Final Report

On

Development of Advanced Life Cycle Costing Methods for Technology Benefit/Cost/Risk Assessment

Covering Tasks Performed During Year 3
Grant Number NAG-1-2149

Submitted to

NASA Langley Research Center
Grants and Contracting Office
Hampton VA 23681-2199

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April 11, 2002

OBJECTIVE REVIEW

The overall objective of this three-year grant is to provide NASA Langley's System Analysis Branch with improved affordability tools and methods based on probabilistic cost assessment techniques. In order to accomplish this objective, the Aerospace Systems Design Laboratory (ASDL) needs to pursue more detailed affordability, technology impact, and risk prediction methods and to demonstrate them on variety of advanced commercial transports. The affordability assessment, which is a cornerstone of ASDL methods, relies on the Aircraft Life Cycle Cost Analysis (ALCCA) program originally developed by NASA Ames Research Center and enhanced by ASDL. This grant proposed to improve ALCCA in support of the project objective by updating the research, design, test, and evaluation cost module, as well as the engine development cost module. Investigations into enhancements to ALCCA include improved engine development cost, process based costing, supportability cost, and system reliability with airline loss of revenue for system downtime. A probabilistic, stand-alone version of ALCCA/FLOPS will also be developed under this grant in order to capture the uncertainty involved in technology assessments. FLOPS (FLight Optimization System program) [Ref. 1] is an aircraft synthesis and sizing code developed by NASA Langley Research Center. This probabilistic version of the coupled program will be used within a Technology Impact Forecasting (TIF) method to determine what types of technologies would have to be infused in a system in order to meet customer requirements. A probabilistic analysis of the CER's (cost estimating relationships) within ALCCA will also be carried out under this contract in order to gain some insight as to the most influential costs and the impact that code fidelity could have on future RDS (Robust Design Simulation) studies.

PROPOSAL TASK REVIEW

The tasks for this three-year program are listed below as a review of what was proposed in the original statement of work. A short description for each task is offered, and a summary of the tasks accomplished can be found in Table 1.

Task 1: *Probabilistic Cost Assessment Program*
A stand alone probabilistic ALCCA (e.g. ALCCA coupled with FPI [Ref. 2]) will be created as a subset of the more comprehensive FLOPS/ALCCA/FPI program which will be utilized to show cost/benefit/risk tradeoffs.

Task 2: *Detailed RDT&E Costing*
A new RDT&E module with a more detailed cost breakdown, and the capability of accounting for the development of new technologies will be developed.

Task 3: *Assessment of Impact of New Technologies*
The infusion of new technologies for a given configuration must be considered when all other alternatives (optimization, opening design space, etc.) have been explored. However, the impact of a technology can be qualitatively assessed through the use of technology metric "k-factors". These "k-factors" modify technical metrics, such as specific fuel consumption (SFC), lift to drag ratio (L/D), and component weights, that result from some analysis or sizing tool.

Task 4: *Code Fidelity*
The development of a method to be used for evaluating the fidelity of an economic analysis code was proposed. The economic code chosen for this case study is Aircraft Life Cycle Cost Analysis (ALCCA).

Task 5: *Detailed Process Based Engine Costing*
This task proposes to develop several Response Surface Equations (RSEs) using COMPEAT. These RSEs will be used to link the most important cost parameters with their most important cost drivers. COMPEAT is an engine cost estimation tool developed and maintained by General Electric Aircraft Engines in Evendale, OH. It is a "state of the art" tool, capable of estimating program costs for any type of aircraft turbofan engine. Its accuracy is limited only by the accuracy of the database.

Task 6: *Inclusion of TAROC and DOC+I*
This task proposes to restructure the cost calculations internal to ALCCA to generate the desired cost metrics for the airframe manufacturer.

Task 7: *Supportability in Cost Estimation*
This task proposes to investigate the impact of supportability issues on the overall economic viability of commercial aircraft. Also, the impact of supporting new engine technology on the overall economic viability of the HSCT is to be investigated.

Table 1: Summary of Task Status

Task No.	Description	Status
1	*Probabilistic Cost Assessment Program*	Completed in Year 1.
2	*Detailed RDT&E Costing*	Completed in Year 1.
3	*Assessment of Impact of New Technologies*	Feasibility and Viability are assessed in Year 1. Technology identification and TIF environment are determined in Year 2. Technologies evaluated and task completed in Year 3.
4	*Code Fidelity*	Completed in Year 3.
5	*Detailed Process Based Engine Costing*	New Capacity Focus
6	*Inclusion of TAROC and DOC+I*	Completed in Year 1
7	*Supportability in Cost Estimation*	New Capacity Focus.

CAPACITY FOCUS

Tasks 5 and 7 have been given a system-level emphasis resulting in a capacity focus task designed to assist NASA Ames Research Center in its efforts to accomplish the Throughput Technology Objectives. The new capacity focus still maintains the research objective of providing NASA Ames with improved affordability tools and methods by developing the capability to assess the economic impact of advanced aviation technologies. More importantly, this capacity focus task will also evaluate how these technologies would be used in the integrated aviation system from a probabilistic standpoint. The capacity task is titled *"Formulation of a Method to Assess Technologies* *for the Improvement of Airport Capacity."* In order to accomplish this task objective, a strong collaboration between the Logistics Management Institute (LMI), the developers of Aviation System Analysis Capability [Ref. 3], has been fostered. The probabilistic approach to evaluate advanced aviation technology in conjunction with a process to understand and evaluate their impact at a system of systems level will assist NASA in realizing their goal of tripling the aviation system throughput, in all weather conditions, within 10 years, while maintaining the current level of safety.

The capacity task is further divided into three subtasks. The first one involves the identification of the most influential factors when assessing capacity at an airport, utilizing LMI's Capacity model, and the subsequent creation of a Technology Impact Forecast environment. Subtask two aims to consider the airspace system as a whole identifying the significant fields involved and their interactions, as well as creating an environment conducive to a system-of-systems technology assessment. The last subtask will then utilize that environment in a sample technology assessment through the use of a methodology such as TIES (Technology Identification, Evaluation and Selection).

PROGRESS ACCOMPLISHED

Task 3: Assessment of Impact of New Technologies

This task proposed to investigate the effect of new technologies on a 600 passenger aircraft. From Year 1 tasks, the design space was investigated for technical feasibility and economic viability based on five performance criteria and four economic criteria. The design space was deemed non-feasible due to the violation of the takeoff gross weight limitation of one million pounds. The focus of Year 2 was to establish technologies that could be infused into the system and create a Technology Impact Forecasting (TIF) Environment based on guidance of the chosen technology impact factors. The focus for the current year involved evaluating those technologies and selecting the technology combinations with the highest potential to create a feasible design.

Technology Compatibility Matrix

A Technology Compatibility Matrix is formalized through Integrated Product Teams (IPTs) to establish physical compatibility rules between technologies previously identified as having the potential to improve system performance and/or cost, thereby increasing the probability of reaching project goals. The Technology Compatibility Matrix for the 600 passenger baseline aircraft is shown in Table 2. The purpose of the matrix is to establish which technologies are compatible and can thus be employed simultaneously. This helps drive the development of the technology space through use of the Technology Impact Matrix (TIM), described in the following section. By identifying those technologies that are not compatible, the matrix also eliminates the possibility of running cases with impossible technology combinations. In this matrix, a 1 indicates compatibility and a 0 indicates incompatibility. Therefore, any two technologies that are assigned a 0 will not be modeled simultaneously in any single case. For example, hybrid laminar flow control (HLFC) is physically incompatible with a composite wing, as the microholes required for HLFC would affect the structural integrity of the composite. Thus, this combination has been labeled with a 0.

Table 2: Technology Compatibility Matrix

		Composite Wing T1	Composite Fuselage T2	Aircraft Morphing T3	Natural Laminar Flow Control T4	Maneuver Load Allevaition T5	AST Engine Concept T6	Integrally Stiffened Aluminum Airframe Structure T7	HLFC T8	IHPTET T9
Composite Wing	T1	1	1	1	1	1	1	0	0	1
Composite Fuselage	T2		1	1	1	1	1	1	1	1
Aircraft Morphing	T3			1	1	1	1	1	1	1
Natural Laminar Flow Control	T4				1	1	1	1	0	1
Maneuver Load Allevaition	T5					1	1	1	1	1
AST Engine Concept	T6						1	1	1	0
Integrally Stiffened Aluminum Airframe Structure	T7							1	0	1
HLFC	T8								1	1
IHPTET	T9									1

Technology Impact Matrix

Once the Technology Compatibility Matrix is determined, the potential system and sub-system level impacts of each technology are established including primary benefits and secondary degradations. Technology Impact Forecasting (TIF) is a method of predicting the effects that future technologies will have on chosen responses, such as takeoff gross weight and NOx emissions. Thus, it creates an environment around the question "What would happen if this element of the design could be improved?" This method does not require information on specific technologies. Instead, it looks at the overall technological improvement needed in a disciplinary metric to reach a constrained target. In addition, this method can be used as a precursor to the determination of the impact of specific technologies on appropriate responses. Such predictions can become incredibly useful when the decision of which new technologies to invest in has to be made.

The factors by which the disciplinary metrics or parameters are multiplied when technologies are added are called k-factors (or technology dials). These k-factors, while representative of the impacts of technology infusion, can also be used without specific technologies to create the Technology Impact Forecast (TIF) environment. That is, changing a disciplinary metric or parameter even if there is not yet a technology identified that can achieve the specified change. This way the effect of that disciplinary metric at the system level can be assessed.

These k-factors are grouped in a vector (i.e. k_vector), since several technologies can influence several disciplinary metrics. Each element in this k_vector corresponds to each of the different k-factors considered. Not all technologies will affect each element of the vector, but the vector must capture all technologies to be assessed. The vector must also include both benefits and penalties to accurately assess the impact of technologies on the objective. These vectors can then be entered into a DoE (Design of Experiments) in place of the original disciplinary metrics to model the impact of the newly infused technologies on the responses. In addition, the impact of combined technologies can be found by adding the k_vectors for each of the technologies being considered. This method assumes that the effect of the combined technologies on the disciplinary metrics is the sum of the effects of the individual technologies being considered.

The Technology Impact Matrix (TIM) is a way of organizing and mapping the technology impacts to the k-factors that will be applied to the disciplinary metrics. The TIM is shown in Table 3, which lists the technologies that are being considered across the top of the columns. There is a disciplinary metric in each row below those headings, which is affected by at least one technology under consideration. Obviously, not each technology is going to impact each disciplinary metric, but as one reads down a column, the expected impact of the technology on the disciplinary metrics can be easily seen. Each of these columns represents the k_vector for that particular technology.

Table 3: Technology Impact Matrix

	Composite Wing	Composite Fuselage	Aircraft Morphing	Natural Laminar Flow Control	Maneuver Load Alleviation	AST Engine Concept	Int. Stiff. Alu. Wing Structure	Hybrid Laminar Flow Control	IHPTET
Technical K Factor Vector	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**	**T8**	**T9**
Wing Area	---	---	---	---	+18%	---	---	---	---
Vertical Tail Area	---	---	---	---	-40%	---	---	---	---
Horizontal Tail Area	---	---	---	---	-36%	---	---	---	---
Drag	-2%	-2%	-3%	-5%	-3%	---	---	-10%	---
Subsonic Fuel Flow	---	-0.50%	-1.50%	---	---	-10%	---	+1%	-5%
Wing Weight	-15%	---	-3%	---	---	---	-15%	+4%	---
Fuselage Weight	---	-25%	-2%	---	---	---	---	---	---
Electrical Weight	---	---	---	---	+5%	+3%	---	+2%	---
Engine Weight	---	---	---	---	---	-30%	---	+0.5%	-20%
Hydraulics Weight	---	---	---	---	-10%	---	---	---	---
AL Wing Stru. Man.Costs	---	---	---	---	---	---	-2.50%	---	---
O & S	+2%	+2%	---	---	---	-3%	-2%	+3%	-3%
RDT&E	+2%	+2%	+2%	+2%	+3%	-4%	---	+4%	+3%
Production Costs	+10%	+10%	-3%	-3%	---	-3%	---	+1%	---
Utilization	-2%	-2%	---	---	---	+3%	+2%	-2%	+2%

There are nine different technologies that are being considered, and fifteen disciplinary metrics that they impact. The non-dimensional k-factors in the TIM are the sum of one plus the percentage impacts. The maximum value of the k-factors for a given disciplinary metric is the sum of all of the increasing impacts, while the minimum value of the k-factor would be the sum of all of the decreasing impacts. To determine the dimensionalized k-factor impacts, the baseline values of each disciplinary metric are multiplied by the minimum and maximum k-factor values.

Once the ranges for the k-factors have been selected, a DoE is generated for these twenty-nine k-factors. The variable values dictated by the DoE are then entered into the analysis tools and new RSEs that relate the effects of the k-factors on the responses to the variation of the disciplinary metrics are created. Once the technologies being considered are mapped to the disciplinary metrics, the effects of the technologies can be found (to be accomplished in the next phase). For now, this mapping allows the TIF environment to be created. This TIF prediction profile is essentially a graphing of the partial derivatives of each response with respect to each technology dial.

Pareto Charts

Pareto charts depicting the relative contributions of the various proposed technologies on the desired responses were created for this task. Pareto charts enable the identification of the most statistically significant contributors. They are a statistical quality improvement tool that shows frequency, relative frequency, and cumulative frequency of a set of variables to a response. They are in the form of a bar chart that displays the influence of a variable. This allows the designer to see which technologies yield the most beneficial changes in a given response.

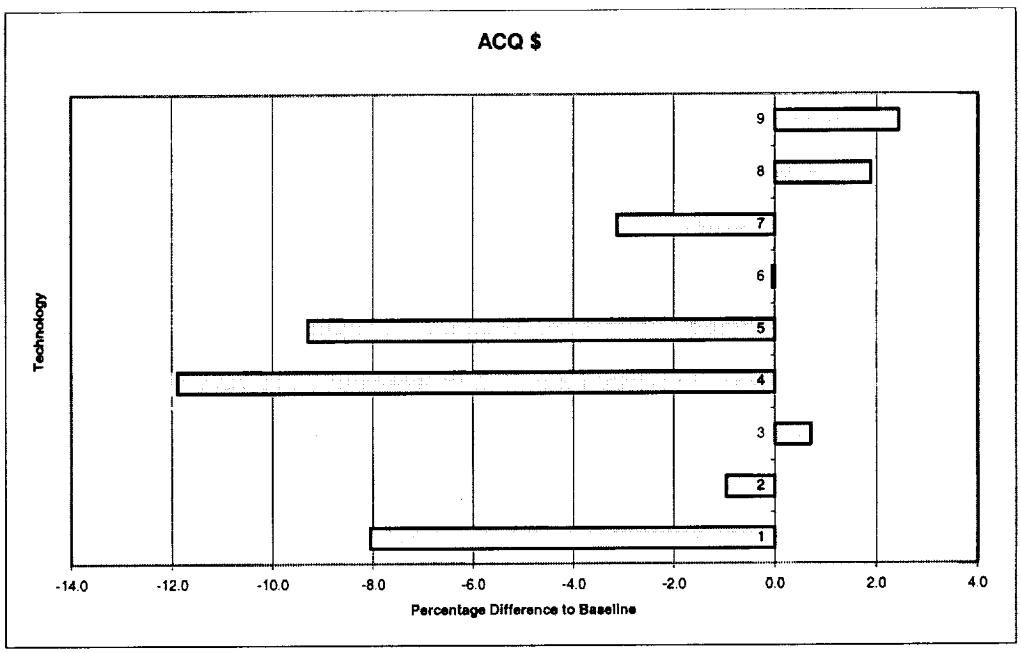


Figure 1: Effect of Technologies on Acquisition Price

As can be seen in the example Figure 1, Technology 4 yields the greatest benefit to the acquisition price by reducing it by nearly 12%. Alternately, Technology 9 has the worst effect on acquisition price, as the infusion of this technology causes a 2.4% increase. Pareto charts for the remaining responses can be seen in Appendix A.

Prediction Profilers

The decision-maker can also identify the technologies that most significantly impact the system metrics through the use of a prediction profiler. The profiler provides a dynamic environment through which trade-offs can be rapidly performed. A key design variable or technology k-factor can be altered to see instantaneously the effect on the responses.

A prediction profiler is shown in Figure 3 and depicts the prediction traces for each technology k-factor. The prediction trace is defined as the predicted response in which one k-factor is changed while the others are held at their current values, effectively, it shows the sensitivity of the response to the technology infusion. Moving the dotted line varies the k-factor; the underlying RSEs are reevaluated, and the prediction traces and response values are updated in real time.

The prediction profilers of the technology mapping can also be interpreted as a forecasting environment as seen in Figure 2. If a decision-maker does not have specific technologies to evaluate, this mapping environment could guide the decision-maker in selecting appropriate technologies for infusion. This technique is called Technology Impact Forecasting (TIF).

For example, since the acquisition price, TOGW, and RDT&E have very little if any feasible space, the decision-maker should select a set of technologies that reduce wing weight, engine weight, and costs. These k-factors significantly influence the metrics mentioned as seen by the large prediction trace slopes. Thus, once the k-factor values are established, the decision-maker must identify specific technologies that provide the desired k-factor values.

Once those specific technologies have been identified, they can be mapped against the responses to see the effects of an individual technology or combinations of technologies on the responses of interest. Effects of the parameters in this prediction profiler are evaluated based on the magnitude and direction of the trace slope, where the "-1" and "1" values indicate whether a technology is "on" or "off." The larger the slope of the line, the greater the influence of a given k-factor. If a k-factor, listed on the abscissa, does not contribute significantly to the response listed on the ordinate, the slope is approximately zero. The sign of the slope, either positive or negative, depicts the direction of influence of the k-factor. Caution should be exercised since the compatibility rules are not inherent in the sensitivities, and care should be taken prior to arbitrarily turning "on" a mix of technologies. The prediction profiler in Figure 3 maps the nine specific technologies against the thirteen desired responses. As shown, this profiler depicts the effects of the combination of T1, T2, T3, T4, and T5.

