

## TOOLKIT FOR ENABLING ADAPTIVE MODELING AND SIMULATION (TEAMS)

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### ABSTRACT

This paper describes the architecture of a Toolkit for Enabling Adaptive Modeling and Simulation (TEAMS). TEAMS addresses key technical problems associated with Space Transportation System operations process modeling and analysis. TEAMS facilitates collaborative and distributed spaceport operations analysis. Functions supported by TEAMS include (i) knowledge management, (ii) operations modeling, and (iii) operations analysis. Key innovations include (i) a process-centered approach that maximizes re-use of domain knowledge for rapid operations analysis model development, (ii) open-architecture, distributed plug and play architecture that allows for mass customization and rapid deployment of TEAMS, and (iii) novel, simulation-based optimization mechanisms. A TEAMS prototype has been developed and demonstrated at Kennedy Space Center.

### 1 MOTIVATION

The increasing complexity of systems has enhanced the use of simulation as a necessary decision-support tool. The popularity of simulation amongst competing quantitative tools can be attributed to the fact that it is both simple and intuitively appealing. It facilitates experimentation with real world systems that would either be impossible or otherwise cost prohibitive. Moreover, simulation is often the only scientific methodology available to practitioners for the analysis of complex systems.

Simulation is useful when (Benjamin et al. 1995):

- analyzing the effect of a change to an existing system,
- a proposed system does not exist,
- quantifying options to improve system performance, and
- other analytic methods become computationally intractable.

Simulation allows one to ask “what if” questions and to derive new information from existing knowledge. The simulation activity, coupled with the evaluation of alternate designs and courses of action can lead to a broader understanding of system operations and management policies. In spite of the advantages, only a small fraction of the potential practical benefits of simulation modeling and analysis have reached the ever burgeoning user community. This is because of the considerable time, effort, and cost required to build, maintain, and rapidly deploy simulation technology. For example, simulation model development practices have benefited greatly from the use of specialized libraries of model components for particular target domains; yet the maintenance of these simulation models still suffers from “find the expert and fix it” syndrome. In other words, the maintenance of the model remains an activity plagued by inconsistencies due to the relationship between the user in the target domain, the intention of the developer, and the capability of the maintainer. There is a need for new methods that allow simulation models to be rapidly reconfigured and maintained in content via the supporting knowledge base without intervention from the developer.

Current simulation practice (i) is afforded little automated support for the initial analysis, problem solving, and design tasks which are largely qualitative in nature, (ii) involves the unproductive use of time from both the domain expert and the simulation analyst in many routine tasks, (iii) requires significant investment of time and money to deploy and maintain simulations over extended periods of time, and (iv) suffers from a lack of widespread acceptance by decision makers due to a number of factors including (i) the semantic gap between the description of a system internalized by the decision maker and the abstract model constructed by the simulation modeler, (ii) the relatively long lead times and communication efforts required to produce a simulation model, and (iii) the extensive training and skill required for the effective design and use of simulation modeling techniques (Benjamin et al. 1998, Benjamin et al. 1995, Delen et al. 1998, KBSI 1994, KBSI 1997).

The broader area of operations/process modeling and analysis has problems similar to those associated with simulation modeling. For example, in the operations cost-modeling arena, there is limited support for Activity Based Cost (ABC) model development and for ABC model maintenance. A similar problem exists for optimization modeling and scheduling. This paper describes a solution architecture that seeks to address the (broader) problems associated with Spaceport or Space Transportation System (STS) operations modeling and analysis. By Spaceport, we refer to a four-dimensional vector of (i) space vehicles, (ii) spaceport technologies, (iii) facilities/assets, and (iv) operations/maintenance processes. This research specifically targets the following technical challenges associated with operations analysis simulation modeling and analysis: (i) inadequate methods and tools for cost effective operations/simulation model development and deployment, and (ii) inadequate methods and tools for cost effective operations/simulation model maintenance.

## 2 TEAMS SOLUTION CONCEPT

We have developed a Toolkit for Enabling Adaptive Modeling and Simulation (TEAMS), a software systems that facilitates collaborative and distributed Spaceport operations analysis. TEAMS provides valuable decision information to Spaceport stakeholders, analysts, and designers. Key functions provided by TEAMS include:

1. Spaceport Knowledge Management: Browse, organize, and share knowledge about spaceports.
2. Collaborative Spaceport Modeling: Facilitate collaborative and distributed Spaceport operations and maintenance activity modeling.

3. Collaborative Spaceport Analysis: Facilitate collaborative and distributed Spaceport operations and maintenance activity analysis.

