small (minimum of 20" or so). Bekker showed that this approximation is good for moderate sinkages ($z_0 < D/6$) so long as there is no significant slip sinkage (wheel excavation) as can occur in very dry sand.



Simplified wheel-soil interaction model, taken from Wong, 'Theory of Land Vehicles', pg. 150; after Bekker's 'Theory of Land Locomotion' which assumes a *rigid* wheel.

The equilibirum conditions for a towed *rigid* wheel are:

$$Rc = b \cdot \int_0^{\theta 0} \sigma \cdot r \sin(\theta)\, d\theta \qquad \text{Eq 7}$$

$$Ww = b \cdot \int_0^{\theta 0} \sigma \cdot r \cos(\theta)\, d\theta \qquad \text{Eq 8}$$

where:

Rc is the motion resistance force

Ww is the vertical load on the wheel's axle

σ is the normal pressure

r is the wheel radius

b is the wheel width

The assumption is made that the normal pressure σ acting on the wheel rim is equal to the normal pressure p beneath a flat plate at the same depth z so that
and

$$p \cdot dz = \sigma \cdot r \cdot \sin(\theta) \cdot d\theta$$

$$p \cdot dx = \sigma \cdot r \cdot \cos(\theta) \cdot d\theta$$

Using Bekker's proposed equation for pressure-sinkage relationships in homogeneous soils (Bekker, 'Introduction to Terrain-Vehicle Systems'):

$$p = \left(\frac{kc}{b} + k\phi\right) \cdot z^n$$

where:
n,kc,kϕ are soil parameters that must be determined empirically in controlled soil tests. Wong describes the process in some detail in 'Theory of Ground Vehicles, 2nd Ed. pp. 115-120
Substituting the expression for p into Eq 7, and performing the integration yields an expression for the compaction resistance Rc, however, the sinkage $z0$ must first be determined. The compaction resistance Rc is equivalent to the vertical work done per unit length in pressing a plate of width b down into the soil to a depth of $z0$. Bekker's assumption is that is that the motion resistance of a rigid wheel in soil is due to the vertical work done in making a rut of depth $z0$ in the soil. yields:

$$Rc = b \cdot \int_0^{z0} \left(\frac{kc}{b} + k\phi\right) \cdot z^n \, dz$$

$$Rc = b \cdot \left[\left(\frac{kc}{b} + k\phi\right) \cdot \frac{z0^{n+1}}{n+1}\right] \qquad \text{Eq 9}$$

To find the sinkage z0, we substitute the expression for p into Eq 8:

$$Ww = b \cdot \int_0^{z0} p \, dx$$

becomes

$$Ww = b \cdot \int_0^{z0} \left(\frac{kc}{b} + k\phi\right) \cdot z^n \, dx$$

From the geometry,

$$x^2 = [D - (z0 - z)] \cdot (z0 - z)$$

and for small $z0$

$$x^2 = D \cdot (z0 - z)$$

so

$$2 \cdot x \cdot dx = -D \cdot dz$$

Substituting back into the equation for Ww to get everything in terms of z and dz:

$$Ww = b \cdot \left(\frac{kc}{b} + k\phi\right) \cdot \int_0^{z0} \frac{z^n \cdot \sqrt{D}}{2 \cdot \sqrt{z0 - z}} \, dz$$

Using a parameter t such that:

$$z0 - z = t$$

then

$dz = -2 \cdot t \cdot dt$

and so:

$$Ww = b \cdot \left(\frac{kc}{b} + k\phi \right) \cdot \sqrt{D} \cdot \int_0^{\sqrt{z0}} \left(z0 - t^2 \right)^n dt$$

Expanding $(z_0-t^2)^n$ as a Taylor series:

$$\left(z0 - t^2 \right)^n$$

on the parameter *t* obtains:

$$z0^n + -z0^n \cdot \frac{n}{z0} \cdot t^2 + \frac{1}{2} \cdot z0^n \cdot \frac{n}{z0^2} \cdot (n-1) \cdot t^4 + ...$$

and taking only the first two terms, an approximate expression for the vertical load Ww is obtained:

$$Ww = \frac{b \cdot \left(\frac{kc}{b} + k\phi \right) \cdot \sqrt{z0 \cdot D}}{3} \cdot z0^n \cdot (3-n)$$

Since the vertical load at the wheel is known (it comes from the equations of motion), rearranging the above equation to solve for the sinkage z0 yeilds:

$$z0 = \left[\frac{3 \cdot W}{b \cdot (3-n) \cdot \left(\frac{kc}{b} + k\phi \right) \cdot \sqrt{D}} \right]^{\left[\frac{2}{(2 \cdot n + 1)} \right]} \qquad \text{Eq 10}$$

A table of values for the soil parameters n, kc, kφ is found in Wong, 'Theory of Ground Vehicles', pg. 118. This table also lists typical values for c and φ as well. An extract of that table listing some typical values for some common soils comprising a range from sand to clay is given below.