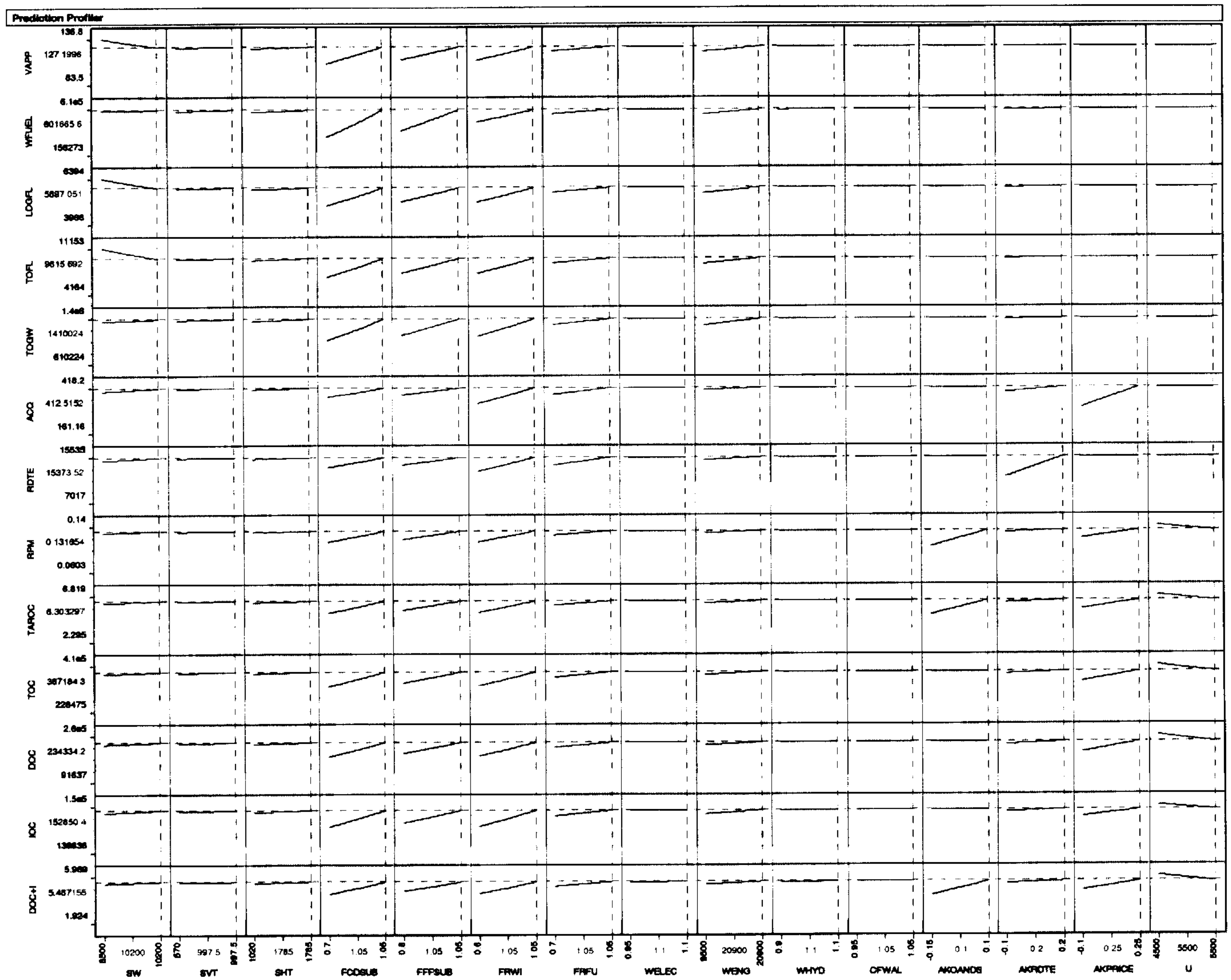


Figure 2: Technology Impact Forecasting Environment

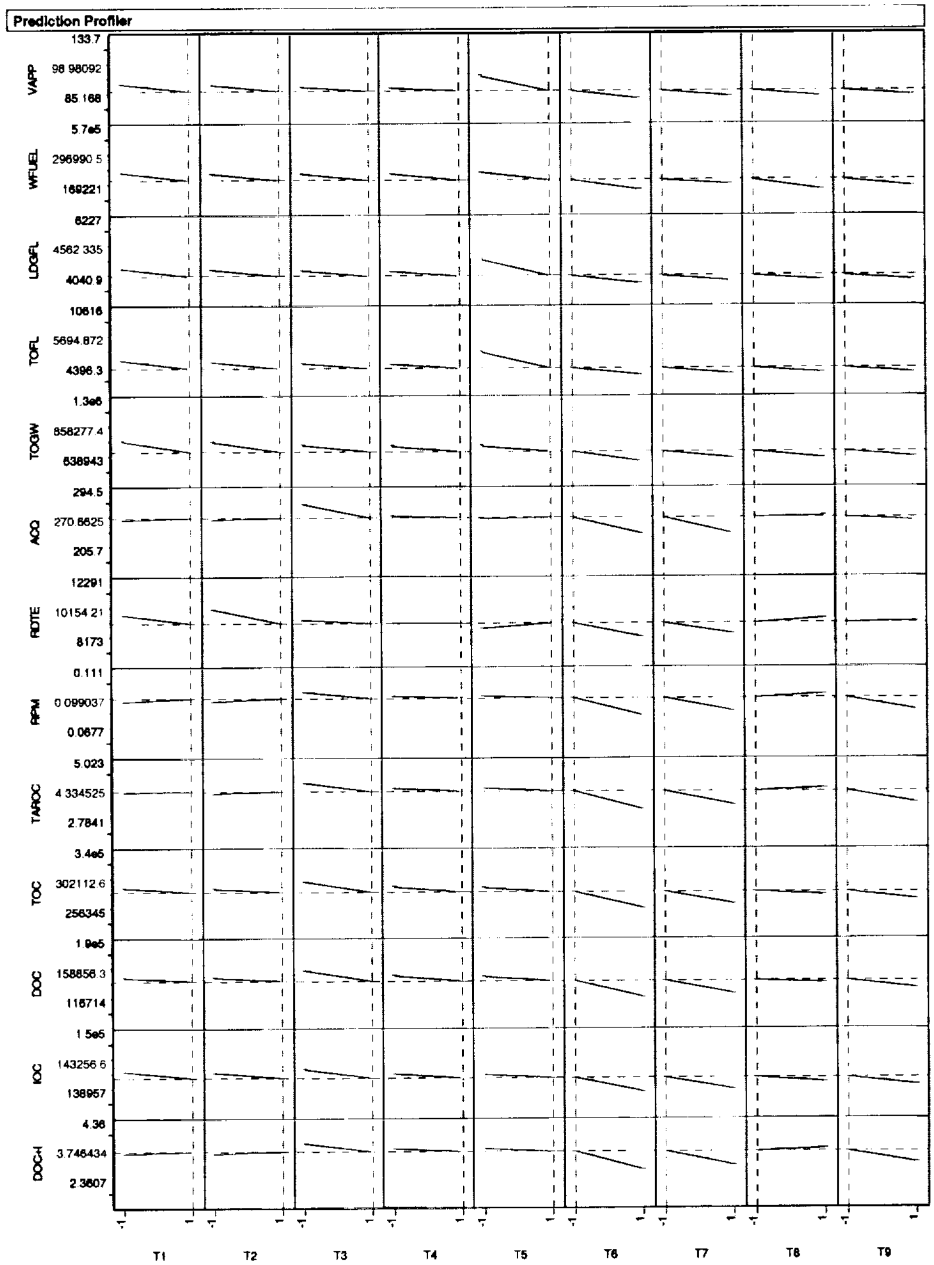


Figure 3: Prediction Profile for Nine Specific Technologies

One should not underestimate the power of the prediction profiler. Once the technology environment is created, the decision-maker can instantaneously quantify the impact that any mix of technologies has on the system under investigation without the need to re-execute any analysis code. Furthermore, if the anticipated impact of a technology changes as the development progresses, again, no analysis code execution is required.

Probabilistic Evaluation of Technologies

The design of complex systems is immersed in uncertainty due to incomplete knowledge about the system and the behavior of the system in a relevant environment. Because of this uncertainty, new paradigm design methods must be probabilistic. Traditional methods of design space exploration were based on the designer's intuitive knowledge of what the responding system might look like. A designer would perform paper study trades, and then build, test, fly, and modify the system as needed. This approach resulted in iterative designs which were both costly and time consuming.

An alternative approach is needed that is probabilistic in nature. The motivation for a probabilistic evaluation is to provide a more realistic assessment of the uncertainty and risk associated with the impact of immature technologies. Probabilistically evaluating a single technology or a combination of technologies is similar to the deterministic evaluation, except that the k-factors are distributions rather than single point values. To quantify the impact on a system metric, a Monte Carlo Simulation (MCS) is performed with user defined frequency distributions *for each k-factor element* and a cumulative distribution function (CDF) obtained for each system metric. A Monte Carlo Simulation (MCS) is the most accurate probabilistic technique to simulate uncertainty, by randomly generating values within a pre-specified range. By linking a sophisticated analysis tool with MCS a cumulative distribution function (CDF) for each of the desired objectives or metrics, as seen in Figure 4, is produced. The CDF represents how the metric behaves as a result of all the possible design variable combinations and in essence, defines and bounds the space of interest, whether the space is design, technological, or economical in nature. At a probability level of 0% (P=0%), the metric value is the best that can ever be achieved with the defined space, assuming that the CDF's probability levels (or P-levels) are increasing with increasing metric values. At P=100%, the entire space falls below the corresponding metric value. Any probability of achieving a solution is favorable since it represents the outcome of design variables. Yet, the decision-maker still strives for alternatives that maximize the feasible and viable design space.

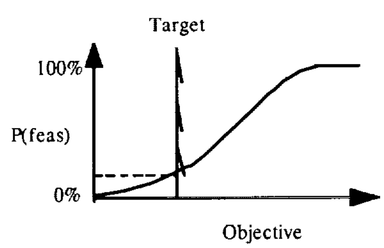


Figure 4: Generic Cumulative Distribution Function

This process can be used to simulate the addition of new technologies to a baseline concept. If one assumes that the technologies are additive, then a combination of two or more technologies remains a simple MCS on the RSE. Now, instead of the response, R, being a function of only one k-vector (i.e., technology), it is a function of the sum of the combination of vectors (i.e., sum of technologies). For example, if one wants to determine a system metric value due to a combination of T1 and T2, distributions are assigned to *each element of both technology k-vectors.* Subsequently, a random number generator selects a value for the first element of the T1 vector and the first element from the T2 vector, based on the user-defined frequency distributions. Then, the two values are added to obtain a "new" first element that is inserted into the RSE and the system metric value calculated. This is done for each element and each time a new combination of technologies is desired. This process is automated with the software package Crystal Ball®, which is a Microsoft EXCEL® "add-in" function.

For this study, a uniform distribution was used to represent each of the fifteen k-factors, with the lower and upper limits established in Table 4.

Table 4: K-factor ranges and corresponding input variables

NAME	NAMELIST	VARIABLE	LOW LIMIT%	HIGH LIMIT%	BASELINE	ACTUAL LOW	ACTUAL HIGH
Wing area	CONFIN	SW	0	20	8500	8500	10200
Vertical tail area	CONFIN	SVT	-40	5	950	570	997.5
Hor. tail area	CONFIN	SHT	-40	5	1700	1020	1785
Cruise drag	MISSIN	FCDSUB	-30	5	1	0.7	1.05
Subsonic fuel flow	MISSIN	FACT	-20	5	1	0.8	1.05
Wing weight	WTIN	FRWI	-40	5	1	0.6	1.05
Fuselage weight	WTIN	FRFU	-30	5	1	0.7	1.05
Elec. Weight	WTIN	WELEC	-5	10	1	0.95	1.1
Engine wt	WTIN	WENG	-50	10	19000	9500	20900
Hydraulics weight	WTIN	WHYD	-10	10	1	0.9	1.1
Al.wing manuf.Costs	RDTE	CFWAL	-5	5	1	0.95	1.05
O & S	IWGT	AKOANDS	-15	10	0	-0.15	0.1
RDT & E	IWGT	AKRDTE	-10	20	0	-0.1	0.2
Production costs	IWGT	AKPRICE	-10	25	0	-0.1	0.25
Utilization	COPER	U	-10	10	5000	4500	5500

The resulting cumulative distribution functions show an increase in the feasible and viable design space. The "new" design space with respect to the metric of takeoff gross weight is shown in Figure 5. Without the application of new technologies, as represented by the aforementioned k-factors, the baseline vehicle had a takeoff gross weight of over 1.3 million pounds. After the improvements in the design, due to the new technologies are simulated, the technology space becomes viable. The baseline value for TOGW was dramatically improved by the application of k-factors, in fact, 90% of the available technology space will allow for the target value of 1,000,000 pounds to be met. The cumulative distribution for the remaining performance and economic metrics are included in Appendix B.

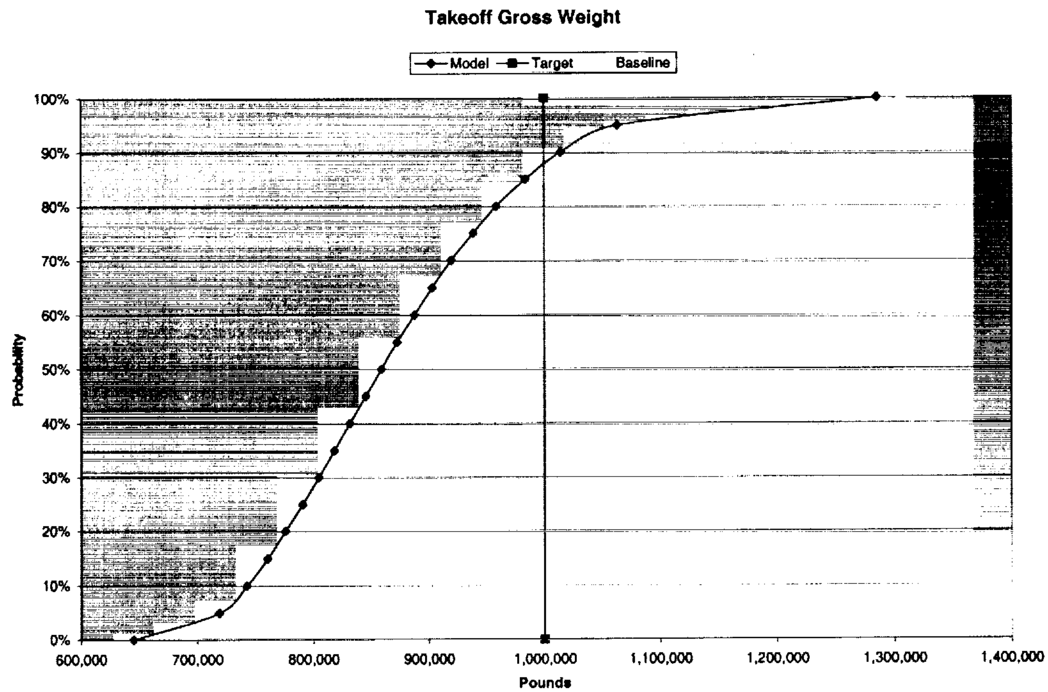


Figure 5 : CDF for Takeoff Gross Weight after the application of k-factors

Table 5 shows the changes in the probability of achieving the targets or constraints for each metric.

Table 5 : Feasible and Viable Design Space

Parameter	Acronym	Target or Constraint	Baseline Feasible Space	Feasible Space after k factors
Performance				
Approach Speed	Vapp	≤ 150 kts	85%	100%
Landing Field Length	LdgFL	≤ 11,000 ft	100%	100%
Takeoff Field Length	TOFL	≤ 11,000 ft	5%	100%
Takeoff Gross Weight	TOGW	≤ 1,000,000 lbs	0%	88%
Economics				
Acquisition Price	Acq $	190 FY96 $M	5%	3%
Research, Development, Testing, and Evaluation	RDT&E	Minimize	~	~
Average Required Yield per Revenue Passenger Mile	$/RPM	~ $0.095 FY96	25%	78%

All of the metrics shown above, except for one, showed significant improvement in their ability to meet the established targets and constraints. It is apparent that the addition of new technologies will be beneficial to the success of this vehicle. The one metric that failed to improve was the acquisition price. It is important to note, as mentioned previously, that the "k-factors" not only include the obvious benefits but also the degradations to the system as well. Often, these degradations appear in the form of increased investment of resources, which tends to negatively affect the acquisition price. Despite this effect, viable design space still exists and the target acquisition price of $190 million can be achieved.

Dynamic Contour Environment

Dynamic contour plots can also be used to depict the technology space, as shown in Figure 6. This screen is interactive and has the power of the RSEs behind it. The top portion of Figure 6 illustrates the control panel used to manipulate the dynamic contour plot. This control panel shows the k-factors that can be adjusted within the specified ranges (see Table 4). Any combination of these k-factors can be used to view the technology space. This display is set to show subsonic fuel flow versus subsonic drag. Therefore, this design space is viewed in terms of the aerodynamics and propulsion disciplines. The bottom of the control panel indicates the color-coded responses as well as their corresponding limits. The display is shaded with the appropriate color for the response that is being violated. Figure 6 shows the baseline settings, meaning that no technologies have been infused in this plot. There is no feasible design space without the infusion of technologies as evidenced by completely shaded regions which indicate that at least one constraint is violated.

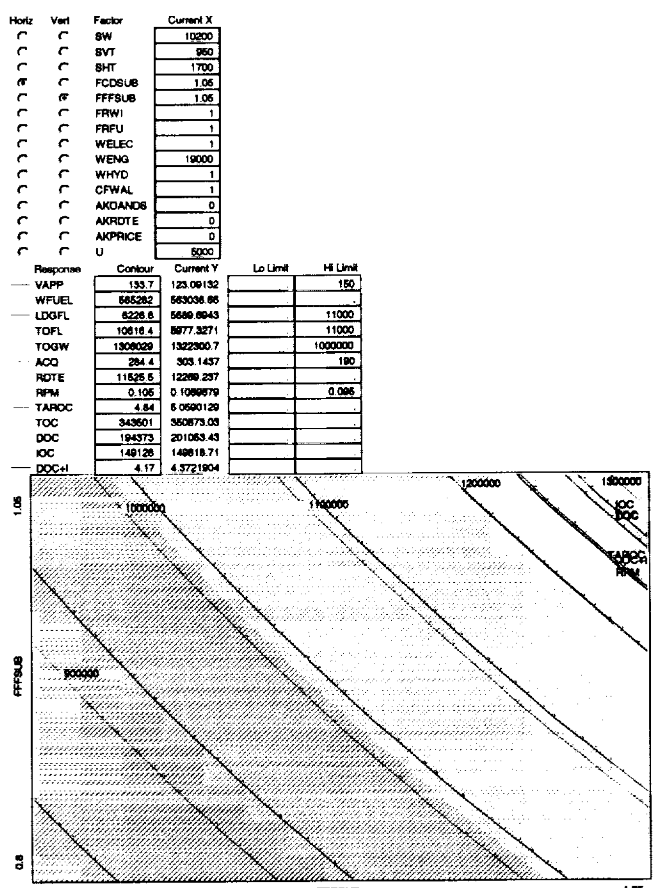


Figure 6: Baseline Contour Plot

Feasible space in the contour plots would be indicated by white (or unshaded) space. In Figure 6, the dynamic contours have been set to show various gross weight (green) and acquisition price (purple) contours. In this way the sensitivity of the system to changing limits is seen. By modifying the k-factor settings in the control panel, the design space can be explored in real time to determine if the constraints can be met as technologies are introduced. The hairlines shown in Figure 6 correspond to the current setting of metric constraints. By moving these crosshairs, the current settings are altered, and the potential for the system to meet gross weight and acquisition price limits is seen.

Figure 7 shows a feasible technology space after the current values of the k-factors were altered to reflect the application of technologies. The feasible space is represented by the unshaded (white) region of the contour plot.

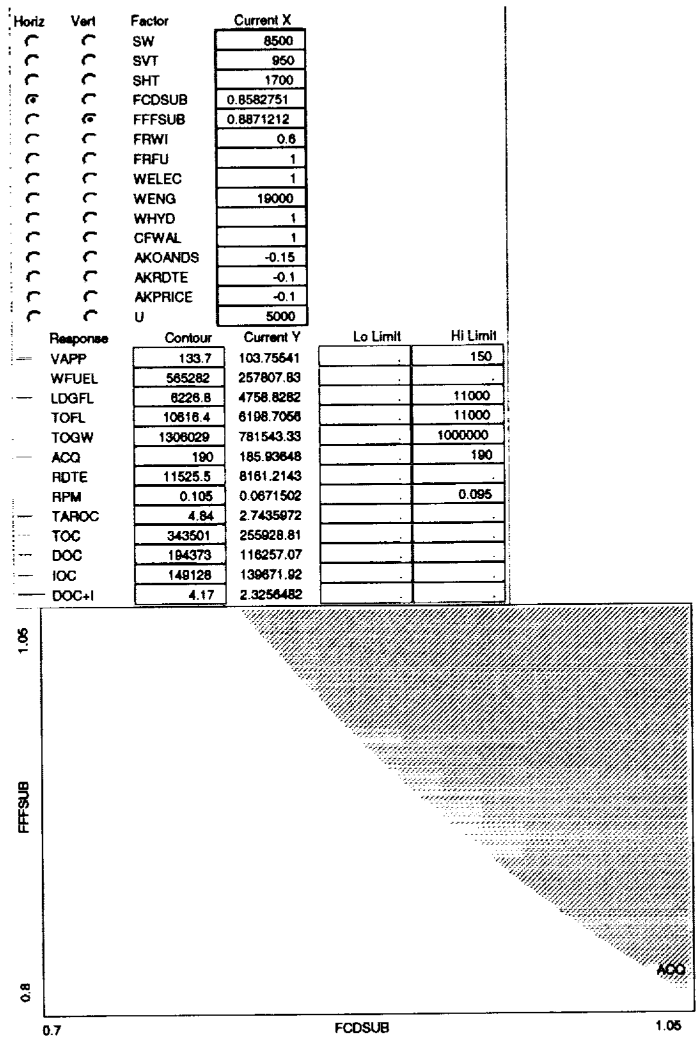


Figure 7: Feasible Technology Space

There is no limit to the number of combinations of k-factor settings that produce this feasible design space. Thus, it is incumbent upon the designer to determine which technologies to pursue, based on the amount of improvement in each k-factor needed for a feasible and viable design. In this case, the settings chosen in Figure 7 were input to the TIF environment. This new TIF can be seen in Figure 8.

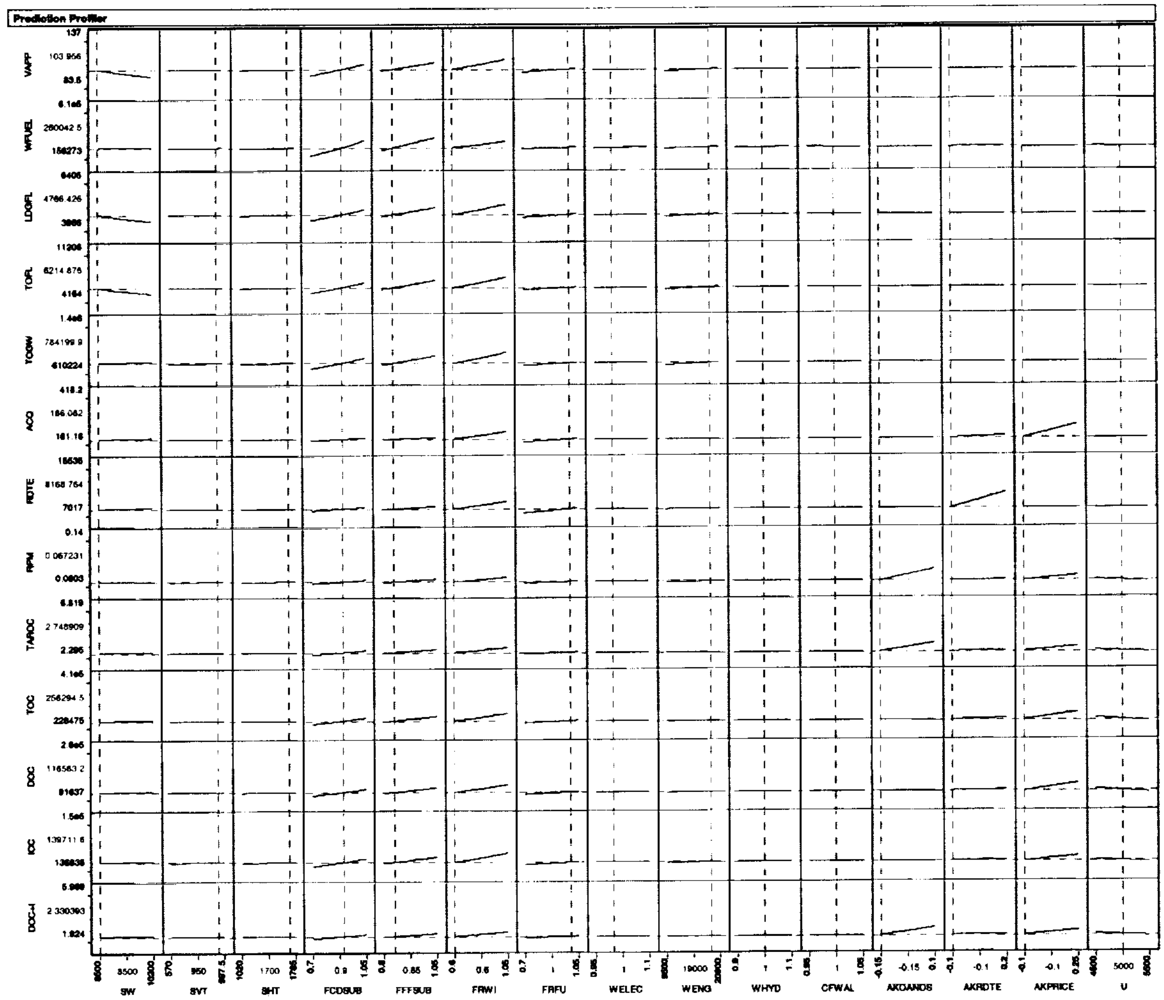


Figure 8: Feasible Design Space TIF

Conclusion

The design method utilized in this study includes a technology impact forecasting (TIF) environment whereby the decision-maker has the ability to easily assess and trade-off the impact of various technologies. This technique provides a methodical approach where technically feasible and economically viable alternatives can be identified with accuracy and speed to reduce design cycle time, and subsequently, life cycle costs. It was achieved through the use of various statistical and probabilistic methods, such as Response Surface Methodology and Monte Carlo Simulations. This methodology allows for more information to be brought into the earlier phases of the design process and will have direct implications on the affordability of the system. The increased knowledge allows for optimum allocation of company resources and quantitative justification for technology program decisions resulting in affordable, high quality products.