The TEAMS solution concept is shown in Figure 1.

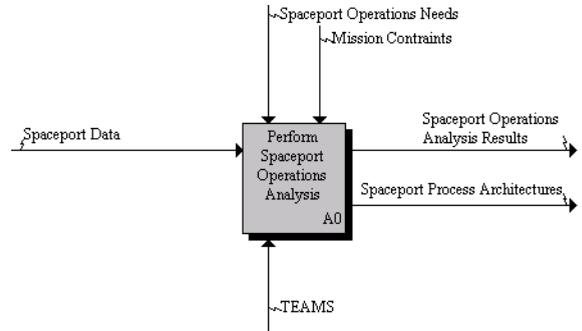


Figure 1: TEAMS Solution Concept

The main activities supported by TEAMS are described in the IDEF0 function model shown in Figure 2.

As shown in Figure 2, the main activities supported by TEAMS are (i) Define Spaceport Analysis Objectives, (ii) Select Vehicle Configuration, (iii) Select Technology Mix, (iv) Configure Spaceport Process, (v) Formulate Analysis Experiment, (vi) Perform Analysis, and (vii) Assess Results. These activities will be performed iteratively by TEAMS end users until the analysis objectives are satisfied.

The primary TEAMS *end user* is a Spaceport Operations Analyst. Secondary users include (i) space transportation systems designers/analysts (e.g., spaceport process/systems engineers, integrators, etc.) and (ii) space transportation system stakeholders/investors (e.g., technology investment and facility/infrastructure decision makers).

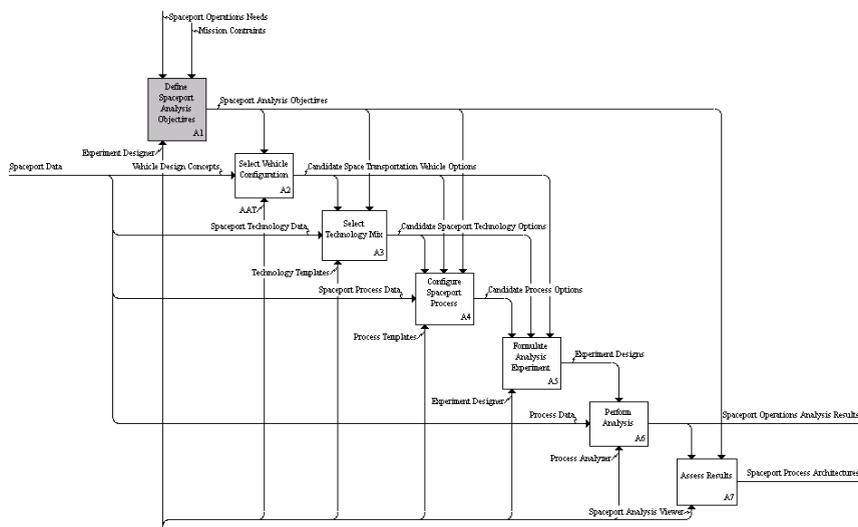


Figure 2: TEAMS Facilitates Distributed Spaceport Operations Modeling and Analysis

### 3 TEAMS ARCHITECTURE

The TEAMS functional architecture is shown in Figure 3.

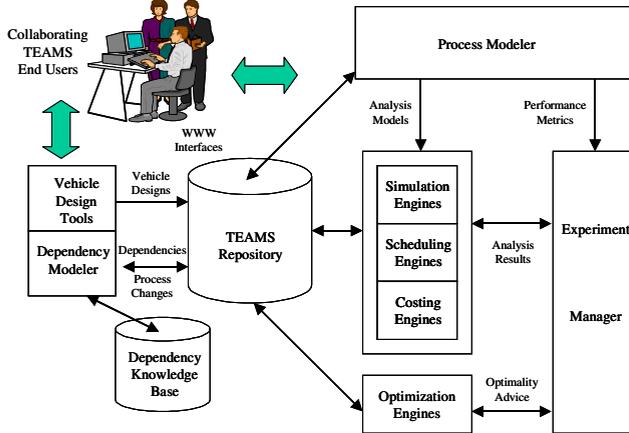


Figure 3: TEAMS Functional Architecture

The main TEAMS functions supported by the above architecture include the following:

- Selection of Spaceport vehicle, technology, and facility design configurations.
- Selection and tailoring of Spaceport operations and maintenance process configurations.
- Specification of operations process analysis experiments to compare alternative candidate Spaceport configurations.
- Execution of process analysis experiments (including simulation, scheduling, cost).
- Analysis and interpretation of Spaceport process analysis results including optimization and sensitivity analysis.