Terrain	n	kc	kφ	c	φ
		kN/m^(n+1)	kN/m^(n+2)	kPa	deg
Dry Sand	1.1	0.95	1528.43	1.04	28
Sandy Loam	0.7	5.27	1515.04	1.72	20
Clayey Soil	0.5	13.19	692.15	4.14	13
Heavy Clay	0.11	1.84	103.27	20.69	6

Substituting Eq 10 into Eq 9 the compaction resistance Rc for a rigid wheel is estimated to be:

$$Rc = \left(\frac{3 \cdot W}{\sqrt{D}} \right)^{\left(\frac{2 \cdot n + 2}{2 \cdot n + 1} \right)} \cdot \left[(3-n)^{\left(\frac{2 \cdot n + 2}{2 \cdot n + 1} \right)} \cdot (n+1) \cdot b^{\left(\frac{1}{2 \cdot n + 1} \right)} \cdot \left(\frac{kc}{b} + k\phi \right)^{\left(\frac{1}{2 \cdot n + 1} \right)} \right]^{\langle -1 \rangle} \qquad \text{Eq 11}$$

Note that the above equation for Rc is obtained by applying a series expansion and taking only the first two terms for the expression $(z_0-t^2)^n$; therefore, it is only valid for values of n up to about 1.3. For values of n greater than 1.3, the first 5 terms of the series should be used to approximate the function $(z_0-t^2)^n$.

See Wong, 'Theory of Ground Vehicles' 2nd Ed. pp. 150-152 for details.

Summary

Given some known information including the vehicle geometry, terrain geometry, and soil type, the following equations can be used to estimate the straight-line motion of the vehicle, assuming some inital conditions and making use of a numerical integration technique.

The dynamic equation of motion for a two-axled wheeled vehicle operating on a sloped terrain is:

$$Ff + Fr - Ra - Rrf - Rrr - Rd - W \cdot \sin(\alpha) = m \cdot a \qquad \text{Eq. 1}$$

where tractive forces are denoted as *F* and resistive forces are denoted as *R*, vehicle weight is *W*, the local slope of the terrain is α, and the vehicle mass and acceleration are *m* and *a*

The maximum tractive forces Ff and Fr available at each wheel are determined by the soil conditions:

$$Fp = b \cdot \left(\frac{1}{2} \cdot \gamma s \cdot hb^2 \cdot N\phi + 2 \cdot c \cdot N\phi^{\frac{1}{2}} \cdot hb \right) \qquad \text{Eq 6}$$

where the soil conditions γs, *c*, ϕ, *n*, *kc*, and $k\phi$ are obtained from a table and the flow value $N\phi$ is found from the relation:

$$N\phi = \left(\tan\left(\frac{\pi}{4} + \frac{\phi}{2} \right) \right)^2$$

The compaction resistance forces Rrf and Rrr present at each wheel are also determined by the soil conditions:

$$Rc = \left(\frac{3 \cdot W}{\sqrt{D}} \right)^{\left(\frac{2 \cdot n+2}{2 \cdot n+1} \right)} \cdot \left[(3-n)^{\left(\frac{2 \cdot n+2}{2 \cdot n+1} \right)} \cdot (n+1) \cdot b^{\left(\frac{1}{2 \cdot n+1} \right)} \cdot \left(\frac{kc}{b} + k\phi \right)^{\left(\frac{1}{2 \cdot n+1} \right)} \right]^{(-1)} \qquad \text{Eq 11}$$

Appendix I.ii Communications (John Harrington; Dept. 153xx SNL)

Warfighting elements that are able to freely share information may possess a considerable advantage over forces that are not so equipped. This advantage stems mainly from sharing information regarding location and status of both friendly and enemy forces, the coordination of logistical support, and the control of fires. This capability can be obtained through the use of packet-switched radios that are tailored for the battlefield as a robust and flexible communication network. In addition to facilitating many aspects of modern-day warfare, this network would permit the introduction of new technologies such as unmanned systems that multiply the effectiveness of a group while mitigating hazards. However, for the communication system to support these functions, the service that each user requires must be understood.