Nine technologies were infused into the 600-passenger commercial transport concept. The Technology Readiness Level (TRL) of each technology was established through a literature review of applied research. From the search, the readiness levels were mapped to a probabilistic space such that technologies could be infused into the vehicle. Physically compatible technology combinations were evaluated and ranked based on the improvements to the customer requirements. The technology space investigation showed that technologies to decrease the acquisition price and to decrease the gross weight of the aircraft were most important. The study also identified three technologies as significant for further investigation, specifically composite fuselage structures (T2), aircraft morphing techniques (T3), and smart, green engine systems (T6). A concept containing these technologies could meet all imposed customer requirements and could create the largest feasible design space in which system trade-offs could occur.

Task 4: Code Fidelity

Objectives and Motivation

In today's globally competitive aerospace marketplace, economic desirability plays just as big a role as technological and performance superiority in capturing the market share. Furthermore, the combined effects of budget restrictions and increasing aircraft systems costs have caused the aerospace community to shift from a design for performance philosophy to a design for affordability philosophy. This has created a growing need and interest in the development of effective cost analysis methods and tools. With this as a driving motivation, much research has been done at the Aerospace Systems Design Laboratory at Georgia Tech in the area of linking sizing and synthesis tools with cost estimating tools, such that the overall technical feasibility and economic viability of design alternatives can be evaluated during the early stages of design. One such method, as outlined in [Ref. 4] involves a Robust Design Simulation (RDS) approach that allows for an assessment of risk and uncertainty with regards to performance, cost and schedule.

The main premise of robust design is the belief that a product should be designed such that a desirable range of performance parameters can be achieved even when variations are experienced within the operating environment of that product. These variations, referred to as noise factors, are considered parameters that are beyond the control of the designer but impact the performance of the system. A robust design is then one that is insensitive to the uncertainty associated with the noise variables that affect its performance. The method developed by ASDL differs from that of traditional design in that the objective is to determine a probability distribution for an overall evaluation criterion rather than an optimized single point design solution. This is done by allowing for variability due to uncontrollable factors (noise variables, economic uncertainty, etc.) while evaluating the relative contributions of key product and process characteristic to the chosen overall evaluation criteria [Ref. 4]. Using this approach a technologically feasible design can be determined and its economic viability evaluated. The difference between technical feasibility and economic viability is illustrated in Figure 9. A technically feasible design is one that is capable of being produced due to an existing technology level. Economic viability is associated with the economic performance of such a concept. As shown in Figure 9, a design that is technically feasible is not necessarily economically viable. If a design is not economically viable, then a way to shift the mean of the response closer to the target must be identified. Therefore, the main thrust of robust design is to identify all the critical design variables and technologies, demonstrate the effect these variables have on the economic viability of the design, and determine ways in which the design can be made more economically desirable.

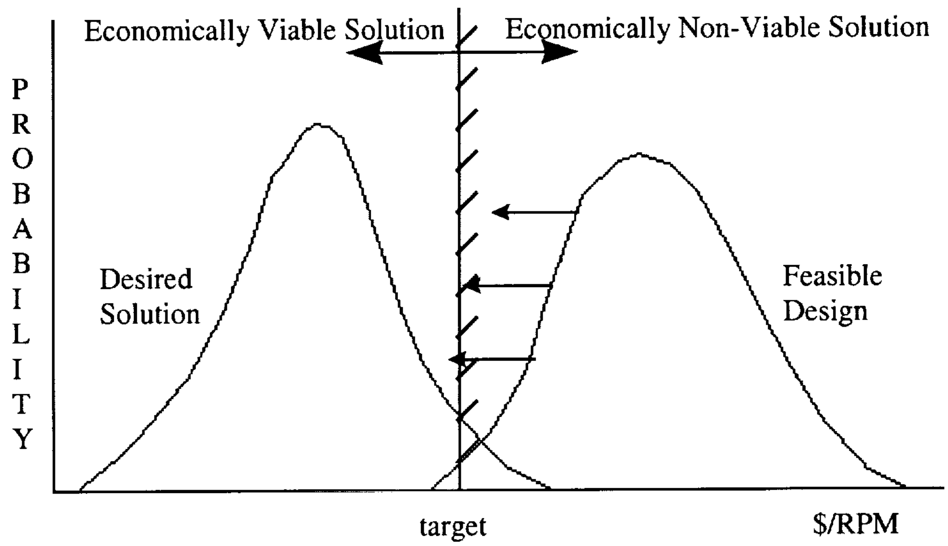


Figure 9: Need To Shift Feasible Design to Economically Viable/Feasible Design

A key element to this process is the economic analysis tool used to estimate the life cycle costs of the product, from research and development through disposal. Due to this increased focus on economics, the methods used to perform life cycle cost estimations are being critically evaluated. Traditionally, cost estimations take the form of exponential equations that have been developed based on historical data from existing systems. Ideally, one would want these estimations to be process or activity based. However, this type of information is very rarely kept track of in a manner that would make it possible to establish adequate relationships. Instead, the estimations are formed based on variables of convenience (i.e. system weights, empty weight of vehicle, etc.) or those characteristics of the system that statistics are available on. While these relationships are adequate for derivatives of existing systems, they become highly unreliable when addressing new technologies. In other words, the equations are only valid over the range for which they were developed. How well they can predict the behavior of a system that performs outside of these initial ranges is unknown. While the need to move to activity or process based costing methods has been recognized, due to a lack of sufficient data, there have not been significant advances made in this area. Therefore, weight based cost estimations continue to be used. However, complexity factors are added to the equations in order to allow the user to scale the costs for new technologies according to the relative increased complexity.

The fidelity of these economic codes represents how well the cost estimations capture reality. The Cost Estimation Relationships (CER's) within the economics analysis codes usually take the form of an exponential equation: $Y = \alpha X^B$, where Y is the cost and X is a regression factor such as gross weight. These equations are developed applying regression techniques to existing data. How well these cost estimations represent reality depends highly on the scatter of the original data, as well as the fit of the regressed curve to that data (see Figure 10). However, the original data is typically considered proprietary and is not available to the public. This requires the development of a means to evaluate the fidelity of the codes without access to the original data.

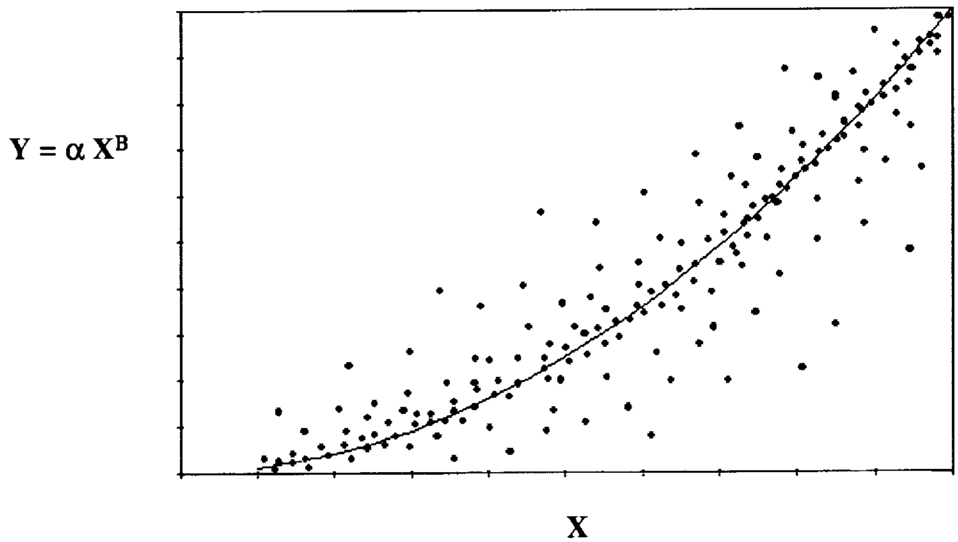


Figure 10: Example of Data Regression

It is important to understand the impact that code fidelity can have on the overall design alternative evaluation process. The fidelity of the economic code used in robust design simulation can potentially negate the benefits of performing an economic uncertainty sensitivity analysis. If the variations in system performance due to the infidelity of the code are more significant than those caused by economic noise variables then the whole idea of design robustness becomes moot. In this circumstance, the variation in system performance cannot be unequivocally attributed to the economic noise. Therefore, it becomes pointless to determine values for design variables that minimize the impact of noise variables.

A method for evaluating the fidelity of an economic analysis code is presented here. The economic code chosen for this case study is Aircraft Life Cycle Cost Analysis (ALCCA). The fidelity evaluation is performed probabilistically by using the complexity factors that are found within the cost estimating equations in ALCCA to cause a shifting of these equations. Each complexity factor is assigned a probability distribution that represents the scatter of the original data around the fit curve. Utilizing the NESSUS/Fast Probability Integration (FPI) software, the complexity factors are allowed to vary based on these distributions, the economic code is run, and the responses of interest are tracked. From this information, cumulative distribution functions and sensitivity factors are generated using the FPI software. This information can then be used to determine the variability in the response that occurs due to shifting of the cost estimating curves, and to which specific CER's each response is most sensitive.

Tools implemented

In order to implement the fidelity study described in the previous section, two simulation tools were utilized. The first is the economic analysis code under investigation, which is Aircraft Life Cycle Cost Analysis (ALCCA). The second tool is the Numerical Evaluation of Stochastic Structures Under Stress/Fast Probability Integration (NESSUS/FPI) code, which was used to perform the probabilistic analysis.

ALCCA

The roots of the Aircraft Life Cycle Cost Analysis code (ALCCA) can be traced to the early 1970s when a series of computer program subroutines were developed to predict commercial aircraft return on investment based on engineering economic theory. Later, NASA funds would provide the development support for Cost Estimating Relationships that would be used with Anderson's original program to form an extended version of commercial aircraft return on investment analysis code. This more sophisticated code, developed by Bobick et al in the late 1970s was funded through NASA's Analysis of the Benefits and Costs of Aeronautical Research and Technology program. These models were developed in order to analyze the economic viability of applying advanced technology to transport aircraft. The original version contained three main modules: Fleet Accounting, Airframe Manufacturer, and Air Carrier. These modules, with the exception of the Fleet accounting portion, were then used to perform cost estimates in ACSYNT a performance and sizing code developed at NASA-Ames. In 1993, the cost module was removed from ACSYNT and transformed into stand-alone code that became the original version of ALCCA. A number of improvements to ALCCA have since been made at ASDL, including a detailed RDT&E (Research, Development, Test and Evaluation) cost module that was developed as part of this grant, and will be subject to scrutiny in this fidelity study [Ref. 5].

The flow of logic and calculations used by ALCCA is shown in Figure 11. First the aircraft manufacturing costs are calculated including detailed research, development, testing, and evaluation costs. Next the manufacturer's cash flow and discounted Return on Investment (ROI) are calculated for several possible aircraft prices. The aircraft price is then based on the manufacturing costs and the rate of return desired by the manufacturer. With this price the airline operating costs are calculated including revenue loss due to failure and finally, the airline cash flows are calculated and used to determine the airline return on investments for several possible values of the yield per Revenue Passenger Mile($/RPM). The output file from ALCCA includes values for component costs, RDT&E costs, learning curve effects on aircraft costs, manufacturer and airline cashflows and return on investments, acquisition price, and direct, indirect, and total operating costs.

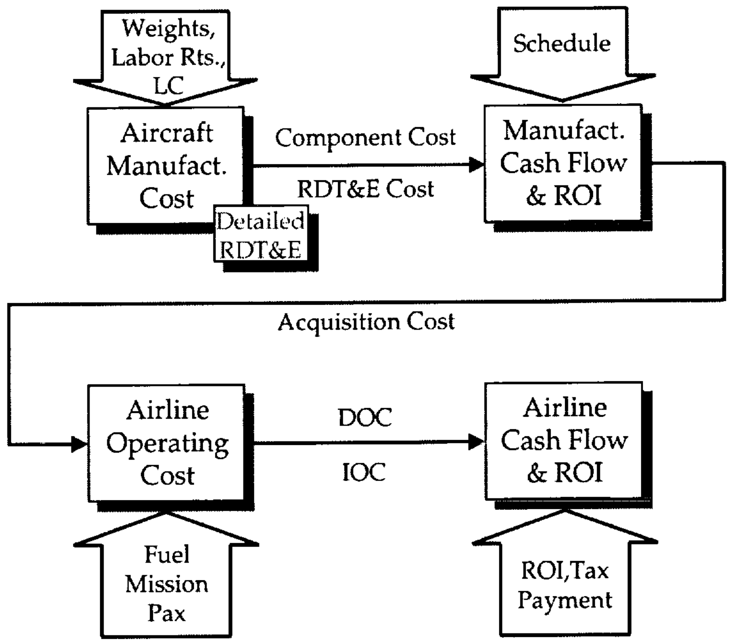


Figure 11: ALCCA Information Flow

NESSUS/FPI

The concept of Fast Probability Integration has its roots in structural reliability analysis where limit states are used to pre-define failure conditions. This technique possesses a multitude of capabilities for computing the probabilistic response or the reliability of deterministic models which are governed by uncertain variables. The deterministic models can be as simple as an analytical expression for the deflection of a beam or as sophisticated as a finite element model. In this study, FPI techniques within NESSUS (Numerical Evaluation of Stochastic Structures Under Stress) are used with the cost estimation of an aircraft as the deterministic model.

NESSUS perform a probabilistic analysis on the system responses based on a set of user defined random variables, and their corresponding statistics in the form of probability distributions. A performance function, and desired probability levels are also required to execute an FPI analysis. With this data FPI generates cumulative distribution functions and sensitivity factors.

The two main elements of an FPI technique are the response or performance function and the limit state function. The response function, referred to as the Z-function can be represented as:

$Z(X) = Z(X_1, X_2, X_3, \ldots, X_n)$, where Xi $(I = 1, n)$ represent the random variables.

The limit state function, also referred to as the g-function is defined as:

$g = Z(X) - z_0 = 0$, where z_0 is a particular value for Z.

The g-function is defined such that $g(X) = 0$ defines the boundary between failure and safe regions in the random variable space. This is used to calculate the CDF (Cumulative

Distribution Function) by varying z_o and computing the point probability. The CDF of Z at z_o equals the probability that failure will occur ($g \leq 0$).

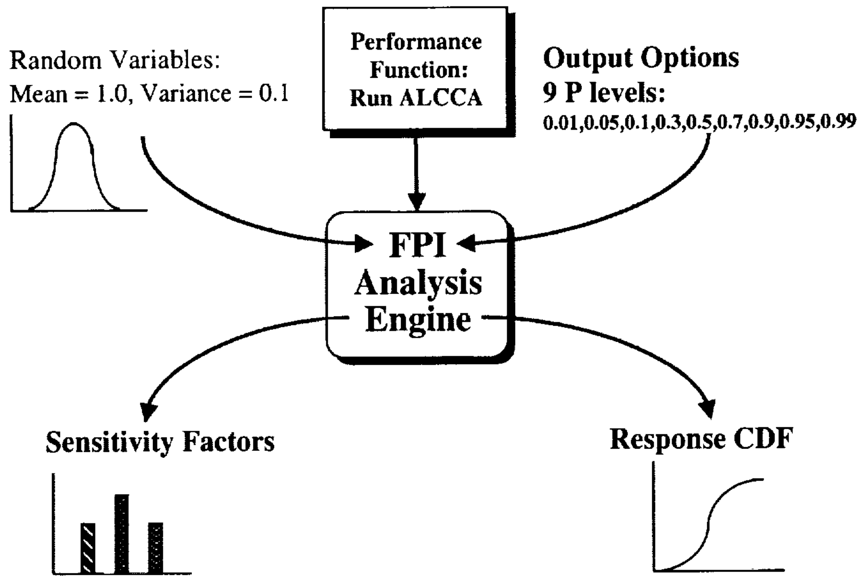


Figure 12: FPI Inputs and Outputs

Given the g-function and a joint probability density function PDF, the probability of failure can be determined using a standard Monte Carlo procedure of random sampling. However, due to the fact that this type of procedure is inefficient for complicated g-functions, FPI offers approximate analysis options. Several of these methods are based on the concept of Most Probable Point (MPP). The MPP, also known as the design point, is defined in u-space which is the coordinate system for an independent, standardized normal vector u. The joint PDF (Probability Density Function) is defined in u-space as rotationally symmetric around the origin. It decays exponentially with the square of the distance from the origin. The transformation of the g(X) function to g(u) allows the MPP to become the minimum distance from the origin to the limit-state surface, which means that the density is a maximum when the distance is a minimum. The concept of MPP is essential to fast probability analysis. For a detailed description of the distribution transformation used to transform g(X) to g(u) and the MPP search procedure that is implemented within FPI please refer to Reference 6.

There currently exist 9 methods within NESSUS for performing the probabilistic analysis, which are:

- First-Order Reliability Method
- Second-Order Reliability Method
- Advanced First-Order Method
- Fast Convolution Method
- Radius-based Importance sampling with radius reduction factor
- Standard Monte Carlo Method
- Radius-based Importance Sampling with user-defined radius

- Adaptive Importance Sampling Method
- Mean Based Methods (MV, AMV, and AMV+)

Of these methods, the Advanced Mean Value (AMV), a mean based method, was chosen for this study. The mean based methods are used with complicated g-functions that require time intensive calculations. The mean value method (MV) uses an approximate g-function that is generated by linearizing g at the mean values of the random variables. The advanced mean value method (AMV) takes the MV solution and improves it by applying the Most Probable Point Locus (MPPL) of the MV g-function. The AMV+ method improves this even further by using the MPPL of the exact g-function [Ref. 6].

Method of Implementation

Utilizing the tools discussed in the previous section, the fidelity of ALCCA was analyzed. The first step was to identify the cost estimations within ALCCA which would be evaluated. The RDTE module (subRDTE.f) and the Manufacturing Cost Module (accost.f) were chosen due to the fact that most of the cost estimation equations can be found in these two modules. Figure 13 summarizes the breakdown of costs within the manufacturing cost module. Within each category there are a number of cost equations, as listed next to the category titles in parenthesis. There are a total of 30 manufacturing cost estimation relationships (CER's) that were evaluated. For each of these equations the complexity factor was identified and designated as a random variable within FPI. Each complexity factor was then assigned a distribution. Ideally, if historical data were accessible, these distributions would be assigned based on the actual statistics of the data. However, since this information is not available for this study, the shape functions for each complexity factor are assumed. A normal distribution was assigned to each of the manufacturing complexity factors.

- Wing Group (3)
- Tail Group (3)
- Body Group (3)
- Alighting Gear Group Structure (3)
- Nacelle Group (3)
- Propulsion Group (15)

Figure 13: Manufacturing Cost Approximations Evaluated (30 total)

For this study, the values of the complexity factors are set to fall within ±30% of the mean value ($3\sigma = 0.3$), varying from 0.7 to 1.3. Hence, each complexity factor has a mean of 1.0 and a standard deviation of 0.1 as illustrated in Figure 14.

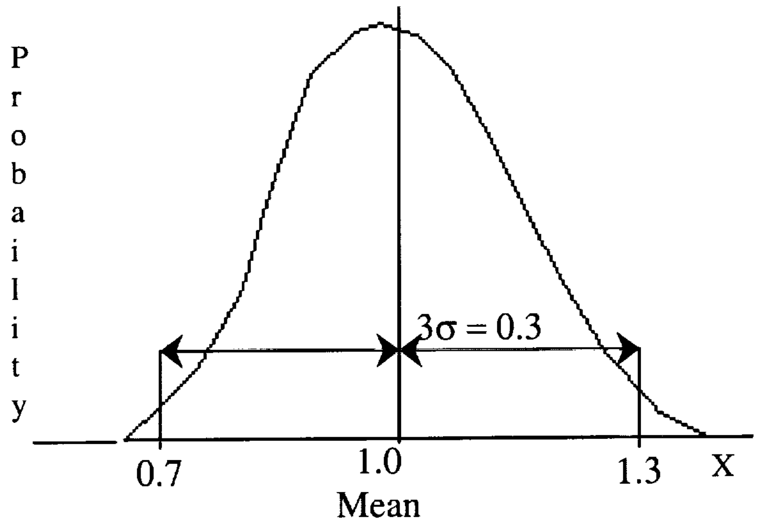


Figure 14: Illustration of Mean and Standard Deviation for Normal Distribution

These distributions are defined for each of the random variables (complexity factors) within the FPI input file. Additionally, the probability levels for which the cumulative distribution function should be computed are specified within the FPI input file. Nine probability levels are defined for the Cumulative Distribution Functions (CDF): 0.01, 0.05, 0.1, 0.3, 0.5, 0.7, 0.9, 0.95, and 0.99. As previously stated, the AMV method was chosen in order to generate the first unit cost CDF.