TEAMS is a decision support system that is designed to generate information to enable well-informed and scientifically-grounded decision-making about NASA investments in new space vehicles, technologies, facilities, resources, and infrastructure.

The following subsections describe the functionality of the different TEAMS component tools in greater detail.

#### 3.1 Interface

TEAMS is designed to run in any web browser. The web-interface (Figure 4) is intended to facilitate distributed and collaborative spaceport modeling and analysis. Thus, for example, Spaceport model developers and analysts from multiple NASA centers could collaboratively build and execute the processing and launch process simulation model of a next generation space vehicle rapidly and cost-effectively. Figure 4 shows multiple window panes, each indicating a key aspect of a “spaceport” configuration. The top right pane in the figure shows a physical view of the spaceport facilities and assets overlaid on a geographical map (the view shown in this example depicts part of the Cape Canaveral spaceport). The bottom right pane shows an IDEF3-based process model of the shuttle flow through the spaceport. The IDEF3 process visualization capabilities are provided by KBSI’s commercial process modeling tool, PROSIM® (see <<http://www.kbsi.com/> and <http://www.ideal.com/>>). The tree views on the left panes provide quick and easy-to-understand visibility to the spaceport dimensions data: facility, technology, process, and space vehicle.

TEAMS allows for information and data flow from different space vehicle design tools. Information about space vehicle design concepts is stored in the TEAMS Repository. An example of a space vehicle concept design tool

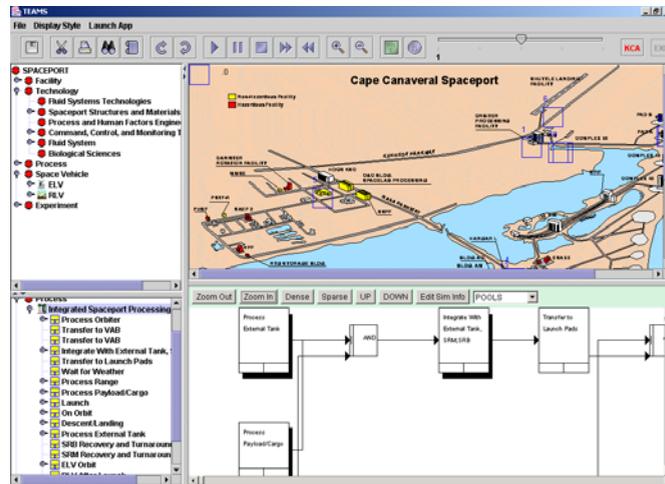


Figure 4: TEAMS Web-Based Multi-Pane User Interface Vehicle Design Tools

used by NASA is the Architectural Assessment Tool – enhanced (AATE) (NASA 2001). TEAMS end users will define alternative space vehicle design concepts at multiple levels of abstraction. The AATE tool, for example, allows for the definition of high level space transportation system/vehicle design concepts. AATE is used for assessing, at a high level, multiple metrics such as costs and cycle time of alternative space transportation architectures (Figure 5 and Figure 6). Proposed vehicle design concepts/changes are propagated to the TEAMS knowledge Repository. The TEAMS Knowledge Agent (described later in this subsection) uses information about proposed spaceport (vehicle, technology, facility) changes to “automatically deduce” changes to the spaceport operations and maintenance processes.