Reconnaissance and targeting

Future systems will contain many conventional, manned systems that are to be linked into this information system under C4ISR. Coordination of these assets will occur via the network instead of conventional voice radios. The load to the communication network from manned systems is typically low compared to unmanned systems because humans are fairly autonomous and can perform diverse tasks without constant supervision. In the case of reconnaissance and targeting functions, humans readily process visual information and need only to burden the network with target information once identified and may require a few hundred bits to be communicated within a few seconds. If this function is replaced with a simple imaging sensor, a video stream of nearly 800 kilobits per second (kbps) must be continually conveyed when a person interprets the imagery. Using advanced data compression techniques, this requirement can drop to 15 kbps. If ATR techniques are employed along with data compression, only 5000 bits (which includes an image) may need to be communicated for each target, and there is no constant human supervision.

Control of robotic ground vehicles

Manned and unmanned mobile platforms present many of the same requirements to the network. If a manned ground vehicle is linked with the communication system, only periodic messages need to be sent with position and status while receiving occasional commands. The network load may only be 300 bits every minute in this case since a human is responsible for controlling the vehicle. However, if an unmanned ground vehicle (UGV) is to be teleoperated, at least five video frames per second with low latency are required to achieve minimal performance. This information can be conveyed using 20 kbps to 1 Mbps depending on the level of compression. Latency must be held to less than 0.25 seconds. Communication load can be cut to a few hundred bits per minute if the vehicle is highly autonomous, but there may always be an intermittent requirement for teleoperation or imagery that will stress the network.

Unmanned Aerial Vehicles (UAV)

UAVs are another class of robotic vehicle that is already in use. These devices have similar communication requirements as UGVs. The main difference is that it is easier to make UAVs autonomous since there are fewer objects to avoid once the vehicle is well above the ground. A prime mission for UAVs is to provide imagery back to a command location via radio. In this case, whether the vehicle is autonomous or not, a constant stream of information must be conveyed and this may load a network considerably if the data is not compressed.

Network connectivity

Up to this point, only loads on the network have been considered, but another important parameter is network connectivity. With Line-of-sight (LOS) communications, direct links between many network nodes may not be possible because of obstacles in the terrain. However, a distinguishing feature of networked radios compared to conventional radios is their ability to relay messages for other nodes. Each network node, whether aboard a UGV, UAV, or manned system, is capable of relaying messages. If the area of operation is highly populated with these radios, many redundant paths may exist between any two nodes wishing to communicate a situation which results in a robust system. Nodes that are positioned at high elevation points such as hilltops or aboard UAVs or satellites may serve as communication hubs that provide links to most of the nodes over a wide area. However, because of loading constraints and the vulnerability of low flying UAVs, terrestrial links may mitigate these problems.

Routing is critical because this property is what creates a seamless and robust communication grid. This task becomes exceptionally challenging because of the mobile nature of the nodes. As a node moves along the ground, links to other nodes will be broken and new links created. It is imperative that the network adjust to these changing conditions if a seamless grid is to be maintained. Considerable amounts of network control data must be added as overhead if the network is to maintain this routing capability. The load this data presents must be added to the user data already being handled by the network.

Communication latency

Latency and routing are two more crucial aspects of a network. Many of the services provided by the network are time critical. If targeting information is not received and acted upon within a few seconds, fire missions will miss their opportunity. Teleoperation of robotic platforms creates the greatest stress to the system because of the large amounts of information that must be conveyed with very little delay. Communications that are relayed through intermediate nodes typically experience additional delays because of retransmission time. These additional delays must be carefully controlled for those users that have strict quality of service requirements.

The entire communication network can be analyzed for loading and latency values but the number of users and their particular functions at any point in time must be considered. Routing algorithms and propagation models over various terrains are important factors that affect the analysis. Multiple frequency channels and frequency reutilization greatly affect the problem of routing but can provide additional data bandwidth. A detailed analysis would also include specific radio parameters such as synchronization time, attack time, inter-symbol interference, modulation techniques, coding, and link margins. Most of these factors impact overall throughput as a consequence of bit errors and retransmissions.