The final element that the user must specify for FPI is the Performance Function or *Z*. For time consuming codes, a relationship can be determined using a design of experiment and developing a response surface equation. However, given ALCCA's fast execution time, FPI was directly linked to ALCCA and the value of the desired response was tracked. For the Manufacturing Cost approximations, the final aircraft price was used as the performance function since variations of the final aircraft price as manufacturing complexity factors change is of interest.

In addition to the manufacturing cost approximations, the RDT&E cost approximations (subRDTE.f in ALCCA RDT&E cost module) are also observed in evaluating the fidelity of ALCCA. The RDT&E costs fall into 6 main categories as shown in Figure 15. Within each of these categories there are a number of subcategories that the cost approximation equations are divided into, as listed next to the category titles in parentheses. There are a total of 269 cost estimating equations for the RDT&E costs. Due to limitations of FPI (which can only handle up to 100 random variables at one time) six separate cases are run for each of the six main categories in the RDTE cost. Each of these cases was set up in the same manner as was described for the manufacturing cost case. The response tracked for these cases was the total RDT&E cost. The same 9 probability levels as were defined for the final aircraft price CDF were used for the total RDT&E cost. Similarly, the AMV method was used to generate the CDF.

Basic Engineering (55)
- Design Engineering
  - SPFTi Structures (2)
  - THPL/other Structures (8)
  - Propulsion group (5)
  - Fixed Equipment (12)
  - Laminar Flow System (3)
  - Avionics (4)
- Software Engineering
  - Operational Flight Software (18)

Test Programs and Mockups (16)
- Ground Test Engineering (5)
- Flight Test Engineering (1)
- Mockups/EDF Engineering (2)
- Ground Test Development (5)
- Flight Test Development (1)
- Mockups/EDF Development (2)

Tooling and Factory Test Equipment (35)
- SPFTi Structures (2)
- THPL/other Structures (8)
- Propulsion group (5)
- Fixed Equipment (12)
- Laminar Flow System (3)
- Avionics (4)
- Integration/Assembly (1)

Supplier Non-recurring Cost (66)
- Flight Articles
  - SPFTi Structures (2)
  - THPL/Other Structures (6)
  - Propulsion (5)
  - Fixed Equipment (11)
  - Laminar Flow Control (3)
  - Avionics (2)
- DAC Avionics
  - Computers and Digital Equipment (5)
  - Displays and Controls (3)
  - Sensors (3)
  - Navigation (3)
  - Communications- Autopilot (3)
- BFE Avionics
  - Displays and Controls (1)
  - Sensors (1)
  - Navigation (9)
  - Communications (8)
  - Autopilot/Flight Management (1)

Material Cost (65)
- SPFTi Structures (2)
- THPL/Other Structures (6)
- Propulsion 4)
- Fixed Equipment (11)
- Laminar Flow Control (3)
- Avionics (2)
- Computers and Digital Equipment (5)
- Displays and Controls (4)
- Sensors (4)
- Navigation (12)
- Communications (8)
- Autopilot/Flight Management (4)

Basic Factory Labor (32)
- SPFTi Structures (2)
- THPL/Other Structures (6)
- Propulsion Group (5)
- Fixed Equipment (11)
- Laminar Flow System(3)
- Avionics(4)
- Integration/Assembly (1)

Figure 15: RDT&E Cost Approximations Evaluated (269 totals)

In order to streamline the execution of studies such as this one a subroutine named RESPON.f was added to the NESSUS code. This subroutine identifies the factors to be treated as random variables as well as their probability distribution parameters. Within this subroutine a shell script is executed to set up the appropriate input files and run the program that is to be used as the performance function, as well as collect the resulting response values. Samples of this subroutine and shell script, as well as a more detailed description of the FPI input file can be found in Appendix C.

FPI will generate a number of outputs. In this case the resulting response CDF and variable sensitivity factors are of interest. The Z-levels (response values) corresponding to the input P-levels (probability levels) can be plotted. The sensitivity factors of each random variable listed in the FPI input file can be displayed as bar charts comparing the relative influence of each CER considered on the overall response.

Case Study Results

Implementation of the study yielded output files (one for each successive run) that contain the CDF for each response and the corresponding sensitivity factors. Two main observations are made. Firstly, the variability of the two responses (final aircraft price and RDT&E cost) due to shifting of the cost estimating curves is observed from the CDF. Secondly, the specific cost estimating equations to which each response is most sensitive are identified from the sensitivity factors.

Manufacturing Cost Module

Figure 16 shows the CDF for the final aircraft price due to variation in the manufacturing complexity factors. With the complexity factors varying ±30% from 0.7 to 1.3, the final aircraft price range is captured between $165.16M (99% probability) and $162.93M (1% probability). Overall change of the final aircraft price is calculated to be $2.22M or a 1.36% total variation from a mean value of $164.09M. Also, the standard deviation is calculated to be $0.78M, which means that 68% of the total population falls within a mere ±0.48% of the mean. These two characteristics show that the variability is relatively small in comparison with the value of the final aircraft price. Hence, it can be deduced that fidelity of the Manufacturing Cost module of ALCCA is high.

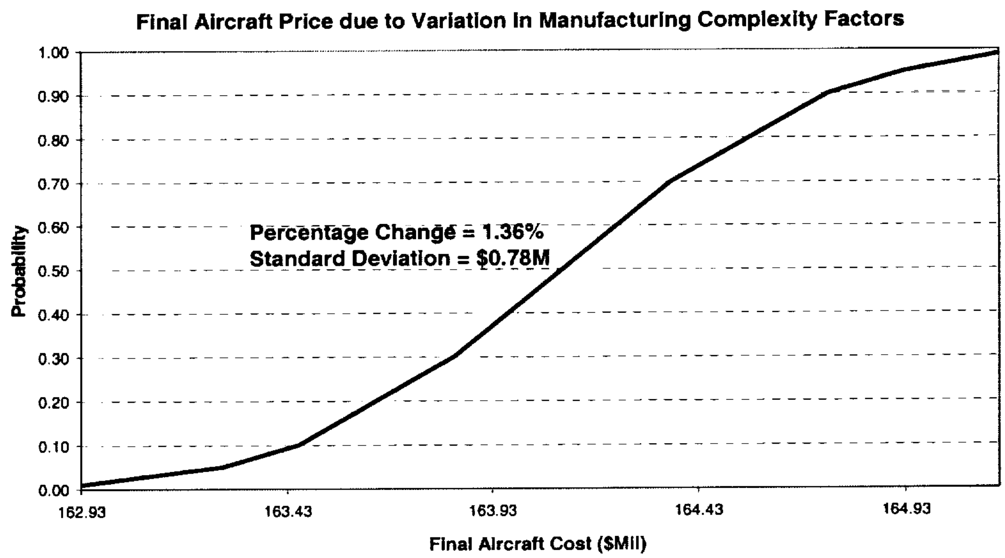


Figure 16: Final Aircraft Price Cumulative Distribution Function

Figure 17 below shows the top 10 out of 30 cost estimating equations that the final aircraft price is significantly sensitive to. By varying the complexity factors of the manufacturing cost module while keeping all others equal, the final aircraft price is found to be most sensitive to:

- Aerodynamic Controls Manufacturing
- Engine Nacelle Structure Titanium Manufacturing
- Passenger Accommodations Manufacturing
- Avionics System Manufacturing
- Landing Gear Structure Aluminum Manufacturing
- Landing Gear Structure Titanium Manufacturing
- Instrument System Manufacturing
- Empennage Structure Titanium Manufacturing
- Hydraulic System Manufacturing
- Electrical System Manufacturing

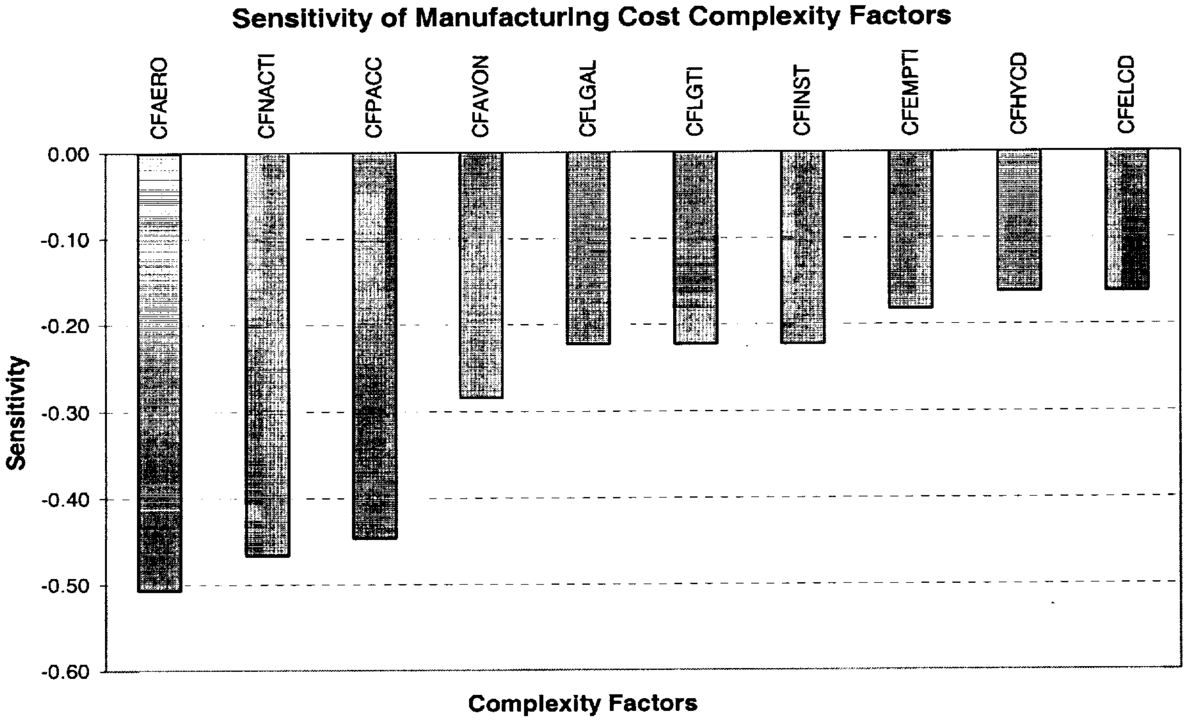


Figure 17: Manufacturing Cost Estimations Sensitivity Factors

RDT&E Cost Module

As discussed previously, six different cases were run for the RDT&E cost module, each representing a different component of the RDT&E cost. Table 6 shows the summary of RDT&E cost variability in each component when the corresponding complexity factors vary ±30% from 0.7 to 1.3. The largest variability in RDT&E cost is only a little over 6%, resulting from the variation in Basic Factory Labor components. Meanwhile, the smallest variability, 0.74%, occurs when complexity factors in Material Cost component are varied. The cost estimating equations that are most influential to the variability of the RDT&E cost for each component are listed in Table 7. Individual CDF plots and sensitivity factor charts for each RDT&E cost category are shown in Appendix D.

Table 6: Summary of Total RDT&E Cost Variability for Each Cost Component

RDT&E Component	Max. Change ($M) and Percentage Change*(%)	Mean ($M)	Std. Dev. ($M)
Basic Engineering	$291.43M (4.54%)	$6417M	$99.2M
Test Programs & Mockups	$185.81M (2.93%)	$6343M	$63.2M
Material Cost	$47.55M (0.74%)	$6401M	$16.1M
Supplier Non-recurring Cost	$102.97M (1.57%)	$6555M	$35.0M
Basic Factory Labor	$386.92M (6.08%)	$6368M	$131.7M
Tool & Factory Test Equip.	$209.58M (3.73%)	$5620M	$71.4M

*** Calculated relative to the mean value of RDT&E Cost**

From Table 6, it can be deduced that all six RDT&E Cost components have relatively high degrees of fidelity since the variability of each component is small in comparison with the value of the RDT&E cost. However, this deduction is only applicable to each component independently since the results tabulated in Table 6 are obtained from six independent and separate runs. With that being clarified, no conclusion can be drawn on the overall fidelity of the RDT&E Cost module. Hence, a technique that can somehow provide an insight on the overall fidelity of the RDT&E Cost module is needed.

Table 7: Most Influential CER's for Each RDT&E Cost Component

Basic Engineering	- Fuselage Structure Design - Surface Controls Design - Anti-Icing Design - Loading and Handling Equipment Design - Nacelle Structure Design	- Pneumatic Equipment Design - Electrical Group Design - Fault Management and Reconfiguration - SPFTi Wing Structure Design
Test Programs & Mockups	- Flight Testing Engineering - Other Ground Testing Development - Flight Testing Development - Ground Testing Engineering	- Static Ground Testing Development - Fatigue Ground Testing Development
Material Cost	- Landing Gear Structure - Wing Titanium Structure - Fuselage Structure - Instruments	- Seats and Galleys - Fuel System - Surface Controls
Supplier Non-recurring Cost	- Air Conditioning System - Weather Radar - Surface Controls - Instruments	- Electrical Group - Landing Gear - EO/TV Surveillance System
Basic Factory Labor	- Fuselage - Wing Titanium Structure - Nacelles	- Integration/Assembly/Co - VG Inlet
Tooling & Factory Test Equipment	- SPFTi Wing Structure - Fuselage Structure - Nacelle Structure - Integration/Assembly/Co	- VG Inlet System - Electrical Group - SPFTi Empennage

The challenge in obtaining an estimate of overall variability in RDT&E is to overcome the main limitation of FPI, which can only handle up to 100 random variables in a single run. The approach taken is to screen all 269 RDT&E cost estimating equations that were analyzed for the six independent RDT&E Cost module runs in terms of their sensitivity factors. Screening and ranking these cost estimating equations based on sensitivity factors makes perfect sense from a numerical perspective because these sensitivity factors are normalized. Hence, the 99 most influential cost estimating equations out of the 269 are selected as input random variables for a full FPI run that aims to disclose the overall fidelity of the RDT&E Cost module.

Figure 18 shows the CDF for RDT&E Cost due to variation in the complexity factors of these 99 cost estimating equations. With these complexity factors varying ±30% from 0.7 to 1.3, the RDT&E cost is captured with 99% probability between $6,028.6M and $5,459.7M. The variability of the final aircraft price is calculated to be $568.9M or a 9.9% total variation from the mean RDT&E cost of $5,744.0M. Also, the standard deviation is calculated to be $193.7M, which means that 68% of the total population falls within ±3.4% from the mean. This 9.9% variability is not particularly small, especially when compared to the 1.36% variability for the Manufacturing Cost module shown earlier. However, the possibility of an increase in the number of variables as a contributing factor to the increasing variability must be considered. Hence, for this 99-variables, a 9.9% variability in the RDT&E cost may still reflect a reasonably good fidelity for the RDT&E Cost module of ALCCA.

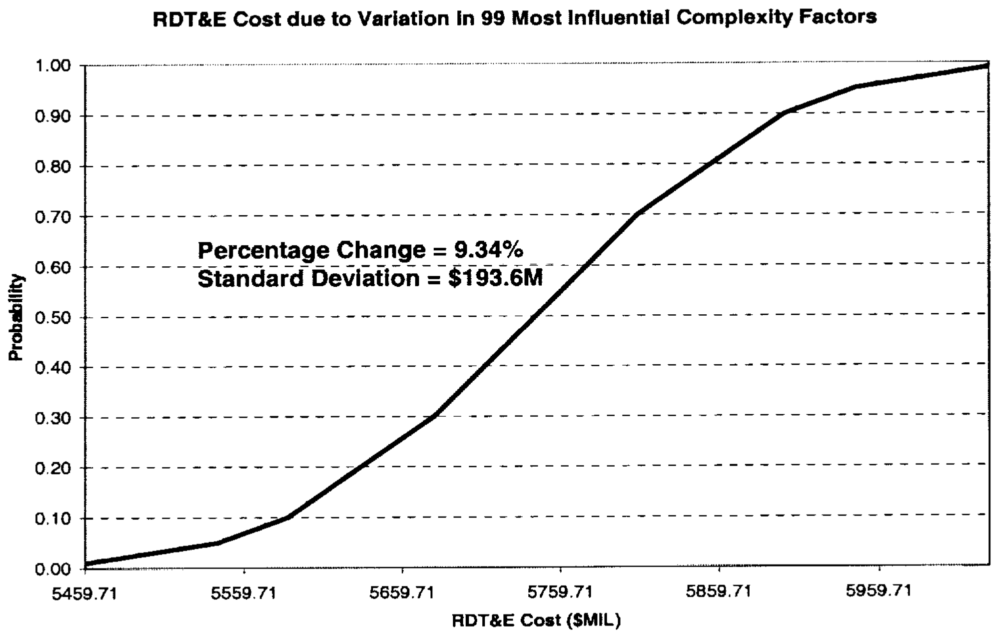


Figure 18: RDT&E Cost Cumulative Distribution Function

A comparison is made between the 10 most influential CER's for the overall RDT&E Cost and the 10 most influential cost estimating equations for the six independent RDT&E cost components. The purpose of this comparison is to validate the screening and ranking of the 269 RDT&E cost estimating equations based on their sensitivity factors. Unsurprisingly, 9 out of 10 of the cost estimating equations considered in the overall case match the most prominent factors for each of the six sub-cost cases with minimal changes in rankings. In fact, as shown below, all top 10 CER's for the overall case are ranked within the top 3 of the each independent RDT&E cost component. This comparison further reinforces the validity of the screening technique. The most influential CER's for the overall case are:

- Basic Factory Labor for Fuselage
  Ranked 1st in Basic Factory Labor component

- Fuselage Structure Basic Design
  Ranked 1st in Basic Engineering component

- SPFTi Wing Structure Tooling and Factory Test Equipment
  Ranked 1st in Tooling & Factory Test Equipment component

- Fuselage Structure Tooling and Factory Test Equipment
  Ranked 2nd in Tooling & Factory Test Equipment component

- Flight Testing Engineering
  Ranked 1st in Test Programs & Mockup component
- Other Ground Testing Development
  Ranked 2nd in Test Programs & Mockup component
- Flight Testing Development
  Ranked 3rd in Test Programs & Mockup component
- Basic Factory Labor for Wing Ti Structure
  Ranked 2nd in Basic Factory Labor component
- Supplier Non-recurring for Air Conditioning System
  Ranked 1st in Supplier Non-recurring Cost component
- Supplier Non-recurring for Weather Radar
  Ranked 2nd in Supplier Non-recurring Cost component

As shown in Figure 19 wing and fuselage related CER's dominate the RDT&E costs estimates. Note that engine development costs would dominate the RDT&E variation if they were included. However, in this case the engine is considered to be a purchased item with a fixed input price which includes a share of development costs as well as the engine manufacturer's profit margin.

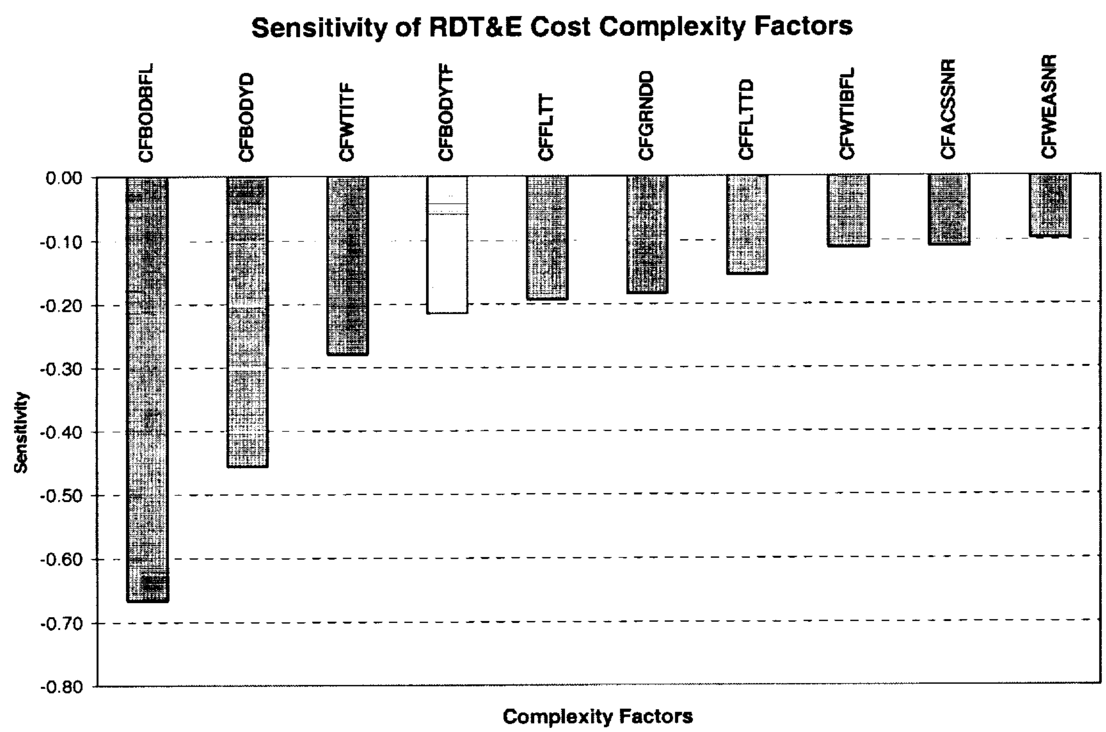


Figure 19: RDT&E Cost Estimations Sensitivity Factors

Fidelity vs. Noise

The motive for this study is to observe whether the impact of code infidelity overshadows the impact of economic noise variables on the variability in system performance. Thus, the study would not be complete without comparing the variability due to the changes in CER's, to that caused by changes in economic factors such as learning curves and labor rates. The results from this technique would determine if using ALCCA for Robust Design Simulation (RDS) is valid. The following are the key assumptions made:

i. The baseline complexity factors (1.0) are assumed to capture reality conditions with a high degree of fidelity.
ii. The identified economic uncertainties are assumed to have significant impact on the variability of the responses.
iii. A similar 3-Sigma, normal distribution design is desired for characterizing the distribution of the economic uncertainties.