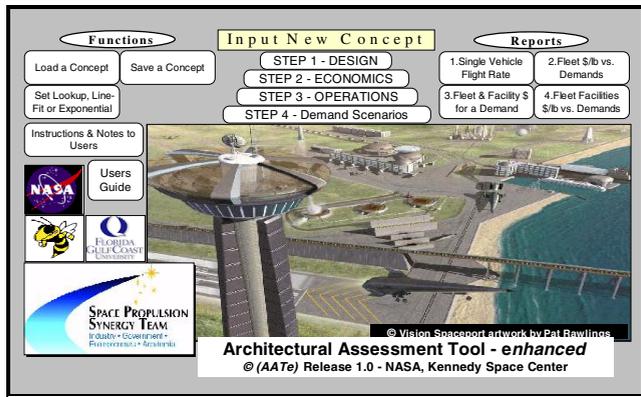


Figure 5: Top Level AATE User Interface

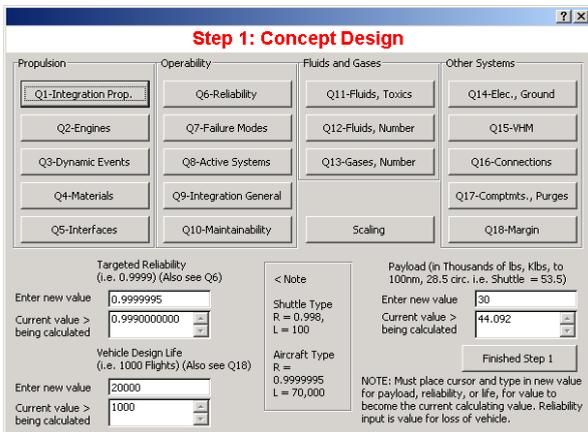


Figure 6: AATE Facilitates Rapid Capture of Space Transportation System Concepts

### 3.2 Dependency Modeler

The Dependency Modeler facilitates the modeling of spaceport dependencies. The types of dependencies modeled include (i) Space Vehicle -> Process Dependencies, (ii) Technology -> Process Dependencies, and (iii) Facility

-> Process Dependencies. The dependencies are stored as “rules” within the TEAMS Dependency Knowledge Base and are used to aid the automated analysis of the spaceport processes. For example, knowledge of the dependency between “Level of Hazard Material Usage Level (High, Medium, or Low)” and the spaceport operations and maintenance process steps will help to automatically set a spaceport process configuration parameter based on the end user’s selection of the Level of Hazard Material Usage Level. Example conceptual/qualitative dependencies between space vehicle design options and the spaceport operations and maintenance processes are shown in Table 1.

Table 1: Example Dependencies

Product (Space Vehicle) Design Concept Options	Spaceport Operations / Maintenance Process Implications
Number of Propulsion Engine Elements (2 – 6)	The greater the number of engines, the greater the vehicle processing and maintenance time
Number of Stages in Architecture (Single, Multi)	Single stage minimizes component replacement requirements, reduced gas interfaces, reduced fluid interfaces, reduced safety procedures
Hazard Material Usage Level (High, Medium, Low)	High usage level implies need for additional pollutant/toxicity containment during vehicle mfg. and maintenance; need provisions for waste management
Level of propulsion system design integrity (High, Medium, Low)	Minimizes number of different fluid systems, reduced maintenance and safety procedures
Level of vehicle design modularity (High, Medium, Low)	Ease of manufacturability, maintainability and reliability (reduced safety procedure requirements)
Failure Mode Tolerance Level (High, Medium, Low)	Higher manufacturing time, maintenance, and safety

### 3.3 Knowledge Agent

The Knowledge Agent (KA) propagates the implications of proposed spaceport vehicle and technology changes to the spaceport operations and maintenance process models (Figure 7).

The KA is a rule-based embedded expert system that uses a production rule inference engine to propagate the implications of proposed spaceport design changes

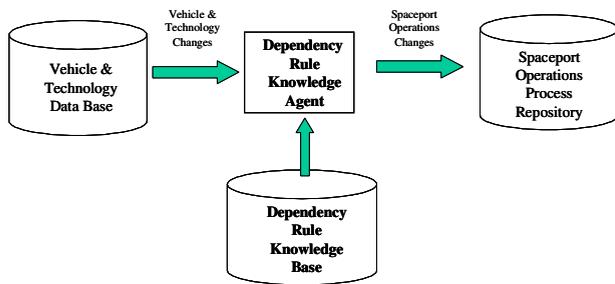


Figure 7: The Knowledge Agent Propagates Process Implications of Proposed Spaceport Decisions

(through an explicit encoding of spaceport dependencies or “rules”).

Model are displayed by the KA. The user then confirms or rejects the agent-discovered process change implications; the “accepted” process changes are committed to the process knowledge repository (Figure 8).

### 3.4 Dependency Knowledge Base

The spaceport dependencies are stored in a structured form in the TEAMS Dependency Knowledge Base. The dependencies are stored in the form of “If Then Else” production rules encoded in the CLIPS language <<http://www.ghg.net/clips/CLIPS.html>>. An example dependency rule is of the form:

*IF* (Maintainability Index is (1, 2, 3, 4, 5))  
*THEN* (Reduce Process Time for “Perform Maintenance” process step  
 by multiplicative factor (1, 0.8, 0.6, 0.25, 0.1)) (1)

The KA is triggered by proposed changes in Vehicle and Technology attributes (stored as part of the TEAMS Repository). The “firing” of one or more Dependency Rules automatically propagates implied changes (through dependencies) to the spaceport operations/maintenance process models in the Spaceport Operations Process Repository (part of the TEAMS Knowledge Repository). The list of change implications to the spaceport process

### 3.5 Process Modeler

The Process Modeler facilitates the capture and organization of spaceport operations and maintenance process models. The process information will be represented in the IDEF3 <<http://www.idef.com/>> process description capture language and KBSI’s commercial process modeling and analysis tool, PROSIM®. A key aspect of the process modeler is the organization of the spaceport process models as a Process Template Libraries (PTL). The idea is to provide a structured, re-usable, and extendible repository of spaceport process knowledge for use by a wide range of TEAMS end users. The PTL may also be used as a training tool on spaceport operations and maintenance procedures. An example IDEF3-based spaceport is shown in Figure 9.