Radio Propagation for Simulation of FCS Links

A radio antenna may be thought of as a transducer that converts guided electromagnetic (EM) waves into free-space waves, or vice versa [1]. If the free-space wave travels uniformly in all directions as an expanding sphere, the antenna is defined as an isotropic radiator. In this case, power is evenly distributed over the surface of the sphere of radius, *r*.

$$\text{Spherical Area} = 4\pi r^2 \qquad \text{Eq. 1}$$

A receiving antenna on the surface of the sphere will intercept a fraction of this power which is proportional to its effective aperture or cross-sectional area [2]. This area is a function of the antenna size, λ which is also related to operating frequency.

$$\text{Effective Aperture} = A_e = \frac{\lambda^2}{4\pi} \qquad \text{Eq. 2}$$

Receive (P_r) power is also directly proportional to transmit power (P_t) so that the power received is [3]

$$P_r = \frac{P_t A_e}{4\pi r^2} = P_t\left(\frac{\lambda}{4\pi r}\right)^2 \qquad \text{Eq. 3}$$

As already stated, antenna size is related to frequency where *c*, is the speed of light and *f*, is frequency (Hertz)

$$\lambda = \frac{c}{f} \qquad \text{Eq. 4}$$

Substituting the above equation into equation (3) yields

$$P_r = P_t\left(\frac{c}{4\pi r f}\right)^2 \qquad \text{Eq. 5}$$

Path loss due to propagation is the ratio of transmit power, P_t to receive power P_r so

$$\text{Path Loss} = \frac{P_t}{P_r} \approx \left(\frac{4\pi r f}{c}\right)^2 \qquad \text{Eq. 6}$$

The following expression restates equation (6) using units of meters, Megahertz, and decibels
Path Loss = -27.6 + 20 log (f) + 20 log (r) (dB) (7)
Equation (7) describes free-space propagation with isotropic antennas at both the transmitting and receiving ends and makes no allowance for other path losses such as absorption. These additional losses are sometimes modeled in equation (7) by increasing the coefficient of the log (r) term. It is worth noting that the coefficient of '20' is actually composed of the coefficient '2' that describes squaring of distance r, that is then multiplied by 10 because of units of decibel. This coefficient of '20' is sometimes arbitrarily increased upwards to '40' to account for losses due to absorption and diffraction, depending on the area of propagation.
A free-space path implies that a line-of-sight path exists between the transmitting and receiving antenna, but, if the signal passes near ground (or other objects), diffraction of the signal may occur. Huygens principle explains this phenomenon which can be modeled as a set of concentric ellipsoids, called Fresnel zones, that surround the direct path. The even numbered zones tend to cancel the direct wave and odd zones reinforce it. Empirical tests have shown that if ground obscures 60% of the first zone, a good link can be established because all higher order zones are blocked. The following equation defines the radius (in feet) of the first Fresnel zone at an object that is located d_1 (miles) from the first antenna and d_2 (miles) from the second antenna. [2]

$$\text{Fresnel \#1} \approx 2280\sqrt{\frac{d_1 d_2}{MHz(d_1 + d_2)}} \qquad \text{Eq. 8}$$

Notwithstanding natural and man-made objects, terrestrial propagation is usually limited by the earth's curvature. The radio horizon is slightly longer than the physical horizon because of atmospheric refraction. This effect can be modeled by assuming the earth's radius is 4/3 its actual dimension. The real radius is 6250km so a close approximation is as follows where h is in meters of one of the antennas. The horizon distance of the transmitting and receiving antenna should be computed separately then added together. The most reliable path will typically occur when the direct path passes above the horizon 60% of the height calculated in equation 8.

$$\text{Horizon distance (km)} \approx \sqrt{2 \times 4/3 \times 6.25 \times h} \qquad \text{Eq. 9}$$

The radio signal may experience additional losses from free space propagation if the signal passes through foliage. The following table lists some of these attenuation factors for several popular bands that varies due to foliage density and water content.