The next step is to identify the possible economic uncertainties that may significantly impact the variability of the responses (Final Aircraft Price and RDT&E Costs). After a series of screening and test runs, the variables listed in Table 8 and Table 9 are identified as the economic uncertainties that are most influential to the variability of the final aircraft price (for Manufacturing Cost module) and the total RDT&E cost (for RDT&E Cost module) respectively. As mentioned in assumption iii above, all variables are normally distributed over a 0.1 standard deviation over their respective baseline values except for variable $CMAN NFV, that is, the number of flight test vehicles. Since this variable is discrete, it cannot be an input random variable in FPI. However, NFV is one of the most influential variables amongst the other economic uncertainties. Hence, NFV is manually changed to have the values of 1, 2 (baseline value), and 3 for each FPI run.

Table 8: Economic Uncertainties for the Manufacturing Cost Module (14 Variables)

Economic Uncertainties	**Description**	Baseline Values
$CMAN FEE	Manufacturer Fee (%/100)	**0.05**
$CMAN RTRTN	Manufacturer Return of Investment (%)	**12.0**
$CMAN RTRTNA	Airline Return of Investment (%)	**10.0**
$CMAN RE	Engineering Labor Rate ($/hr)	**85.0**
$CMAN RT	Tooling Labor Rate ($/hr)	**55.0**
$CMAN LEARN1	Airframe Learning Curve Factor for 1st Lot (%)	**82.0**
$CMAN LEARN2	Airframe Learning Curve Factor for 2nd Lot (%)	**82.0**
$CMAN LEARNA1	Avionics Learning Curve Factor for 1st Lot (%)	**82.0**
$CMAN LEARNA2	Avionics Learning Curve Factor for 2nd Lot (%)	**82.0**
$CMAN LEARNAS1	Assembly Learning Curve Factor for 1st Lot (%)	**82.0**
$CMAN LEARNAS2	Assembly Learning Curve Factor for 2nd Lot (%)	**82.0**
$CMAN LEARNFE1	Fixed Equipment Learning Curve Factor for 1st Lot (%)	**82.0**
$CMAN LEARNFE2	Fixed Equipment Learning Curve Factor for 2nd Lot (%)	**82.0**
$CMAN NFV	Number of Flight Test Vehicles	**2.0**

Table 9: Economic Uncertainties for the RDT&E Cost Module (23 Variables)

Economic Uncertainties	Description	Baseline Values
$RDTE FLTHRS	Flight Hours for Flight Testing (hr)	**6000.0**
$RDTE CMATFLTR	Cost of Flight Test Material per Flight Hour ($/hr)	**8500.0**
$RDTE RMFGMAT	Rate for Manufacturing Material Cost	**1.04**
$RDTE RTENGMHR	Cost per Test Engineering Manhour ($/MHR)	**86.51**
$RDTE RDEVPMHR	Cost per Development Manhour ($/MHR)	**50.64**
$RDTE RMANUMHR	Cost per Manufacturing Manhour ($/MHR)	**50.64**
$RDTE RMANSUP	Cost per Manufacturing Support Manhour ($/MHR)	**54.86**
$RDTE RQA	Cost per Quality Assurance Manhour ($/MHR)	**56.97**
$RDTE RLOG	Logistic Rate, $/ILS Manhour ($/MHR)	**82.29**
$RDTE RPMGT	Cost per Management Manhour ($/MHR)	**94.95**
$RDTE LEARNTIM	Airframe Material LC for Ti Structure for 1st Lot/Prototype (%)	**95.0**
$RDTE LEARNM	Airframe Material LC for other Mat'l for 1st Lot/Prototype (%)	**95.0**
$RDTE LEARNPRM	Propulsion System Material LC for 1st Lot/Prototype (%)	**93.5**
$RDTE LEARNENM	Engine Material LC for 1st Lot/Prototype (%)	**93.5**
$RDTE LEARNFEM	Fixed Equipment Material LC for 1st Lot/Prototype (%)	**93.5**
$RDTE LEARNAAM	Avionics Group A LC for 1st Lot/Prototype (%)	**93.5**
$RDTE LEARNABM	Avionics Group B LC for 1st Lot/Prototype (%)	**92.0**
$RDTE LEARNLFM	Laminar Flow Control Material LC for 1st Lot/Prototype (%)	**93.5**
$CMAN FEE	Manufacturer Fee (%/100)	**0.05**
$CMAN RTRTN	Manufacturer Return of Investment (%)	**12.0**
$CMAN RE	Engineering Labor Rate ($/hr)	**85.0**
$CMAN RT	Tooling Labor Rate ($/hr)	**55.0**
$CMAN NFV	Number of Flight Test Vehicles	**2.0**

The noise related uncertainty study is carried out in a manner similar to the fidelity analysis. The noise factors identified as significant for manufacturing and RDT&E costs are designated as random variables within FPI, the automated link between FPI and ALCCA is executed, and the resulting response is tracked. Figure 20 and Figure 21 display the response CDF's that result from the uncertainty defined for the economics factors. In this case the sensitivity factors, although generated, are not as interesting, since the economic factors to be varied were already chosen based on their expected influence.

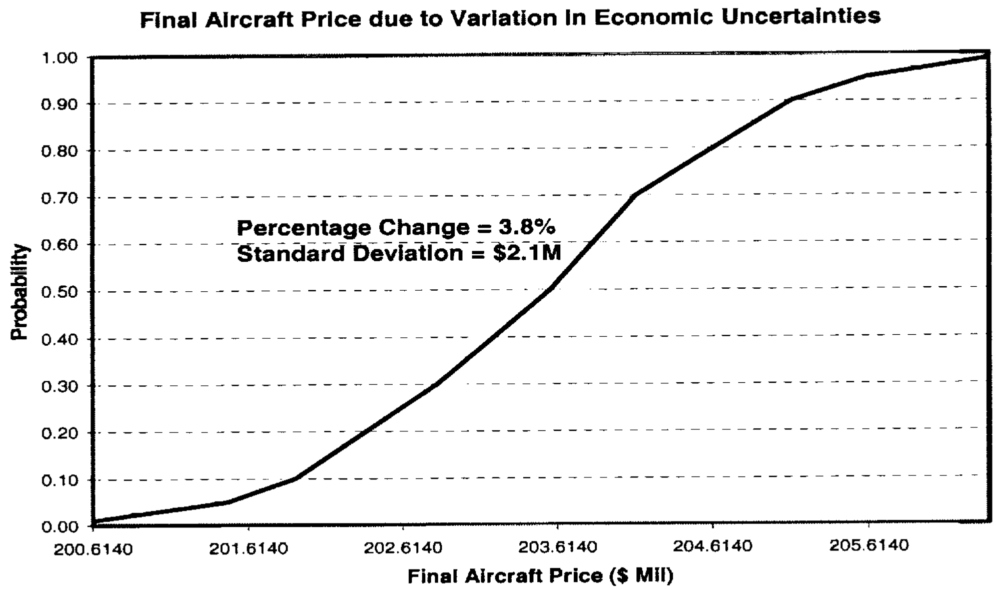


Figure 20: CDF for Final Aircraft Price Variation due to Economic Uncertainties

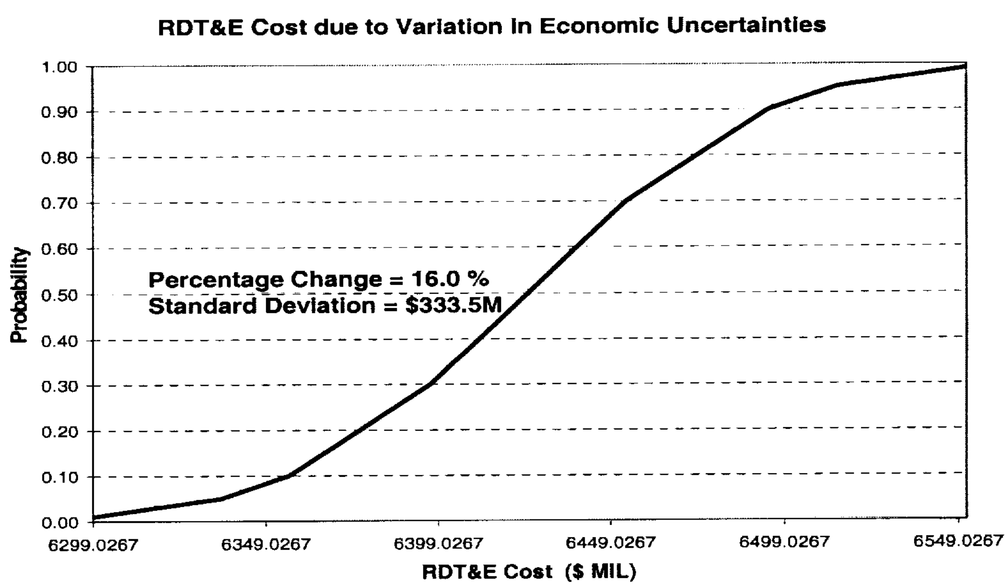


Figure 21: CDF for RDT&E Costs Variation due to Economic Uncertainties

Table 10 and Table 11 compare the variability and standard deviation caused by code infidelity with that caused by the noise factors (economic uncertainties). The data in these tables clearly shows that the economic uncertainties caused significantly more variability to the system performance than code fidelity. This implies that RDS can be successfully implemented using ALCCA without worrying about the impact of code fidelity overshadowing the changes due to economic uncertainties

Table 10: Variability Caused by Code Infidelity vs. by Economic Uncertainties

	Percentage Change relative to Mean Cost		
	Fidelity Investigation Run A	**Noise Var. Run B**	**% Difference [100*(B-A)/A]**
Manuf. Cost Module	1.36%	3.80%	180.02%
RDT&E Cost Module	9.90%	16.01%	61.62%

Table 11: Comparing Standard Deviation of Variability Caused by Code Infidelity and by Economic Uncertainties

	Standard Deviation from Mean Cost		
	Fidelity Investigation Run A	**Noise Var. Run B**	**% Difference [100*(B-A)/A]**
Manuf. Cost Module	$0.78M	$2.06M	166.1%
RDT&E Cost Module	$193.7M	$333.5M	72.23%

Graphically, the difference in the way that these two sources of uncertainty influence overall costs can be seen in Figure 22. This figure shows a shallower, but wider CDF resulting from the economic uncertainty study as is expected given the differences in standard deviations. Furthermore, the mean cost is also shifted higher due to the exponential nature of cost relationships. The effect of the factor raised to a power in an exponential equation is magnified when it increases, and diminished when it decreases, whereas the complexity factors used in the fidelity study linearly influence cost.

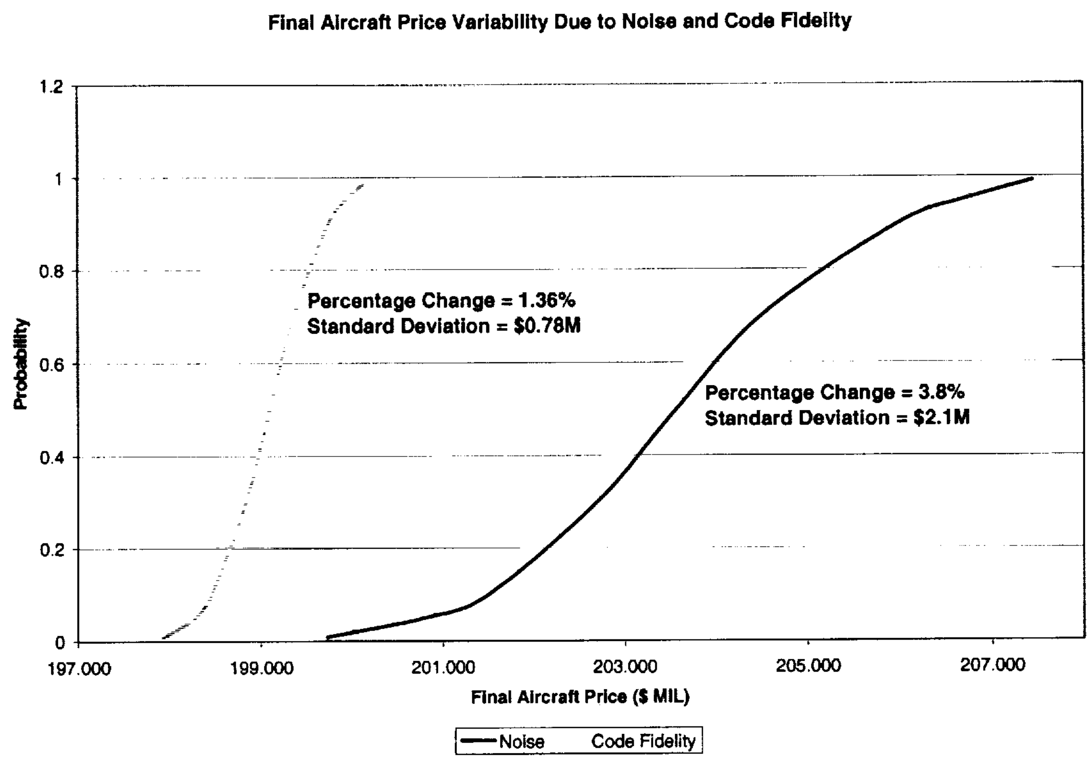


Figure 22: Comparison of Noise vs. Fidelity Uncertainty

Conclusions

The results obtained in this exercise lead to several conclusions. Firstly, the final aircraft price demonstrates a very small change with respect to the mean (1.36% or $0.78M standard deviation). Therefore, Manufacturing Cost module of ALCCA can be considered to have a high degree of fidelity.

Secondly, the variability and standard deviation of each independent component of the RDT&E Cost Module of ALCCA are relatively small in comparison with the value of the RDT&E cost. The outcome of the FPI run that encapsulates the impact of 99 most influential cost estimating equations on the variability of overall RDT&E cost showed promising results. Comparison between the 10 cost estimating equations that RDT&E cost is most sensitive to for both the 6 independent component runs and the 99-variables run validates the technique of screening and ranking the 269 RDT&E cost estimating equations based on their sensitivity factors. RDT&E cost was shown to have a 9.9% total change with respect to the mean while the standard deviation was $193.7M. Taking into strong consideration the contributory impact of the increased number of variables for this 99-variables FPI analysis, it is concluded that the 9.9% variability may still reflect a reasonable overall fidelity for the RDT&E Cost module of ALCCA.

Thirdly, under similar assumptions and probabilistic settings as the fidelity investigations, the comparison of fidelity results to economic variability showed that the variability caused by economic uncertainties clearly surpasses the variability caused by code infidelity. This implies that using ALCCA to perform RDS in order to reduce the sensitivity of a design to uncontrollable economic factors is indeed a valid option.

Based on the relatively small variabilities observed in the RDT&E and Manufacturing Cost modules, and backed by the comparison between code fidelity and economic uncertainties, the overall conclusion drawn for this study is that these two main modules of ALCCA have shown reasonably high degrees of fidelity. This implies that the use of weight-based cost estimation relationships (CER's) in ALCCA still provides accurate cost estimates for existing aircraft with infusion of derivative technologies. Nevertheless, the motivation for shifting to process and activity based costing still exists in the aerospace community in order to be more accurate and versatile when estimating costs of future aircraft where revolutionary technologies and concepts will refine the science of aviation.

Capacity Focus Task: Formulation of a Method to Assess Technologies for the Improvement of Airport Capacity

The globalization of the worldwide economy, coupled with airline deregulation and trade expansion, has caused a boom in air travel. This rapid growth has not been paralleled by a similar expansion in the national airspace infrastructure, resulting in congestion, delays and widespread frustration. The problem is quickly reaching gridlock proportions and the pressure for solutions is increasing. However, the National Airspace is not a flexible system. Solutions implemented today will only be felt in the long term. These solutions will also require a significant capital investment for system-wide execution. Thus, a careful process to determine which solutions will provide the highest payoff with the lowest risk is essential. The development of such a process and the modeling environment that it relies on are the goals of this research.

Motivation

Increasing Demand

Norman Mineta, the Secretary for the Department of Transportation, tells us: "The only sure remedy for air traffic control congestion in the near term would be a recession, which would suppress demand" [Ref. 7]. Indeed, it is the growth in demand beyond the system capabilities that has caused today's congestion. However, the increase in air travel has been a direct consequence of economic well-being, and has also resulted in a better quality of life. Thus, it is important to find ways to accommodate the demand generated and alleviate congestion.

As Mr. Mineta mentioned there is a direct relationship between economic health and demand for transportation. In fact, the relationship between GDP (Gross Domestic Product) and air travel is one widely recognized and often used to estimate future demand. However, the GDP does not explain air travel demand completely, as the percentage growth in RPK (Revenue Passenger Kilometers) slightly outpaces the growth in GDP, see Figure 23. Lower airline rates following deregulation, nearly 40% cheaper than those prior to the Deregulation Act, may account for a portion of that disparity. The convenience of today's air market, with multiple departure times and numerous non-stop flights, may also have contributed to an increase in demand beyond that justifiable by economic growth. However, as the airlines strive to provide customer satisfaction by scheduling more frequent flights at convenient times, they may also be aggravating the congestion problem.

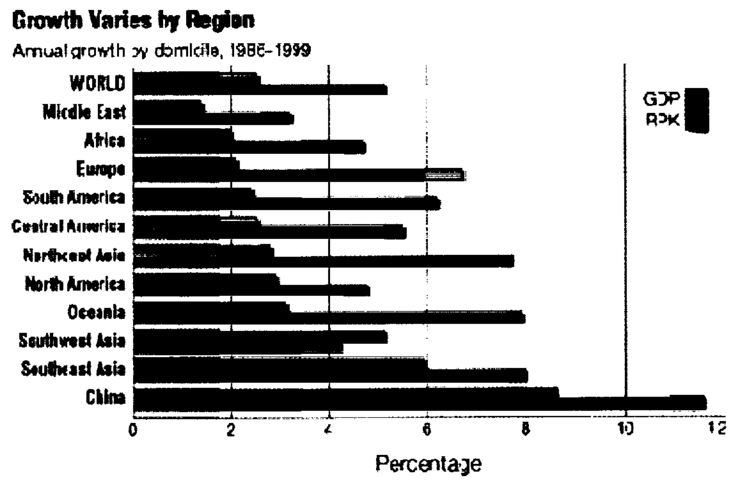


Figure 23: Annual GDP and RPK growth by Region [Ref. 8]

Just as demand is one of the main ingredients of today's plaguing congestion, the distribution of that demand has a very important role to play in the capacity deficit that the National Airspace System (NAS) is experiencing. Looking at Figure 24, obtained from the OAG (Official Airline Guide) schedules, one can see that operations at a hub airport like Atlanta Hartsfield International Airport are not even remotely uniform. It is also interesting to observe that a bank of arrivals is immediately followed by a bank of departures, possibly reflecting today's interconnectivity of flights. It is obvious from these figures that airline scheduling to maximize passenger convenience and utilization of its aircraft has resulted in peaks of arrivals and departures at certain times of the day. The number of operations at these peak times often approaches or surpasses the capacity limits of major U.S. airports. Thus, it is at these times that the worst delays are generally recorded.

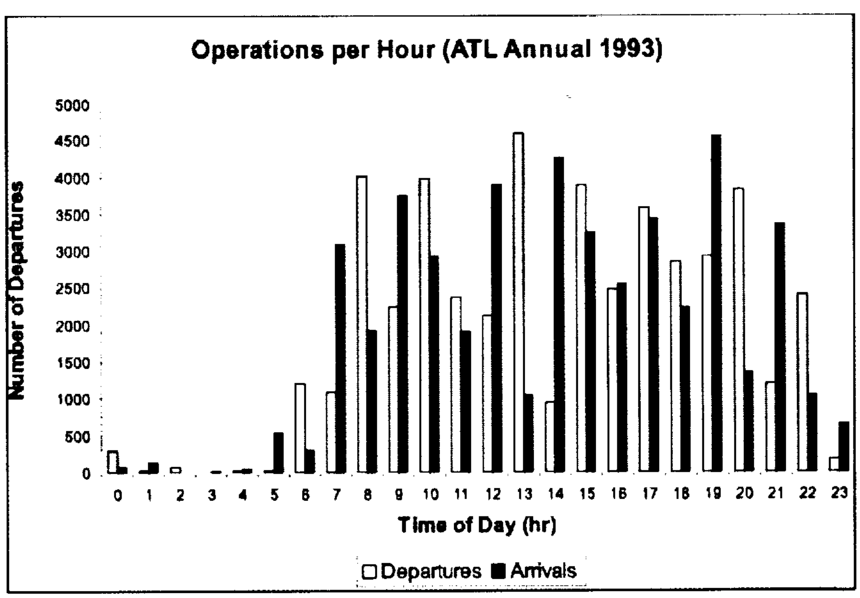


Figure 24: Annual Operations at ATL per Hour

Those delays are likely to continue getting worse, even considering current plans for capacity increases, due to the forecasted growth in both the airline and the freighter market. Based on GDP growth and the other factors mentioned, major aircraft manufacturers are predicting an average annual growth in world air travel demand of 5% over the next 20 years. The increase in e-commerce and world trade will result in an even higher growth rate, approaching 6%, for the world's air cargo market. These growth rates, when translated to the number of aircraft required to service the demand, mean that the world's fleet will double by the year 2019, both in terms of airliners, and in terms of freighters [Ref. 8 and 9]. If the trend to increase flight frequencies for customer convenience continues, a large portion of that forecasted demand may be serviced with single-aisle and regional aircraft, as shown in Figure 25 . Such a trend, very prevalent in the United States, would pose an even larger threat of collapsing the NAS [Ref. 10].