The IDEF3-based process representation will provide a standard and extendible mechanism to capture and store spaceport operations and maintenance models. The maintenance models will provide the basis for the rapid generation of multiple types of process analysis tools as described in the next subsection.

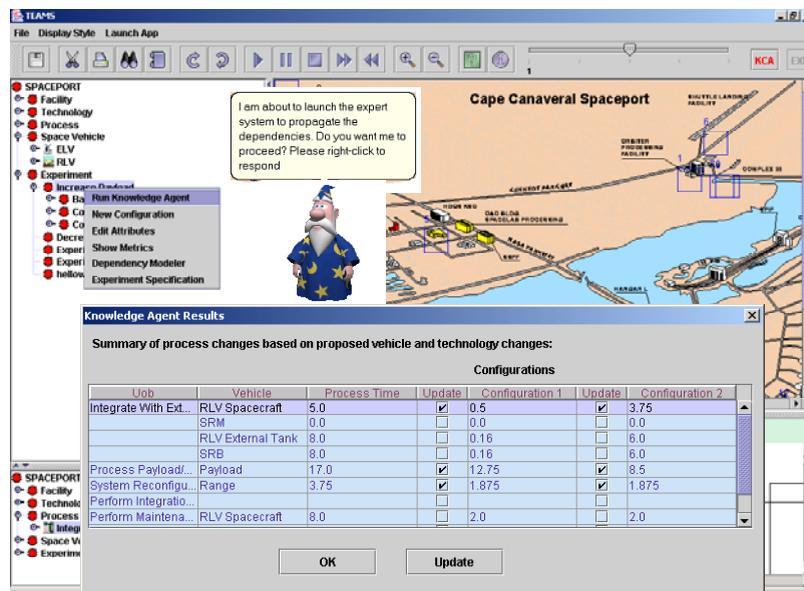


Figure 8: KA Process Change Propagation for a Proposed New Vehicle Concept Design

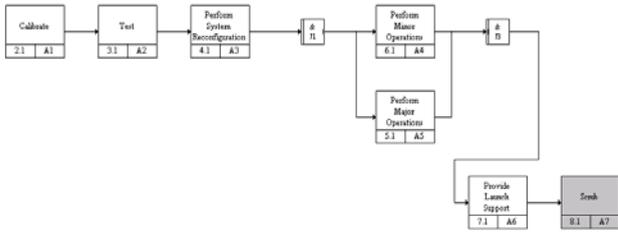


Figure 9: Example Spaceport (Range) Operations Process Template

### 3.6 Process Analysis Tools

TEAMS facilitates comprehensive spaceport operations process analysis using multiple analysis methods including simulation, scheduling, and cost analysis. Process optimization is enabled through multiple optimization methods including Genetic Algorithms (GA) and Simulated Annealing (SA). The use of a standard and expressively rich process modeling language, IDEF3, provides the basis for rapid generation of analysis models. Automated support for generating Witness, WorkSim, MSPProject, SMARTCOST®, and Genetic Algorithm/Simulated Annealing Optimization analyses have been implemented. Additional analysis tool interfaces are under development to facilitate rapid and cost effective spaceport operations analysis. The TEAMS process-oriented re-configurable, plug-and-play analysis framework solution concept is illustrated in Figure 10.

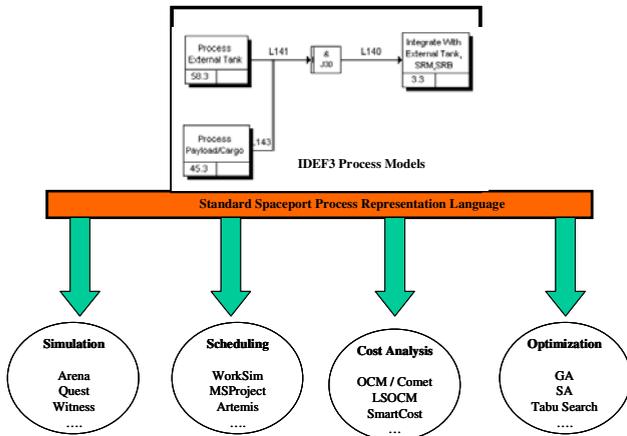


Figure 10: The Process-Centric Plug and Play Operations Analysis Framework Solution Concept

The TEAMS process analysis tools are described in the following subsections.