Frequency (MHz)	Attenuation (dB/meter)
432	0.10 - 0.30
1296	0.15 - 0.60
2304	0.25 - 0.50
3300	0.40 - 0.60
5600	0.50 - 1.50
10000	1.00 - 2.00

Equation (7) assumes isotropic radiators but in practice, all antennas have some directionality. Directionality usually implies a concentration of radiation in a preferred direction that results in a signal gain at the receiving position. Antenna gain typically exhibits reciprocity whether transmitting or receiving and the gains at both antennas contribute to the received signal. Gain is achieved at the expense of increased size and a directional antenna must be pointed in the desired direction which may pose a serious problem for a mobile platform. An antenna can be omnidirectional but still possess gain. In this case, a spherical pattern is compressed to resemble a doughnut that radiates in all azimuth directions but has a limited elevation angle. Sometimes the advantage of directionality is not to increase the signal passed between two points but rather to avoid radiating the signal towards an adversary or perhaps rejecting an interfering signal from an adjacent transmitter. These properties are reflected in the antenna's front-to-back ratio and side-lobe radiation specifications. The following equation takes into account antenna gain (G_t for transmitter antenna gain and G_r for receiver antenna gain) and path loss (L_p) as it relates to received power [4].

$$P_r = P_t + G_t + G_r - L_p \text{ (dB)} \qquad \text{Eq. 10}$$

The necessary power that must be received to establish a viable link is a function of the receiver's sensitivity which is set by its bandwidth and noise figure. For every Hertz of bandwidth, a given amount of noise will be amplified along with the desired signal. This noise level stems from thermal energy which Boltzmann's constant relates as being 1.3803 E-23 W/K/Hz. At normal temperatures, this amounts to -174 dBm/Hz of bandwidth (B) [5]. The receiver itself generates additional noise that is specified as a noise figure (N_f). Intelligence is recovered through a demodulation process that is limited by the signal to noise ratio (SNR). The following equation states the minimum power that must received to achieve the quality that the demodulation process and SNR is capable of providing.

$$P_r \geq -174\,dB_m + 10\log(B) + \mathrm{SNR} + \mathrm{N_f} \qquad \text{Eq. 11}$$

Given the bandwidth and signal quality, the amount of data that can be theoretically communicated is expressed below by Shannon's [6] limit where C is the data rate in bits per second (bps)

$$C = 1.45B\ln(1+SNR) \qquad \text{Eq. 12}$$

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Appendix I.iii Network Analytics

I wanted to include a short introduction to an fundamental approach for the analysis of networks that I think folds nicely into the evolutionary computational approaches identified throughout the analytical framework of this effort. I believe the edited text by Corne has collected an interesting vision of working with networks and may provide some insight into dealing with ad hoc secure networks. This book breaks the problem into three problems; network planning and design, routing and protocols, and traffic management. The editors have collected examples of work in these areas that employ evolutionary optimization and evolutionary gamming approaches for analyzing networks.

The section dealing with design explores a number of genetic techniques for designing networks and identifies sets of metrics that are used in these optimization techniques. Some of the measures identified in these optimization approaches include cost minimization, information flow maximization, efficient routing, redundancy, delays, multi-commodity flow which is used as a constraint, and a conservation of information flow at a node. The idea is to use a genetic construct for the optimization and where possible accelerate the convergence using heuristics from the field of network analysis. Instead of using a brute force approach with randomly defined network topologies, the GA's operate in an environment defined by some heuristic method. Acceptable permutations are based on the heuristic being employed. There are also examples of Tabu search methodologies, simulated annealing, and a novel approach that employs genetic programming principles on node-link combinations.

The routing analytics explored a number of techniques involving fuzzy logic and neural networks. There seems to be a bias towards statistically based methods and a learning aspect to identify the best routing. It would seem that a Bayesian approach might also be applied to this problem to deal with dynamic networks. The methods discussed focused on static networks but did introduce the idea of a partial failure and eventual restoration of the network. The causal nature of the Bayesian network may have unique characteristics that might be useful in working with ad hoc networks.

The last area focused on network traffic control. An interesting perspective in this section viewed information flow as an economics problem in which, a collection of users are competing for a limited set of resources and the structure the problem is based on a quality of service metric. This naturally leads to a game theoretic approach of which evolutionary game theory is the best approach in this situation. Much of the effort involves re-thinking the mathematics that form the basis for solving the problem; i.e., moving from linear programming or integer programming techniques to evolutionary based technologies. Once in this domain it is a "simple" mater of identifying the right fitness functions. One issue that has not been identified in the literature is the multi-objective nature of the optimization problem and the potential for Pareto optimization methodologies being used to solve these problems, especially in the design phase.

References

Network Analysis Methodology

[1] Corne, D. Oates, M. Smith, G.; *Telecommunicatons Optimization: Heuristic and Adaptive Techniques*; Wiley& Sons, England; ISBN 0-471-98855-3; 2000

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