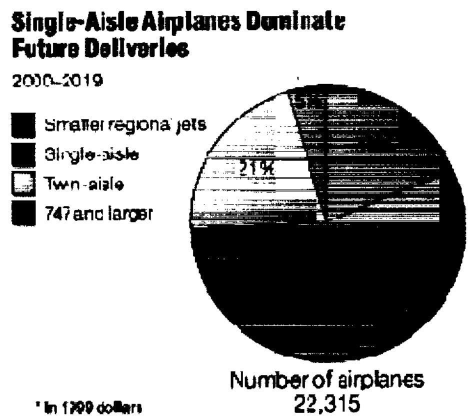


Figure 25: Forecasted 2019 Fleet Breakdown by Size [Ref. 8]

In 1997 a report from the National Civil Aviation Review Commission warned of the impending gridlock [Ref. 11]. All signs indicate that that gridlock is here today, and it is here to stay. As the Secretary of Transportation put it in his recent speech to the senate: "I need to be very candid with you in this point – we are very likely to have similar, or worse, delay problems this year as well" [Ref. 7]. Therefore, changes to the NAS to accommodate current and future demand must be made now, for the sake of their future benefits. The capacity of the system must grow and keep pace with demand lest it hamper transportation and the economic well-being that it signifies.

Limited Capacity

The steady increase in air travel demand in recent years has pushed the National Airspace System to its limit, but it is the inability of the system to expand accordingly that has caused today's delays. Indeed, with the system operating so close to its maximum capacity it is not unusual for a relatively small event, such as a local thunderstorm, to cause widespread delays, far beyond the area affected by the weather. An example of such an occurrence, where an unexpected hold of aircraft in the Newark airspace for 5 minutes affected 250 aircraft throughout the East and Midwest in less than 20 minutes, was compared by reporters to the behavior of a virus spreading uncontrollably [Ref. 12]. It's like walking a high wire, the slightest disturbance can have disastrous results.

Since flights are generally not scheduled to surpass the capacity of the airports they serve, one must assume that full theoretical capacity is not being achieved. It has been suggested that the first step toward a reduction of delays is a better management of the existing capacity. Having a uniform distribution of demand, or transporting more passengers per departure would be relatively easy to implement short-term solutions. However, as described in the previous section, the airline profitability could suffer from such regulations. Furthermore, better capacity management would not solve the long-term congestion of the system. Including all currently planned runway construction as potential capacity, the system is currently operating at 57% of its maximum capacity, and by 2010 it will be operating at 70% capacity if no expansion policies are implemented. Considering that significant delays start occurring at 40% capacity utilization, and grow exponentially from there, the delays experienced thus far may be only the tip of the iceberg. [Ref. 13].

Airport capacities are often described in terms of Pareto frontiers which show a boundary curve of arrivals vs. departures similar to the one shown in Figure 26. These curves depend on a variety of factors such as runway configuration, safety separations, equipment at the Air Traffic Control (ATC) center, navigation aids within the aircraft and the weather conditions. However, these curves are not sufficient to characterize the capacity of the system. The sectors that are crossed between arrival and destination airports also have a limited capacity dictated by human and technical factors. In the United States capacity at the airports is generally more limited and therefore considered the constraining factor. However, there are a few exceptions like the airspace around New York City and Chicago, and in Europe the en-route capacity poses a significant concern.

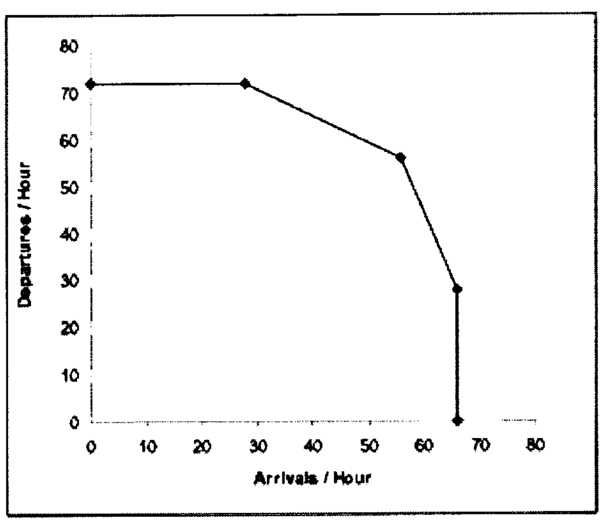


Figure 26: A Pareto frontier Example

It could be argued that to properly model an airport these Pareto Frontiers are also insufficient. Airside congestion is not the only problem plaguing major airports in the United States. Baggage handling, immigration and customs facilities, airport access roads and parking lots also have a limited capacity. As the airspace becomes crowded so does the terminal demonstrating why system growth is not easy to implement. The complexity and interdependency of all the airspace system components makes changes difficult, costly and lagging.

Complexity of the System

The need to increase capacity is pressing, but ATC budgets are limited, airport communities resist expansion, noise regulations restrict approach and departure paths. The solution to the capacity problem is not a simple one due to the complexity of the NAS and its different, and often conflicting, interests.

Airline strategies often conflict with airport and ATC concerns. As an example, the recent increase in regional jet departures at peak times in the La Guardia airport, and the resulting delays, have forced the airport authorities to impose a limit on the number of flights that can use the airport at those times of the day [Ref. 14]. A very large aircraft, such as the one currently being developed by Airbus Industrie could serve as a further example of the interdependency within the NAS. Such an aircraft would increase the demand served per departure alleviating the capacity constraint. However, it would have to meet airport restrictions in terms of runway and gate dimensions, it would have to follow ATC instructions in terms of required separation with other aircraft, and it would have to overcome the current airline tendency to favor smaller more frequent flights [Ref. 15]. Unfortunately, when analyzing solutions to the NAS congestion problem, researchers often focus on a single aspect of the problem, without thoroughly considering the effects a change in one of the NAS components will have on the other pieces of the air transportation puzzle. As the Secretary Of Transportation puts it: "There must be more synchronization and more coordination between these groups if we are going to solve the [capacity] problem" [Ref. 7]. Figure 27 illustrates the four main components of the NAS, and adds three considerations which are vital when assessing capacity and throughput technologies: Safety, Environment and Economics.

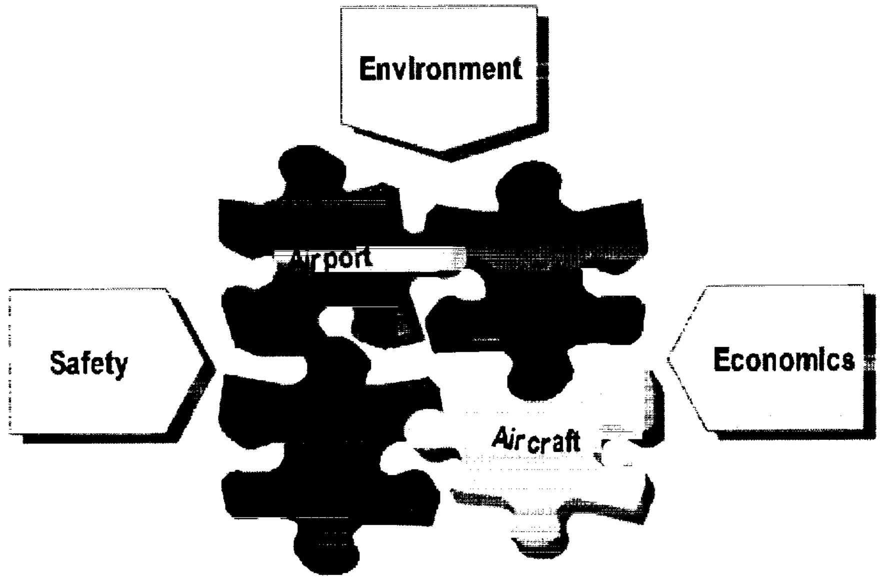


Figure 27: Components of the NAS

Economics drive the demand which has made the system capacity inadequate. As described earlier, the GDP is a clear indicator for air travel demand. Economics also drive the search for solutions to the delay problem as airlines lose revenue and passengers lose time. Last year 450,000 flights were delayed 15 minutes or more beyond the delays already built in to airline schedules. These delays are very costly to the airlines, both in terms of customer satisfaction costs and also in terms of the ripple effects throughout their schedule. When a flight into an airline hub is delayed the many passengers who have missed their connections must be accommodated with hotels, meals or transportation with other airlines. Added to that are the extra labor and airport facility costs. But it doesn't stop there; it is likely that the delayed flight was scheduled to continue on to some other location, and so the delay spreads. Delay costs for an early morning flight are often multiplied by four to account for the effect that will be felt throughout the day. Furthermore, economics dictate budgets which limit the range of solutions that can be implemented. When considering potential solutions to the delay problem, one must also consider whose budget the funds for the project will come from, and who will reap the benefits of the improvement. Airport improvements often require substantial capital investments that the airport authorities translate into increased landing fees for the airlines, who, if the market will withstand it, proceed to pass those costs on to the travelers. However, the bulk of capacity improvement technologies are being researched by government organizations such as NASA and the FAA (Federal Aviation Administration) for the sake of economic well-being and voter satisfaction. Indeed, public pressures are a very important factor to contend with.

The environment in terms of governmental and community pressures can influence airport capacity greatly. Community noise has become an increasing concern in the neighborhoods surrounding major airports to the point that arrival paths are being diverted to avoid populated areas, with the subsequent efficiency loss [Ref. 16]. On the other hand, the community needs for air travel can prompt government action, such as the recent approval of the AIR21 bill, that provides funds for airport improvement and the inclusion of runway independent aircraft in ATC procedures [Ref. 17, 18, 19]. Indeed, it has been the widespread dissatisfaction of the traveling public that has encouraged recent Congress probes of the delay problem and has stayed potential aviation budget cuts [Ref. 12]. As it stands today the FAA budget intends to cover the improvement of ATC equipment so as to alleviate the congestion of our airspace. This effort is to include research into alternate approaches such as Free Flight. The FAA will also provide grants for airport expansion and improvement, not only for capacity enhancements, but also to mitigate noise and increase safety [Ref. 20]

Safety can be viewed as a capacity constraint. It is safety that dictates aircraft separation on arrival, a major traffic volume limitation. It is also safety that prescribes bad weather procedures further straining system capacity. New technologies designed to relieve congestion will not be implemented unless they demonstrate a good safety record. Even more, safety must be improved if capacity is to increase; today's accident rates would result in a major accident occurring every three days at 2005 demand levels [Ref. 21]. Indeed, the goal of the FAA is to reduce today's fatal accident rates by 80% with a good portion of their budget dedicated to that purpose [Ref. 20]. Thus, an assessment of capacity and throughput technologies without due consideration to safety issues would be incomplete.

A thorough analysis of the NAS is further complicated by the variability it is subject to. The economic environment can fluctuate widely with periods of economic boom alternating with phases of recession, influencing GDP values accordingly, and affecting not only the demand for air travel, but also the revenue yield that can be obtained without loss of market-share. Furthermore, many of the day-to-day costs in the NAS are driven by factors beyond an analyst's control, such as OPEC fuel production levels or labor union agreements. Government policies, often driven by electoral polls, can also have a great influence on the funds available for ATC improvements. These factors influence both demand and capacity, but capacity is even more deeply affected by weather, which judging by the forecasts is rather unpredictable. The inherent uncertainty in the system alone would justify a statistical approach to the capacity problem, yielding results in terms of probabilities, rather than deterministic values. But an additional degree of imprecision is also introduced by the fidelity of the modeling codes used, as accuracy is traded off with model efficiency and technologies push the system beyond existing databases. Furthermore, the forecasted impacts of technologies which are still in the development stage are often not entirely reliable, and a probability associated to the potential improvement is often preferred to a deterministic impact prediction. This uncertainty in the potential effect of a technology also applies to its negative impacts, which are often overlooked or not researched as thoroughly. The complexity and uncertainty inherent to the NAS, coupled with the varied nature of the capacity improving technologies that have been proposed or are under investigation, clearly establishes a need for a statistically based method to assess those technologies from an overall-system point of view.

Subtask 1: Capacity Model Analysis

The first step toward assessing capacity and throughput technologies is to attain an understanding of the factors that influence capacity in the terminal airspace. To accomplish this, a capacity code developed by the Logistics Management Institute was used within a Response Surface Methodology such as that described in Reference 4. This methodology uses statistically based sampling to reduce the number of cases required to ascertain the influence of factors, and their interactions, on a response of interest. In this case the response of interest is capacity under different weather conditions and the factors varied include approach separation, runway occupancy time and fleet mix among others.

Initially the Atlanta capacity model created as part of the Aviation System Analysis Capability was executed according to the variable ranges described in Table 12 and a suitable 2-level Design of Experiments (DoE) aimed at identifying those variables with the most influence on capacity. Unfortunately, upon investigation of the results obtained it became apparent that the Atlanta capacity code accessible online [Ref. 22] contained a small error since the Runway Occupancy Time (ROT) defined for departures was appearing as a significant factor in arrival capacity, in spite of the fact that the Atlanta airport generally operates two dedicated departure and two dedicated arrival runways.

				Allowable			For DOE			
	Variable	Units	Default	Min.	Max.	Comments	-1	+1	Name	Comments
	Number of Aircraft Classes	--	4	3	27	*FAA Defined*	*Default*			*FAA Defined*
For Each Class	Class Name	--	--	--	--	*10 chars or less*	*Default*			
	Heavy Class Flag	--	--	0	1	*FAA Defined*	*Default*			*FAA Defined*
	Approach Speed	knots	--	100.0	300.0		0.9	1.1	KVAPP	*% change across all classes*
	Approach Speed σ	knots	5.00	0.0	60.0	*< Mean /5*	0.24	1.05	KVAPPSTD	*% change across all classes*
	IMC ROT	minutes	--	0.0	3.0		0.75	1.25	KIROT	*% change across all classes*
	IMC ROT σ	minutes	0.13	0.0	0.6	*< Mean /5*	0.8	1.1	KIROTSTD	*% change across all classes*
	VMC ROT	minutes	--	0.0	3.0		0.95	1.05	KVROT	*% change across all classes*
	VMC ROT σ	minutes	0.13	0.0	0.6	*< Mean /5*	0.9	1.2	KVROTSTD	*% change across all classes*
	Departure ROT	minutes	--	0.0	2.0		0.95	1.05	KDROT	*% change across all classes*
	Departure ROT σ	minutes	0.10	0.0	0.4	*< Mean /5*	0.95	1.05	KDROTSTD	*% change across all classes*
	Departure Speed	knots	--	0.0	400.0		0.9	1.1	KVDEP	*% change across all classes*
	Departure Speed σ	knots	5.00	0.0	80.0	*< Mean /5*	0.24	1.05	KVDEPSTD	*% change across all classes*
	Percent of Total Traffic	--	--	0.0	1.0		11 79 6 4	34 37 9 20	MIX1 (small) MIX2 (Large) MIX3 (B757) MIX4 (Heavy)	*make mix 2 calculated*
	Positional Uncertainty	nmi	0.25	0.0	--	*Non-negative*	0.2	0.3	UNKPOS	*this value same for all classes*

Table 12: Variable Ranges for Airport Capacity Model

Upon consultation with LMI, a revised capacity code, albeit for a single runway simplified case, was obtained and a new design of experiments using the previously defined variable ranges was executed. In this case, each of the capacity points generally used to define a Pareto frontier were tracked: Max. Arrivals (A), Max. Departures (D), Balanced Arrival and Departures (E), and Free Departures between arrivals (F). The variables listed in Table 13 were found to be the most influential for each category. As expected, departure related variables such as a departure path and speed dominated the D response, whereas approach separation and ROT appeared as most influential for the A response. Free-departures and Equal-use capacities showed a mix of the variables identified for A and D, and the fleet mix related variables had a pervading influence on all responses tracked.

Table 13: Most Influential Capacity Variables

VMC1				VMC2			
D	E	A	F	D	E	A	F
kvdep	krot	kvapp	krot	kvdep	krot	kvapp	krot
deppth	kvapp	apppth	kvapp	deppth	kvapp	apppth	kvapp
mix1	apppth	krot	apppth	mix1	apppth	krot	apppth
mix4	winds	winds	winds	mix4	winds	winds	winds
kvdeps	kvapps	mix4	ksep22	kvdeps	mix4	mix4	ksep22
mix3	kdeprot	kvapps	mix1	mix3	ksep12	kvapps	mix1
	mix4	ksep12	kdeprot		kvapps	ksep12	krots
	unkpos	ksep22	mix4		unkpos	ksep22	kdeprot
		unkpos	krots		kdeprot	mix1	mix4
IMC1				**IMC2**			
D	E	A	F	D	E	A	F
kvdep	krot	kvapp	krot	kvdep	krot	kvapp	krot
deppth	kvapp	apppth	kvapp	deppth	kvapp	apppth	apppth
mix1	apppth	winds	ksep22	mix1	apppth	krot	kvapp
mix4	winds	ksep22	apppth	mix4	winds	mix4	winds
kvdeps	kcomdly	mix4	kcomdly	kvdeps	kcomdly	ksep22	kcomdly
kcomdly	kvapps	ksep12	winds	kcomdly	kvapps	ksep12	mix1
mix3	kdeprot	krot	mix1	mix3	kdeprot	kvapps	ksep24
	mix4	kvapps	mix4		mix4	ksep24	
	unkpos	unkpos			unkpos	mix1	

The variables identified as most influential were then used to create a Response Surface Equation (RSE) that approximated the behavior of the code itself. A quadratic response surface equation can be created from a statistical analysis of data gathered in the execution of a three-level DoE with the ranges previously defined and a center point calculated for each variable. This RSE can then be used within a dynamic environment called a prediction profile to quickly assess the effect that changing one of the variables of interest would have on any of the responses tracked. A sample of one such prediction profile can be found in Figure 28.

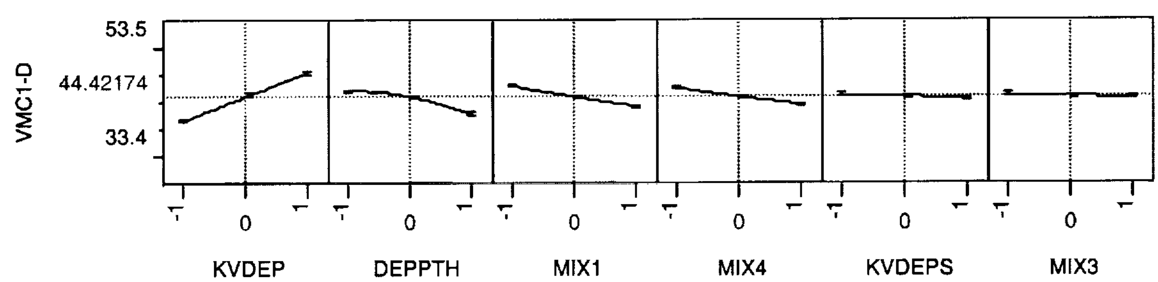


Figure 28: Prediction Profile for Max. Departures in VMC1 Weather conditions

The fit for the departure curves was excellent, since departure capacity is governed only by the time required to take off and clear the runway. For approaches and mixed-use runways the fit of the model was good, but validation tests indicate that the RSE generated is only valid when one constraint dominates. Approach capacity is governed by two main constraints Miles-in-Trail (MIT) and ROT. RSE's are continuous, therefore they cannot capture the discontinuity in capacity behavior caused by a sudden change in dominant constraints, therefore in the region where one constraint gives way to the other, the RSE is not as accurate an approximation as would be desired. A possible way to get around this limitation of RSE's is to track the capacity dictated by MIT and ROT separately, rather than letting the code select the lowest of the two for its output. However, this would require additional modification of the LMI code, and the purpose of this task, which was to identify the main factors affecting airport capacity, has already been accomplished. If this RSE were necessary for integration into a larger environment further exploration of the constraints would be necessary, but the execution speed of the LMI capacity code is such that the full code can be used in the NAS simulation environment without need for an approximate RSE.

Subtask 2: Modeling the National Airspace System

The need for a comprehensive NAS model that places aircraft within airline fleets, and those airlines within a competitive environment, under airport and ATC restrictions, in order to assess capacity and throughput technologies has been established. It has been further determined that such a model must also include economic, safety and environmental impact assessments. And the model must be versatile enough to accept a statistical treatment of the variability existing within the NAS. However, in order to create such a model, a through understanding of the NAS and its components is necessary.

The National Airspace System

The United States contains over 18,000 airports, 3,304 of which are considered part of the national system. More than 450 of these are considered primary airports rating an FAA control tower to direct traffic during landing and takeoff. Airports provide a gateway for air carriers to serve their customers, while ATC provides a framework for the safe flight of their fleets. Thus, when considering problems related to the NAS, one must consider what air travel demand needs to be served, what aircraft will be chosen to serve that demand, how the airline will operate the aircraft, and what infrastructure will be necessary for a safe and efficient flight environment.

Passenger Demand

Looking up at the night skies over any major city and observing the many lights of aircraft flying overhead, one cannot doubt that a demand for air transportation exists. But the driving forces behind that demand, and the factors that make a passenger or a cargo forwarder choose a particular carrier at a particular time from a particular airport have been the subject of extensive research.

Air travel demand and economic prosperity are closely tied. GDP forecasts are often used to determine future demand for air travel. At times GDP data is combined with other economic indicators such as unemployment or income per capita to determine the availability of expendable income in a particular location. This is done based on the assumption that travel, and specially air travel, is considered a luxury. As such, air travel traditionally included many services not directly related to the transportation aspect, and catered to a limited demographic group. However, with the advent of deregulation and fares that were no longer determined by costs, but rather by competition, fares dropped and airlines were forced to reconsider who their customers were.