#### 3.6.1 Simulation Engines

TEAMS enables discrete event simulation analysis using multiple simulation engines. Currently, TEAMS uses three simulation tools: Witness, Arena, and KBSI’s E-Sim

engine. An example simulation output from E-Sim is shown in Figure 11.



Figure 11: Simulation Performance Trades Between Flow Time and Resource Utilization

#### 3.6.2 Scheduling Engines

The IDEF3 process models are used to automatically generate scheduling models in MSPProject. The scheduling capability allows for detailed process analysis and the opportunity to “baseline” the spaceport performance with the resource-loaded KSC schedule. Another advantage of an integrated scheduling capability is the ability to use TEAMS as a day-to-day/weekly planning and scheduling decision support tool. The schedule displays shown in Figure 12 and Figure 13 provide a flavor of the schedule analysis capabilities provided in TEAMS.

#### 3.6.3 Costing Engines

Information from the PROSIM® spaceport operations model is propagated to the SMARTCOST® cost analysis tool <<http://www.kbsi.com/>> (Figure 14).

### 3.7 Experiment Manager

The Experiment Manager defines spaceport process performance metrics and analysis experiment parameters such as run length and number of runs (Figure 15).

### 3.8 Optimization Engines

The Optimization Engine provides mechanisms for searching through the “spaceport design space” to find an optimal or near optimal spaceport configuration. The TEAMS optimization engine uses the techniques of Genetic Algorithms (GAs) and Simulated Annealing (SA) to search for an optimum solution using “Simulation-Based Optimization.” Because spaceport design optimization is a multi-criteria search problem, heuristic mechanisms are used to arrive at acceptable solutions through trade-offs between competing criteria.