Today's airline demand studies often require detailed demographic data considering the age and gender of their customer along with factors such as the purpose of the journey [Ref. 23]. This enables airlines to tailor their product to meet a wide range of customer demands, from the business traveler that seeks comfortable and timely service, to the student traveling for spring break that is willing to fly stand-by if that will lower the ticket cost.

Passenger demand is indeed very varied in nature. The minimum requirements could be efficient, safe service at a reasonable price, but what is considered a reasonable price or efficient service is not set in stone. Thus, the business traveler who puts emphasis on comfort and convenience would be willing to pay a higher price, but demands more services, for the same seat that an individual on vacation would rather pay less and do without the niceties of meals and in-flight entertainment. And an airline must be able to serve both to maintain profitability. While the business travelers make up only 10% of the total number of passengers, they account for about 40% of all the trips, as well as a large portion of the overall passenger revenues. However, an airline cannot cater only to this type of passenger since it must meet a minimum load factor (% of seats filled) to break even. Thus, 90% of all tickets sold in the United Stated are deeply discounted in order to undercut the competition, and fill one more seat, which might make the difference between earning a profit or recording a loss for that flight [Ref. 24].

Airline Characterization

Airlines provide a service for their customers transporting them and their belongings from one point to another for an agreed price [Ref. 24]. This service orientation is what makes the airline business so susceptible to variation in customer demand. Diverse customers and the perishability of the airline product, a seat in a particular itinerary at a particular time, dictate the ever-changing prices and fierce competition found in today's deregulated market.

The competitiveness of the airline market is further complicated by minimal product differentiation and soft brand loyalty. Airlines tend to fly similar routes at similar times with similar equipment and service and often matching prices. Frequent flyer programs have been relatively successful in introducing a type of brand loyalty, but one that is easily put aside for a better price or a more convenient schedule. This is why revenue management and scheduling have become such important factors in airline operations [Ref. 25].

Revenue management allows the airline to price seats, even within the same class, differently depending on time of purchase, competition, season or day of the week. This allows the airline to capture a larger share of the market as shown in Figure 29. Yield management has also given rise to the frequent practice of overbooking to ensure as many seats as possible in any given flight are filled in spite of last minute cancellations or no-shows. These practices are often distasteful to the customer, but they have allowed airlines to increase their average load factors, thereby increasing the potential for profitability and reducing losses due to unused inventory.

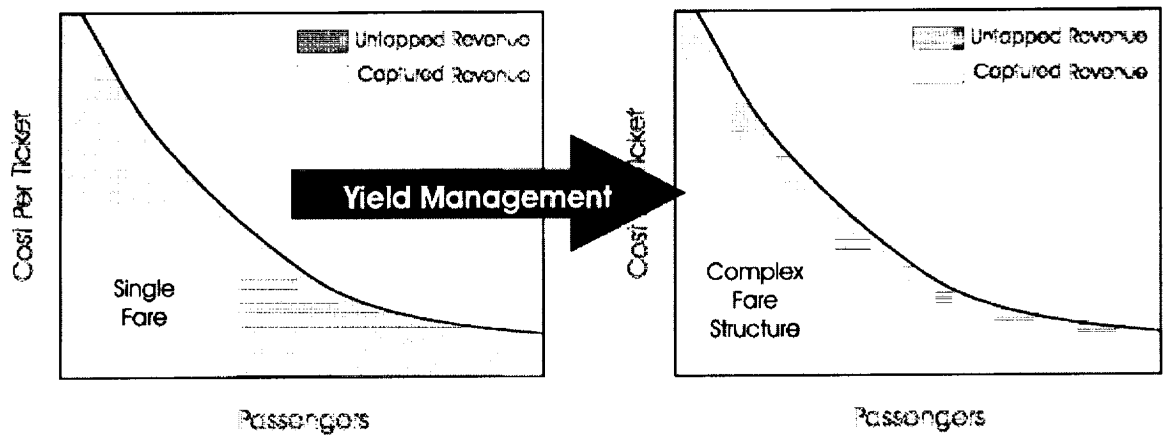


Figure 29: The Effect of Yield Management

Airline scheduling practices can also greatly influence their appeal to the customer and therefore their revenue stream. Business customers will be more attracted to an airline with multiple flights in their itinerary, closely matching their desired departure time, and offering them the flexibility of a later or earlier flight if their plans change. Furthermore, frequent flights will provide connection opportunities generating additional demand that would otherwise not have existed for that city pair. However, the airline desire to increase flight frequencies is countered by the cost of increasing carrier capacity and the complexity of combining crew schedules, aircraft availability and maintenance needs.

New aircraft cost millions of dollars making the airline industry very capital intensive. These high acquisition costs are coupled with long order times that have wreaked havoc on airline economics. Airlines have often ordered new aircraft at times of economic growth when the demand would support increased capacity, but have received them when the economy was slowing down and demand required downsizing not expansion. This has prompted the airlines to place a lot of emphasis on fleet selection weighing the costs of a new aircraft, as compared to the maintenance requirements and higher fuel consumption of older, but cheaper or already owned aircraft. In some cases airlines have also chosen newer aircraft, or newer engines, for their compliance with new noise and emissions regulations. Such a decision capitalizes on the additional fuel and maintenance savings of newer equipment, rather than using the less expensive, but shorter term, solution of a retrofit. Oftentimes, a new mission with a longer range or faster speeds can be behind the purchase of new equipment. Aircraft with longer range capabilities open the possibility of serving longer non-stop routes. Faster aircraft, such as supersonic transports or business jets, can increase utilization, thus affecting the number of trips per day an aircraft can cover, as well as addressing the issue of passenger value of time. Aircraft size and seating configurations are also factors to consider in fleet planning. Larger aircraft can accommodate more passengers per operation, thus increasing capacity without a negative effect on airspace congestion or an increase in delays. However, the extra seats must be filled to cover the higher cost per operation. Denser seating configurations can also increase the revenue potential per operation without increasing operating costs, however, passengers tend to object to cramped flying conditions. All options to serve additional demand have one common danger, the potential oversupply of seats. While additional seats present a revenue opportunity, the need to fill those seats to cover costs may lead the airline to lower ticket prices resulting in little overall profit.

Airlines, like any business, seek to maximize profit, but they are often caught between the finicky consumer that dictates market share and revenue, and costs beyond their direct control. This results in net profit margins in the order of 1 to 2% compared to a 5% average for the US industry [Ref. 24]. Southwest Airlines has found a recipe to solve this problem by offering a simplified product, point-to-point service with fast turn-around times, and dramatically reduced overhead costs. Unfortunately, traditional airlines, fruit of a previously regulated market, have a history of very strong unions that capitalize on the intensive training required for pilots and maintenance personnel. The impact of labor costs is amplified because air transportation, as a service industry, is heavily dependant on the availability of qualified labor in almost all aspects of its operations. Thus, labor typically accounts for 35% of an airline's operating expenses, and threats of a strike often force airline operators to consent to union demands, whether the revenue structure can support them or not [Ref. 24 and 26]. Labor costs can be specially burdensome when dealing with delays because aircraft crews are limited on the number of continued flight hours they can operate, and additional ground personnel is required to reroute and mollify vexed passengers.

Fuel and maintenance costs are the next highest for an airline, and are the most influenced by the type of aircraft flown. Airlines tend to prefer aircraft of the same family or at least of the same make to maximize part commonality and minimize mechanic training required. Reliability and maintenance schedules are related to aircraft selection and the age of the fleet. Fuel consumption also depends on engine and aircraft selection, but it is heavily impacted by delays due to the additional fuel burnt during airborne holding at inefficient cruise altitudes.

Another cost that has become increasingly significant in airline operations has been landing fees and terminal space rental. Airports have been forced to expand and remodel to meet increased demand with the subsequent need for higher revenues, and therefore, higher airport use charges. While these costs account for a relatively small percentage of the airline costs, 5% compared to 16% for promotions and sales, they have risen steadily increasing by nearly 70% since 1992 [Ref. 24].

Airport Operations

Airports provide a vital link between the airline and its customer, and will continue to be an essential part of the air transportation puzzle until concepts such as personal air vehicles become more than mere wishful thinking. Airports also represent a significant source of income and a driving force behind economic growth in the communities surrounding them. Airports significantly contribute to pollution and noise in the community as well. As such, they are often driven by public interest and politics, rather than by their customer, the airlines. Thus, commercial airports in the United States are still publicly owned, and therefore eligible for government grants and tax exempt financing. However, with the recent emphasis on concessions and efficient management, many airports have become self-sustaining in terms of day-to-day operations, and only require outside investment to finance airport improvement projects.

Airport improvement projects are financed in a number of ways, all of them in some way resulting from the air transportation business itself. Airport Improvement Grants are awarded by the FAA for specific airport projects meant to improve safety, reduce noise impact on the community or increase capacity. These grants are funded by the Aviation Trust fund that collects taxes on every ticket issued in the Unites States, as well as on aircraft fuel. General Airport Revenue Bonds are also often used as a means to raise funds. These bonds are backed by airport revenue which is generated by landing fees, concessions, parking and rental fees, and recently also by PFC (Passenger Facility Charges). PFC's are approved by the FAA for a specific capital improvement project, but are charged by the airline on a per ticket/per segment basis, and transferred directly to the airport. Airline fees, which include landing fees, rental spaces and, in some cases, refueling and gate parking fees, account for nearly $^2/_3$ of typical airport revenues, while rental fees and, in some cases, a percent of gross receipts from concessions, parking, etc... account for the rest [Ref. 27].

Landing fees are typically calculated based on landing weight, but there are several cost calculation procedures for overall air carrier fees. These computation methods are generally divided into residual and compensatory. In compensatory concepts the airport assumes the risk and benefit of concessions, and airlines are charged based solely on their use. This type of scheme encourages entrepreneurship in airport management in order to generate enough revenue from other sources to cover costs not offset by airline fees. Compensatory methods can be further divided into standard and commercial compensatory. Standard arrangements result in both terminal rental and landing fees for the airline based on their use. The commercial compensatory approach distributes all costs among all users through rental fees only. Residual rate making methods are generally found at airports with less mature revenue streams since they allow the airport to share operating risk with the air carriers. Under these strategies airlines supplement other airport sources of revenue to safeguard airport profitability. Thus, well managed concessions result in lower airline fees, but the airline must assume any costs not offset by other revenue sources. This shared risk gives the airlines more leverage on capital investment decisions, but may harm airline competitiveness, specially on connecting flights, if revenue from other sources falls increasing the airline burden. Residual fee calculation methods can be further divided into cost center vs. airport system residual. This classification is based on whether all airport system expenses are tallied against system-wide revenues, or revenues at each cost center (terminal, airfield, etc...) are compared to expenditures at that center *only* in order to calculate the remaining costs that must be covered by the airline [Ref. 28].

Air carrier fees are the most significant airport influence on airline profitability, however, there are other airport characteristics that can also impact airline operations. Inefficient runway and taxiway layouts can significantly increase taxi times and fuel burnt. These factors can be further increased by congestion and lack of peak capacity at the airport or its surrounding airspace. Nighttime capacity at airports is often limited by community concerns and some airports have curfews that eliminate night traffic altogether. Airlines that operate a minimum cost point-to point service, like Southwest, rely on very short turn-around times to maintain profitability, and can be severely affected by inefficient ground handling. Hub-and-spoke airlines are also affected by inefficient ground handling and terminal layouts, especially in terms of customer convenience and quality of service. Thus, airports are not all alike, and while they generally have a *de facto* monopoly as far as local air traffic is concerned, there is competition for connecting passengers, and therefore, for the establishment of airline hubs where expansion potential becomes an important factor [Ref. 29].

Air Traffic Control

Air Traffic Control facilities are another factor that can differentiate airports from one another. TRACON (Terminal Radar Approach CONtrol) centers, for example, control aircraft during the climb and descent phases, but certain centers control several major airports as in the New York metro area, whereas others are concerned mainly with one airport, as is the case at the Atlanta center. Thus, there are 236 TRACON centers vs. 450 major airports. Beyond the vicinity of major airports, 22 en-route centers guide traffic through the airspace sectors during the cruise segment of flight [Ref. 24 and 30]

Given the current infrastructure a typical flight begins with the filing of a flight plan to inform ATC of the intended flight path, the amount of fuel on board, and alternate airports reachable in case of an emergency. After obtaining approval for the plan, as filed or with pertinent modifications, the aircraft pushes back from the gate when it is given permission to do so by ground control. Ground control also guides the aircraft through the taxiways to the runway of departure coordinating with other ground traffic. Control is then handed over to the tower which supervises the crew through the entire takeoff procedure and dictates the initial heading to follow thereafter. At that point the TRACON center in charge of that area handles the aircraft until it reaches cruise altitude and speed where it is handed off to the controllers at the appropriate en-route center. The sequence is reversed as the aircraft approaches its destination. Thus, the flight was under constant supervision for the entire mission, with ATC assuring proper separation with other traffic. When one considers the number of aircraft in the air following this procedure, as well as a number of other aircraft flying under VFR (Visual Flight Rules) and maintaining their own separation in good weather, but still tracked through the airport airspace, it is no wonder that ATC is approaching saturation [Ref. 24].

The capacity of the existing system can be improved by addressing system inefficiencies and limitations, thereby facilitating maximum use of runways and airspace sectors. Currently a number of safety buffers both laterally and longitudinally are built into every runway operation and these buffers are further expanded in poor weather conditions. While safety is the paramount objective of ATC, these buffers are often far larger than they need to be in order to avoid wake vorticity or aircraft collisions. This is due to inaccuracies in positioning measurements, communication delays and uncertainties in vortex propagation. While addressing these inefficiencies will increase the number of operations a given runway can handle, this is not the only source of congestion. Today's Air Traffic Control system depends on the ability of its controllers to sequence, direct and track traffic. In heavily congested sectors controller workload becomes a significant constraint and traffic must be diverted or rerouted to avoid compromising safety. The issue of controller productivity is addressed by technologies which aim to provide decision support tools for the controller, as well as allowing pilots to maintain their own separation through airborne hazard avoidance systems. Some of the more innovative approaches to ATC capacity issues consider the use of GPS (Global Positioning System) and satellite based systems to locate and guide aircraft through all phases of flight. Free flight environments have also been suggested where collision avoidance is the responsibility of the pilots, rather than a centralized control entity, thus eliminating the ATC bottleneck, and alleviating congestion.

Regardless of the technology options considered, ATC, airport, or aircraft related; a means to translate this qualitative discussion of the NAS components into a quantitative NAS model is vital to the validity of a technology assessment.

Survey of Existing Models

The implementation of a methodology to assess capacity technologies hinges on the availability of a suitable model of the system to be analyzed. Such a model would have to capture all aspects of the NAS relevant to technology implementation, which include not only each of the components (aircraft, airline, airport and ATC), but also the additional pressures mentioned earlier (economics, environment and safety), with special emphasis on the interactions between all of these ingredients. Since certain portions of the NAS have been previously investigated, the first step towards creating a comprehensive model is to obtain those component models that are currently available and, for those areas that have seen multiple modeling efforts, to select the models best suited to the task of technology evaluation.

Aircraft

For the purposes of a NAS model, aircraft are generally characterized in very little detail. The factors generally considered are approach and departure speed, cruise altitude and speed, ROT's, number of passengers and fuel consumption data. However, a number of the technologies to be implemented require additional equipment to be installed in the aircraft affecting its weight and cost. Furthermore, takeoff and landing profiles are often quite complex requiring additional information about climb rates, and new aircraft concepts may find their justification in the effects they have on system congestion. Therefore, a more complete representation of the aircraft is desired within this NAS modeling effort.

FLOPS (FLight OPtimization System) is the model of choice for the definition of fixed wing aircraft. This synthesis and sizing code originally developed by NASA has been extensively modified at the Aerospace Systems Design Laboratory (ASDL) to expand its capabilities. Currently FLOPS is capable of scaling aircraft configurations, in terms of geometry, weights, and propulsion requirements, to meet a specified mission. This capability is necessary to model aircraft not currently in existence such as the A380.

Beyond this basic sizing capability FLOPS also includes a detailed takeoff and landing module which includes all current FAA safety requirements. Furthermore, this model is also linked to a noise module capable of calculating the noise footprint area of a given aircraft, and it can generate the information necessary to estimate CO_2 and NO_X emissions if the engine deck used in the analysis contains the emissions information for the flight conditions. This information is invaluable when considering the introduction of new aircraft to airports surrounded by residential areas.

The economic impact of changes on the aircraft is accounted for through the link of FLOPS with ALCCA (Aircraft Life Cycle Cost Analysis). FLOPS has also been used by ASDL in previous technology assessment projects, and contains a number of technology dials referred to as Kappa Factors. These Kappa factors represent a percent increase or decrease in a particular performance measure. All of these capabilities coupled with the readily available expertise with the FLOPS code make it a candidate to model the aircraft portion of the NAS.

With the introduction of innovative transportation concepts such as SATS and personal air vehicles, other synthesis and sizing tools may be needed capable of modeling small aircraft, or even rotorcraft. GTPDP (Georgia Tech Preliminary Design and Performance), also available at ASDL, is another synthesis and sizing tool which can be used for smaller aircraft. VASCOMP (V/STOL Aircraft Sizing COMputer Program) is used to size rotorcraft, including innovative concepts such as tiltrotors. These codes may be included in a NAS modeling and simulation environment. However, a means to capture the infrastructure related to implementation of such cutting edge programs, as well as an understanding of their style of operations, since they will fall outside of the traditional airline operations model would also be necessary.

Airline

Airlines have multiple options when building their schedules. They can choose when and how to serve demand, however, their choices may affect their market share and their profit margin, ultimately affecting whether there is a demand to be served. The MITRE Corporation has developed a model of airline behavior called IMPACT (Intelligent agent-based Model for Policy Analysis of Collaborative TFM). In this code airlines are modeled as agents driven by market-share or profit depending on the airline personality chosen. These agents are then placed within a system with other agents representing ATC. A disruption such as a bad weather day is introduced in the system and the agents are allowed to react to the event and to each other's decisions according to their predefined personalities. Unfortunately, the reaction of the ATC seems to be limited to the activation of the Ground Delay Program which does not allow aircraft to depart if their destination airport is congested to avoid airborne delays [Ref. 31]. The MITRE Corporation has also developed a model named ACSEM (Air Carrier Service Evolution Model) that models airline behavior in more detail. Within this model economic conditions, airport capacities, demand and costs are translated into a flight schedule, RPM, load factors, and passengers serviced along with average delays. Within this model transfer flights can be used to serve two cities not directly connected and passengers can have either a time or a cost priority. Passenger sets with similar destination and time preferences are grouped together and matched to potential flights which are purchased based on a balance between the closeness with which they match customer desires, and the cost per ticket. The airline agents within the model have the ability to make changes to their strategies, such as varying fares and schedules, the size of the aircraft flown or the number of aircraft owned. As the airlines make changes, the flights in the schedule are flown, delays are calculated and translated into costs, and these costs are then balanced with the profits made. As long as the profit (or the market share) increases, airlines will continue to make the same type of decisions [Ref. 32].

Major airlines also have their own tools to determine schedules and fares, these tools are based specifically on the airports they operate out of and the type of fleet and strategy they operate under. Unfortunately, these tools are proprietary in nature, and very airline specific making the modeling of airline behavior and motivation beyond drives such as those captured in the MITRE model very difficult indeed.

Airport

A number of airport models exist at different levels of detail, ranging form real-time simulations, to quasi-analytical models, see Table 14. For the purpose of safety assessments the real time models are more appropriate, especially when trying to account for the influence of human factors. However, such tools make the simulation of the entire airspace cumbersome, and would not match the level of detail with which other portions of the NAS are being modeled. Therefore, macroscopic models are preferable in this case, especially those that are analytical in nature and are denoted in Table 14 by an asterisk.

	Scope of Model			
Level of Detail (type of study)	**Aprons and taxiways**	**Runways and final approaches**	**Terminal area airspace**	**En route airspace**
Macroscopic (Policy analysis, cost-benefit studies)		LMI Runway Capacity Model* FAA Airfield Capacity Model* DELAYS* AND*		ASIM SDAT* DORATASK
Mesoscopic (Traffic flow analysis, cost-benefit analysis)		NASPAC TMAC FLOWSIM ASCENT		
Microscopic (Detailed analysis and preliminary design)	TAAM SIMMOD			
Same	The Airport Machine HERMES		RAMS	

Table 14: Summary of Capacity and Delay models [Ref. 33]

The FAA airfield capacity model computes capacity for 14 common runway configurations. However, the situation at each airport is as different as their prevailing winds and surrounding landscape, both of which can affect approach paths and therefore capacity. The LMI models, which are similar in structure, but differ from airport to airport in terms of noise restrictions and runway combinations, is thus appropriate, especially when combined with the queuing engine of the LMI delay model. The LMI delay models are also airport specific, selecting the typical configuration for each airport given the input weather conditions. DELAYS is also based on a queuing engine that treats aircraft as customers to a system with capacity dictated by the airports runway layout. Unfortunately, DELAYS does not consider any differences in the aircraft types using the airport and therefore could not accommodate new aircraft-related technology concepts.

The models mentioned so far calculate the delays generated at particular airports, but the system-wide capacity problems are also important since many of the technologies proposed could affect the entire system, and it is this type of generalized effect that raises public interest and government funding. AND is an extension to DELAYS which extends this model to a network of airports, however, it has the same limitations as DELAYS. DPAT developed by the MITRE corporation models the NAS as a sequence of resources that an aircraft uses to move from its origin to its destination. Thus, it models capacity throughout the system, congestion arises as resources become unavailable, and delays when aircraft exceed the resources assigned along their route. It also has the ability to capture random delays which can be used to simulate weather events. Unfortunately, this model relies on detailed data regarding city pairs and the routes used to reach them. LMINet includes a net of 64 airports and the en-route sectors between them and has the ability to calculate cumulative delays accounting for the routes generally flown in current airline schedules. However, this net does not account for the interdependency of flights, and the ripple effects a delay early in the morning can have on that day's schedule [Ref. 34]. Such an effect could be accounted for through a multiplier that considered the time of day and length of a particular delay instance, and multiplied it to account for its downstream effects.