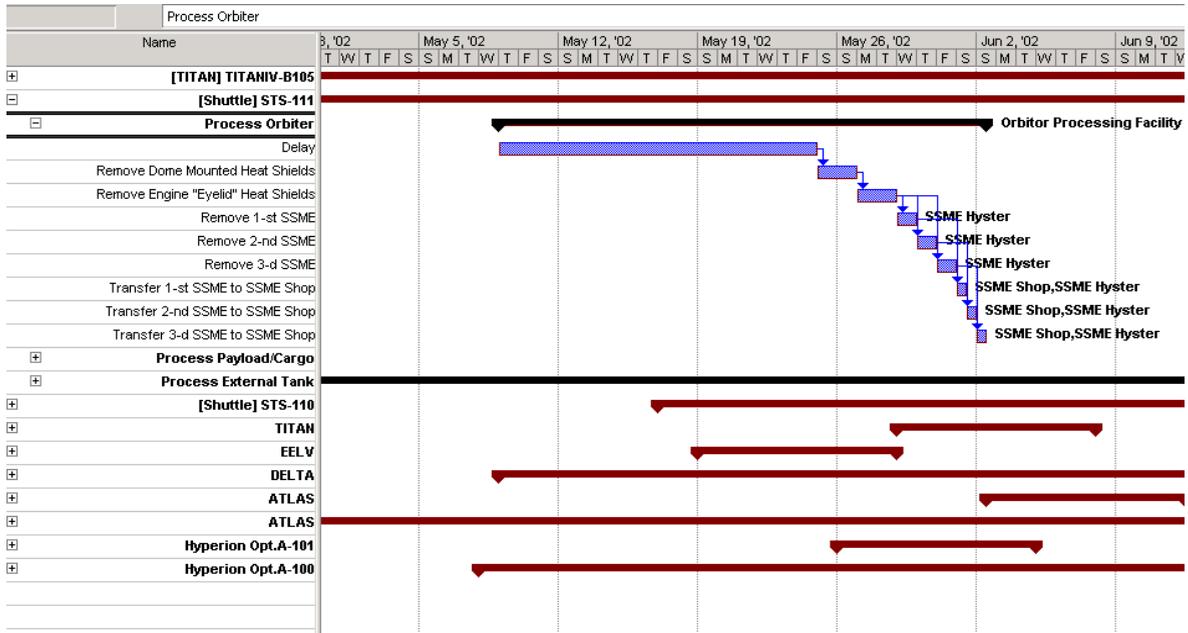


Figure 12: Example Schedule Results in MSProject

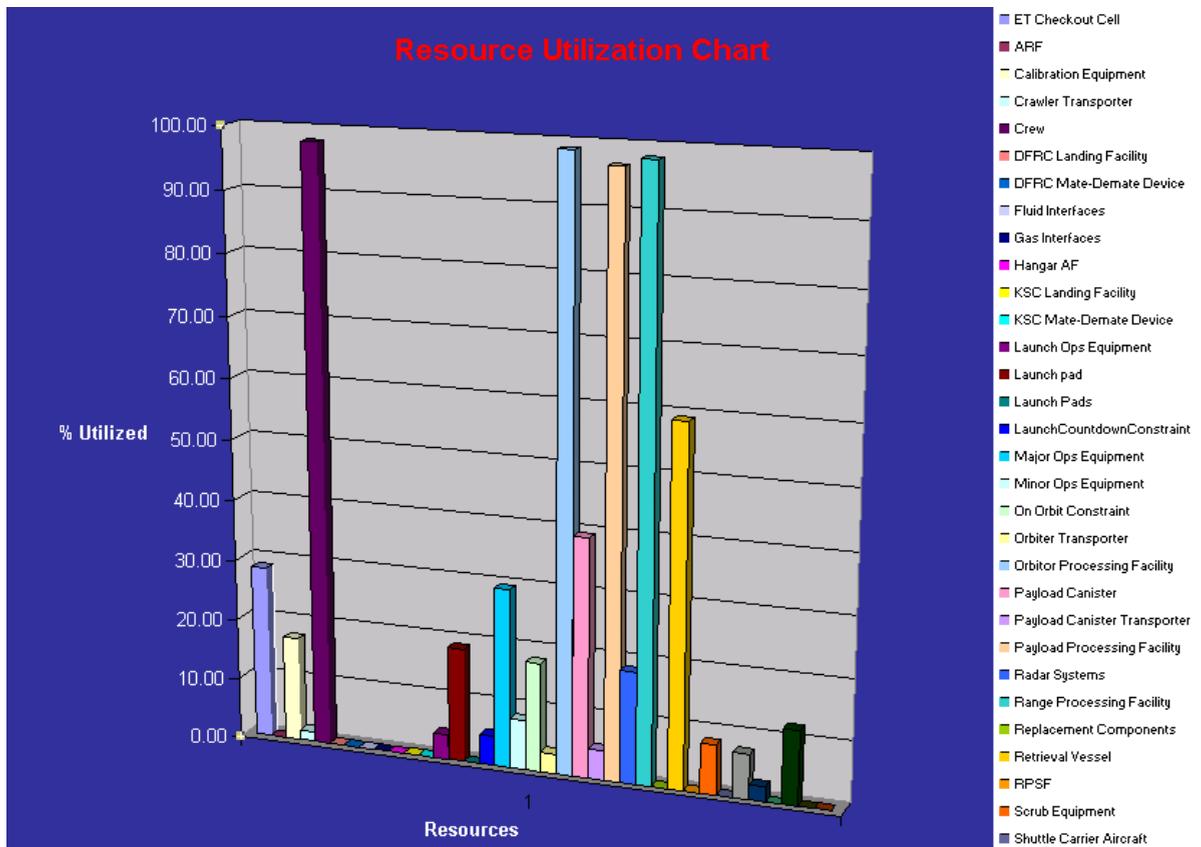


Figure 13: Spaceport Resource Utilization Graphs

ID	Attribute Name	Unit	Input Column	Value Taken
242	BreakDown Maintenance Cost			60000
94	Calibration Cost			30000
161	Command Equipment Reconfiguration Cost			20000
146	Command Equipment Reconfiguration Time			0
162	Communication Reconfiguration Cost			20000
159	Communication Reconfiguration Time			0
163	FCA Reconfiguration Cost			20000
149	FCA Reconfiguration Time			0
98	Launch Support Cost			100000
167	Lights Reconfiguration Cost			20000
148	Lights Reconfiguration Time			0
58	Major Operations Cost			140000
169	Metrics Reconfiguration Cost			2000
153	Metrics Reconfiguration Time			0
60	Minor Operations Cost			40000
244	Number of Breakdowns			0
227	Number of Launches			0
225	Number of Scrubs			0
171	Photo Reconfiguration Cost			20000
147	Photo Reconfiguration Time			0
173	Radar Reconfiguration Cost			0
145	Radar Reconfiguration Time			0
46	Range Crew			0
44	Range Equipment			0
88	Range Maintenance Cost			260000
50	Range Operations and Maintenance Cost			842000
90	Range Operations Cost			582000
48	Range Systems			0
64	Reconfiguration Cost			142000

Figure 14: Example SMARTCOST® Process Cost Output

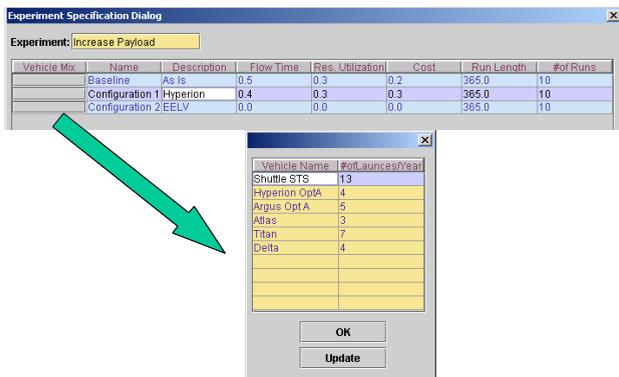


Figure 15: TEAMS Experiment Specification User Interface

Optimization in such complex situations involves searching the solution space (all possible combinations of values for design parameters) for an optimal value. Simulation based optimization is one such strategy in which simulation is used to determine the performance of the system for particular design parameter values. Different heuristic search techniques are then used to intelligently try other settings of design parameter values and seek the optimal setting. At each setting, simulation is used to determine the performance of the system. The high-level algorithm for simulation-based optimization can be summarized in the following steps.

1. Determine the performance of the system for some design parameter settings using simulation.
2. Change the setting of design parameters and again use simulation to determine the performance of the system.

3. Search the solution space (i.e., intelligently changing the design parameters and using simulation to determine the performance of the system) until a reasonably optimal solution is obtained.

Determining the global optimal conditions under such situations necessitates evaluating and searching the entire solution space. Since this will require a significant time overhead, the various simulation-based optimization heuristics attempt to find a reasonably good solution within a short time.

In TEAMS, the simulation model is generated by the Process Modeler and executed with one of the TEAMS Simulation Engines. The goal (objective function to be optimized) and the design parameters whose values are to be determined are defined. The simulation model is then executed using the simulation engine and the resulting performance metrics of the system are passed on to the Optimization Engine. The Optimization Engine uses information about how the system performance is changing with various parameter changes to intelligently guess (using Genetic Algorithm) the parameter values to be tried in the next iteration. The modified simulation model is then executed in the simulation engine. The execution completes when the specified termination condition is reached.

In TEAMS, the simulation model is generated by the Process Modeler and executed with one of the TEAMS Simulation Engines. The goal (objective function to be optimized) and the design parameters are defined. The simulation model is then executed using the simulation engine. The performance metrics of the system, determined in the simulation execution, are passed on to the Optimization Engine which will use information about how the system performance is changing with various parameter changes to intelligently guess (using Genetic Algorithm) the parameter values to be tried in the next iteration. Changes to the parameter values are made in a copy of the simulation model in the simulation modeler. This modified simulation model is then executed in the simulation engine. The execution ceases when the specified termination condition is reached.

#### 4 RESEARCH SIGNIFICANCE AND BENEFITS

Key innovations of the work described in this paper include (i) a *process-centered approach* that maximizes reuse of domain knowledge for *rapid operations analysis model development*, (ii) *open-architecture, distributed plug and play architecture* that allows for mass *customization and rapid deployment* of TEAMS tools, and (iii) novel, simulation-based optimization mechanisms that facilitate *risk minimization* through exploration of *numerous system design configurations at a reduced cost*. A TEAMS prototype has been developed and demonstrated at NASA Kennedy Space Center. Immediate benefits are expected to ac-

crue to the ongoing NASA Space Launch Initiative (SLI) and the NASA Space Shuttle upgrade initiative.

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## AUTHOR BIOGRAPHIES

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figurative, self-maintaining simulation modeling technologies. Dr. Graul has initiated over 70 grass-roots BPR projects and has trained over 300 people in the IDEF family of system modeling methods.

**MADHAV ERRAGUNTILA**, a research scientist at KBSI, received his Master's degree in Industrial Engineering from the National Institute for Training in Industrial Engineering in 1989. He obtained his Ph.D. in Industrial Engineering from Texas A&M University in 1996. Dr. Erraguntla joined KBSI as a research scientist at KBSI in 1994. Dr. Erraguntla has conducted extensive research and development in data mining, analytics, data fusion, simulation, planning, agent based systems, evolutionary computing, activity based costing, knowledge-based systems, optimization, neural networks, and fuzzy logic. In 2000, Dr. Erraguntla was the product manager at i2 Technologies in charge of developing an advanced data mining system for a major retailer.