Air Traffic Control

A number of the technologies being proposed for the improvement of airport capacity are related to improvements of the Air Traffic Control system in terms of easing controller workloads, improving communication between pilots and the tower, or allowing for the reduction of inter-arrival separations. An accurate estimate of the impacts these technologies signify is necessary, as they will influence both capacity and airline behavior. IMPACT, previously mentioned, is capable of modeling the interaction between airlines and ATC. However, only the Ground Hold Policy can currently be implemented within this model. It would be of interest to expand the agent definition for ATC to encompass other types of policies that may be desirable for the alleviation of congestion in the NAS. Some of the mesoscopic models mentioned in the previous section: NASPAC, FLOWSIM, TMAC and ASCENT can be applied to Traffic Flow management problems. As could the microscopic models mentioned, TAMM and SIMMOD. Unfortunately, these models are very detailed requiring extensive inputs and complex set ups. At this point, at a simplified level, the only capability that exists is to model the consequences of those policies rather than the actual interactions that take place in their implementation.

Economics

Economics are the driver behind the capacity problem as well as behind the congestion alleviation projects. Economics drive demand for air traffic. When trade increases the need for air transportation follows. When passengers have higher incomes they will often choose the convenience of flying over other modes of transportation. But this is only true as long as air transportation is affordable and convenient as delays readily translate into cost. Just like economic welfare drives demand for air transportation, a sharp decrease in air travel demand would result in fewer aircraft and associated services being required. This could be severe enough to have a negative impact on the economy, thus closing the supply and demand loop. The ACIM (Air Carrier Investment Model), developed by LMI, and included in their ASAC (Aviation Systems Analysis Capability) suite, aims to capture this two way relationship between demand and economics and is also capable of translating demand into the number of aircraft required to serve it, while accounting for retirement of aircraft currently within the fleet. The airline operating margins are calculated as the sum of a series of cost drivers multiplied by a productivity factor.

The econometric based demand calculated by ACIM could be useful, however, ALCCA, originally developed at NASA, and subsequently improved at ASDL, considers both aircraft and airline costs in more detail. Furthermore, it includes a number of features that make it well suited for this task. Specifically, the airline costs account for the indirect effects of delays and lack of aircraft availability through the revenue loss module added in-house. However, this revenue loss module is currently based on some basic assumptions about airline schedules and could benefit from actual estimates of delays [Ref. 35]

Unfortunately, these economic models do not capture a significant part of the implementation costs of some of the technologies under consideration. Namely they do not include costs incurred by airports and ATC during expansion and upgrade projects. Furthermore, the aircraft acquisition cost model may not be detailed enough to capture the actual cost of navigation aids and display technologies under consideration.

Environment

The analysis of government budgets and motivations is much too complex to include in this modeling effort. However, the tangible effects of government policies such as noise and emissions regulations could be modeled. The aircraft noise module within FLOPS can be used to assess whether new aircraft designs will meet the established regulations, and the noise module within ASAC, based on the FAA's INM (Integrated Noise Model), can then be used to calculate aggregate airport noise footprints and analyze how the community noise restrictions affect approach and departure paths. The effect of these paths on airport efficiency can be very significant and cannot be overlooked if an accurate estimate of system capacity and average delays is to be obtained.

FLOPS engine related data can also be used to estimate CO_2 emissions, and in some cases also NO_x generated. It would be of interest to track these in order to address community concerns with increased airport use.

Safety

The NASA approach to safety is based on a three-prong approach. The first step in the approach is the modeling and simulation of past accidents to identify their causes. Once the causes for accidents are understood an effort can be made to prevent those accidents using the same calibrated modeling and simulation environments. The third step in the NASA approach is accident mitigation and crashworthiness [Ref. 36]. This approach translates to that modeled by a number of safety assessment codes: trajectory generation, trajectory simulation, and conflict resolution. A number of conflict avoidance models along with a summary of their modeling capabilities is shown in Table 15.

Table 15: Summary of Conflict Resolution Models [Ref. 33]

Model	Trajectory Generation	Trajectory Simulation	Conflict Resolution	Multi-aircraft Capability
ARC2000	Input	3D	Rule-based	Pairwise
ASIM	Auto	Node	None	None
BDT	Input	3D	Algorithmic	Complex
FLOWSIM	Input	Node	Delay	None
NARSIM	Input	3D	Human	Human
RAMS	Auto	3D	Rule-based	Pairwise
SIMMOD	Input	Node	Delay	None
TAAM	Input	3D	Rule-based	Pairwise
TMAC	Input	3D	None	None

All of these models revolve around highly detailed descriptions of the aircraft trajectories as well as the dynamic behavior of the aircraft involved. This level of detail is difficult to capture at the NAS level.

Safety seems to be an elusive concept to model, with a particularly difficult balance in the detail captured vs. the complexity of the code. This is further complicated by the human error factor in most accidents, as most models that can include human behavior require in-depth detail, and real-time simulations. The most reasonable approach in this case may be to consider the various scenarios that can occur, attach a probability of occurrence to each possibility, and then estimate what the effects would be in each situation. For example, if one were to reduce separation between incoming aircraft, at the simplest level we could have a 'nothing happens' scenario, a 'recoverable vortex disturbance', and a 'fatal vortex disturbance'. But even this approach is as complex as the safety problem itself.

One of the biggest issues in safety modeling at the NAS level is the disparity in the level of detail required to identify technology effects, as compared to the high level metrics used to define safety goals: accident and incident rates. Even if the resources were available to run a detailed safety model relating to each technology to be considered, a means to relate those safety estimates back to the NAS level would be necessary. This disconnect is illustrated in Figure 30, and would require a detailed decomposition of the safety problem to a point that technology impacts can be directly estimated, as well as a means to roll those technological impacts up to the metrics that are often used for setting future safety goals.

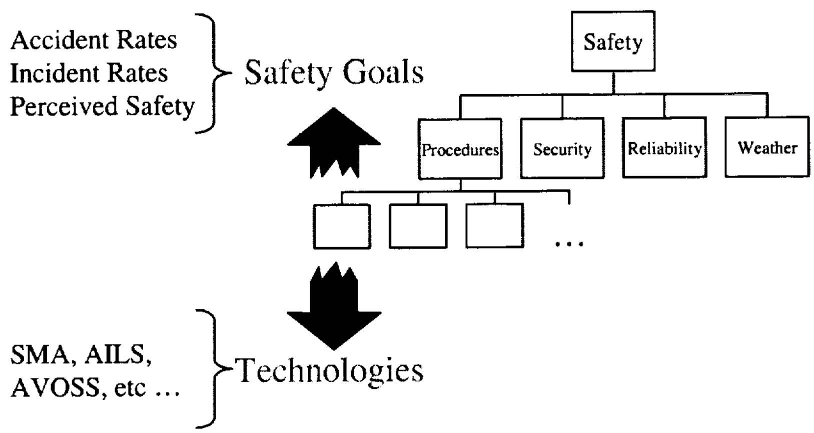


Figure 30: The Safety Disconnect

Integration

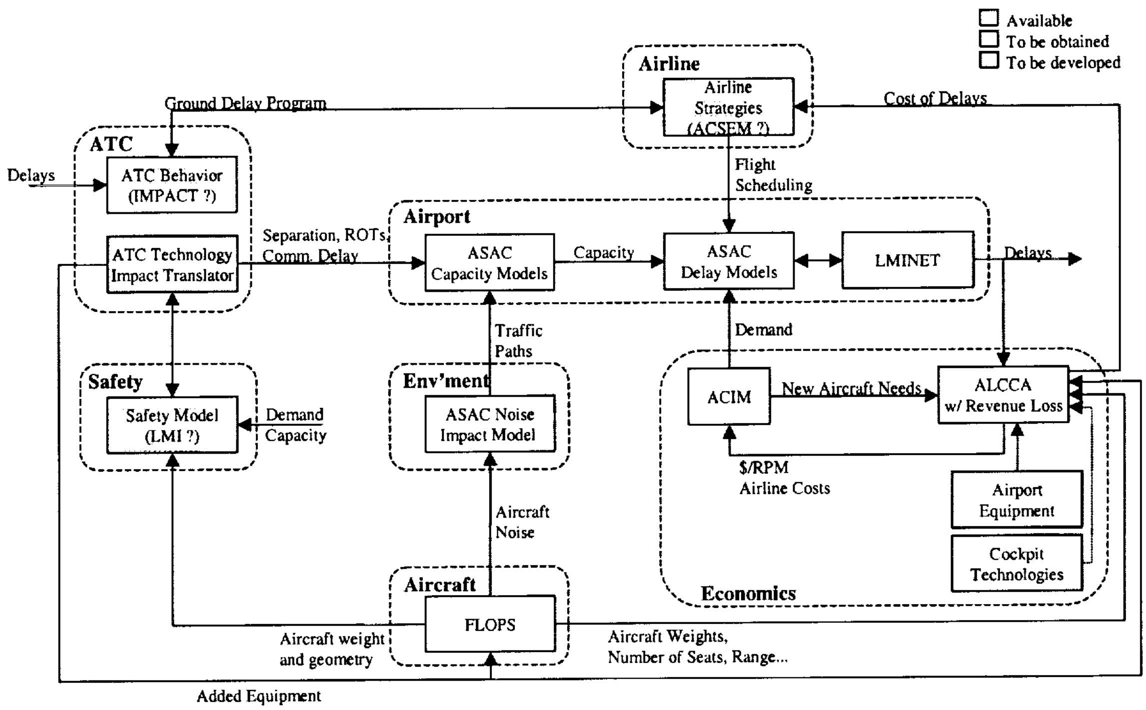
The intention of this task is to obtain an estimate of technological effects throughout the NAS, rather than in a particular research area. Therefore, it is the integration of the models chosen that becomes the central piece of the problem.

The NAS is a complex system whose components are intricately related to each other. For example, economics influence demand; excess demand and insufficient capacity lead to congestion that causes delays. Delays increase airline costs and fares which in turn also influence demand. Furthermore, a sharp drop in demand could cause a drop in employment within the air transportation sector influencing economics. Airlines represent the market for aircraft manufacturer's, therefore airline policies, which are in turn affected by ATC regulations, influence what type of aircraft are produced and may even influence the cost of the aircraft. Noise and emissions regulations can affect airport capacity, and may influence aircraft designs as well. Safety is affected by congestion, airline policies, ATC regulations, the types of aircraft flying and many other factors. These are just a few of the interactions present in the system. A number of methods may be chosen to actually implement the links discussed, and a balance must be attained between the amount of information captured, and the complexity of the system created. This is particularly important when the intent is to carry out a statistically based analysis since a large number of code executions may be required.

The codes to be linked in a NAS simulation environment are varied in nature, analytical codes in different programming languages, agent-based models, real-time models, knowledge based systems... the list goes on. They may also run on different platforms and machines. Thus, the selection of a linking method is not an easy one. Direct linking of codes is an option between codes of the same language. RSM can be used to represent complex codes provided internal constraints can be modeled individually. The linkage between codes of differing natures could also be implemented through an integration environment such as IMAGE (Integration Modeling and Analysis Graphical Environment) [Ref. 37], developed at ASDL, or a commercially available toolbox such as iSIGHT or Model Center. The Logistics Management Institute uses such an approach in their Executive Assistant, to link a number of their tools. Model Center is perhaps the most versatile option for its cross-platform capability. Wrappers developed for each code selected can be published through their Analysis Server and integrated within the Model Center® environment [Ref. 38].

Models Selected

The most suitable models for each component of the NAS were selected from the model survey. And a preliminary attempt to integrate their influences on each other resulted in the environment depicted in Figure 31. Unfortunately, it quickly became apparent that within the scope of this task such a modeling and simulation environment would not be feasible. A number of areas required development of new models, and differences in detail levels arose when attempting to combine safety and ATC models with the



macroscopic models available form the Logistics Management Institute.

Figure 31: Preliminary NAS Simulation Environment

Therefore, the problem was scoped down, focusing on the affordability aspect of technology implementation. This aspect was chosen for its importance both in motivation for the task, as well as for its significance in objectively modeling both benefits *and drawbacks* of technology programs. The scoped down NAS modeling environment is displayed in Figure 32. The models selected to complete this task are described in detail below.

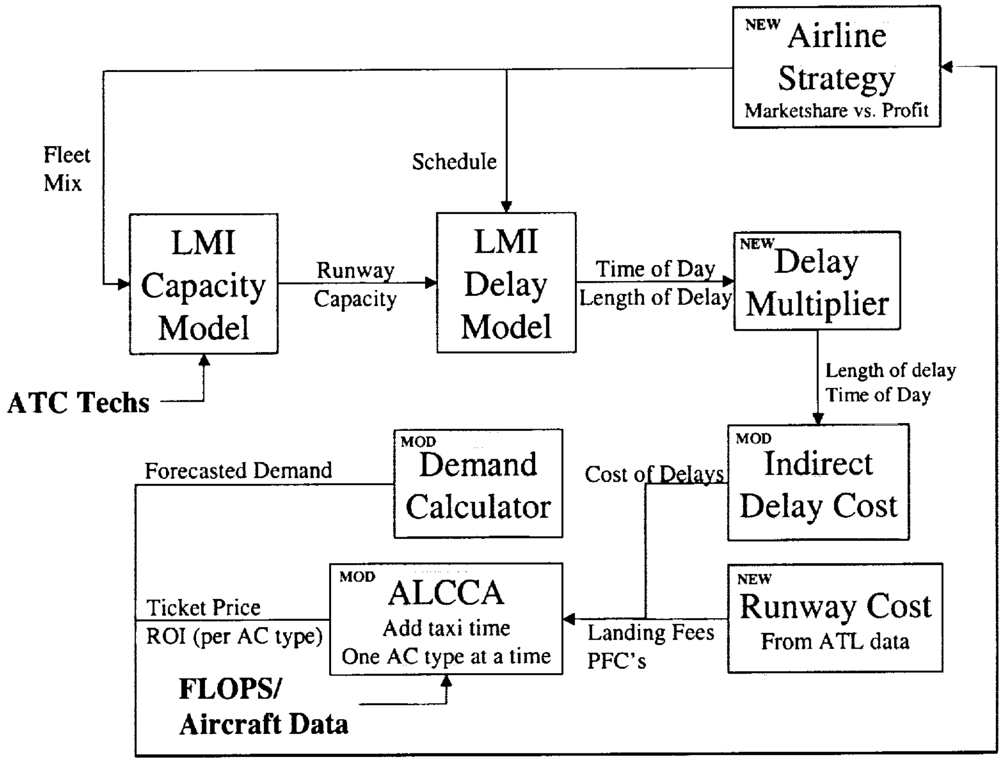


Figure 32: NAS Modeling - Affordability Focus

Aircraft Modeling

The NAS modeling was, in this first approach to the problem, limited to commercial fixed wing aircraft. Modeling of SATS and rotorcraft concepts would require further development in the areas of infrastructure costs and capacity estimates and were deemed beyond the scope of the task.

In order to capture aircraft related capacity improvement concepts FLOPS was included as part of this integrated environment. Some of the qualities that made FLOPS ideal for this modeling effort were already described previously. An additional advantage to this code is that sample files are available from previous studies. These sample files include inputs for a number of different aircraft including the entire range from 50 to 600 passengers. For example, the 600 passenger data was used as a case study for Task 3 in this contract.

FLOPS inputs are in text format and grouped under the namelist format. The main inputs required include a mission definition in terms of range, payload etc…, engine data which can allow the program to set its own engine parameters, or can take an input engine deck, and configuration data regarding wing type etc…

A FLOPS input file may also include ALCCA related outputs if that economic analysis option is selected.

Airport Capacity and Delay

The models available from the Logistic Management Institute for capacity and Delay were chosen for this study, specifically those relating to the Atlanta Hartsfield International Airport (ATL). As discussed in subtask 1, an error had been found in the use of runway occupancy times and a new model for a single runway was employed for that task instead. In combining this model to calculate capacities for the typical ATL runway configurations a number of additional algorithms were supplied by LMI to calculate arrival and departures in closely spaced parallel runways. LMI also undertook a revision of the typical configurations to be considered in order to follow those described in the FAA capacity benchmark [Ref. 39].

The first step in using the capacity LMI models is to provide information about the aircraft mix utilizing the airport, the environment that the airport is subject to, and the separation matrices dictated by ATC. An initial calculation is done to find single runway capacities based on the probability dictated aircraft sequencing, the approach, departure speeds and Runway Occupancy Times (ROT) of the aircraft types defined, and the separations that must be maintained to comply with FAA rules. When noise or other restrictions dictate longer approach or departure paths this is also taken into account. The single runway occupancies are subsequently combined according to the airport runway configurations, not simply in an additive manner. The configurations that yield the highest capacity are then used to generate airport Pareto frontiers for each weather condition. For the ATL version of the LMI capacity model, the task of combining runways and selecting the correct configuration based on weather conditions is actually part of the delay model.

The LMI delay models generally run through a number of days, selecting the Pareto frontiers to define capacity according to weather conditions, and comparing that capacity to the forecasted demand for that day. The weather data is taken in hourly increments from a typical weather year. The demand is generated by taking the current airline schedules and incrementing them according to an input percentage increase in demand while accounting for the average number of seats per flight [Ref. 40].

The LMI models were modified to allow for the inclusion of the planned fifth runway at the Atlanta airport, as well as to track both capacity constraints MIT and ROT. In addition interim data regarding time of day and length of delays was output, as well as the standard averages generated by the typical LMI model outputs.

Estimating Demand

Demand estimates can be based on econometric calculations such as those found within the ACIM demand generation module, based on GDP unemployment, per capita income, etc...However, this will only generate an estimate of demand due to local economic prosperity, and will not account for demand generated by connecting flights at hub airports. These estimates of demand also will not be given on a per hour basis as is required by the delay module, so the approach taken by LMI to take a current schedule and augment it according to future demand estimates is valid. For the Atlanta airport, demand data is available from the 2000 OAG guide on a per hour, per aircraft type basis.

This demand data includes an estimate of what part of that demand is generated by Delta airlines hub operations which is particularly useful in modeling the behavior of a particular airline.

The Cost of Delays

The cost of delays can be divided into two categories, direct and indirect costs. Direct costs are caused by extra fuel burnt and longer crew hours. Indirect costs are related to ground personnel, gate fees, and the preservation of customer satisfaction. Passengers generally choose air travel over other forms of transportation for its time savings, as delays increase and the time to get on and off a flight increases the time saved decreases and the value of flying diminishes. Figure 33 shows an estimate of the costs related to delays as a function of length of delay, and includes comments about the number of passengers that will be dissatisfied enough to choose another airline or another mode of transportation in their next trip.

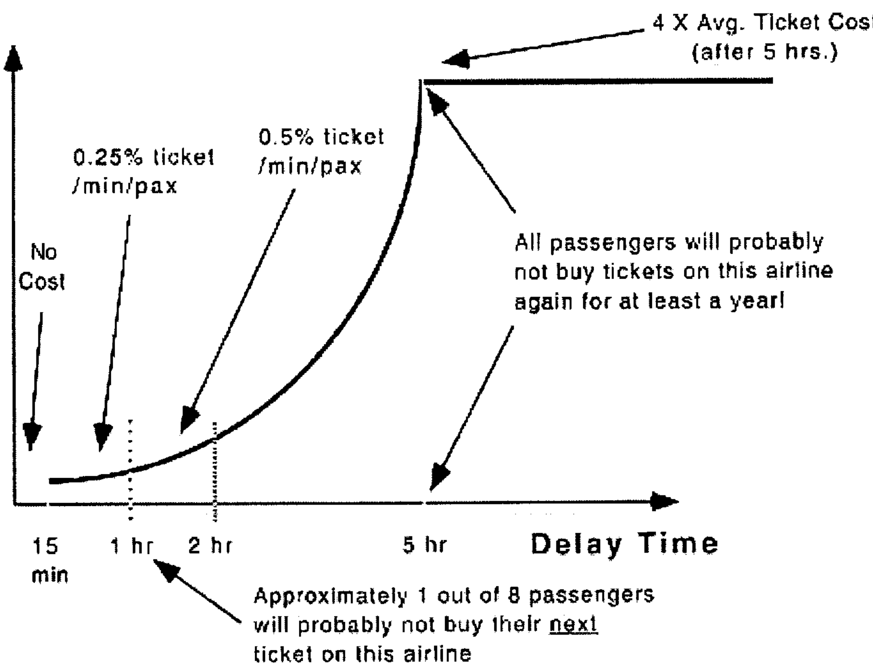


Figure 33: Cost vs. Delay Time [Ref. 41]

ALCCA has the ability to capture both the direct and indirect costs of delays thanks to a module added at ASDL to capture revenue-losses related to delays. This module was separated from ALCCA for this task in order to enable it to take actual data regarding time of day and length of delays directly from the LMI models, rather than using the internal assumptions required when only ALCCA data is available.

Airline Economics

Airline economics are a very complex process. As mentioned earlier, ticket pricing and airline marketing are more of an art than a science. However, ALCCA can calculate the costs incurred by airlines in their daily operations, as well as their predicted cashflows and the resulting return-on-investment. Unfortunately, this can only be done at the aircraft type level, and successive runs are required for each representative aircraft type. Much of the data required to as an ALCCA input is generated by FLOPS which is also run for representative aircraft types.

ALCCA was modified to explicitly include taxi times in its operations costs since many of the delays are incurred while at the tarmac waiting to take off (see Figure 34) and certain technologies such as SMA aim to reduce taxi times and increase safety in ground movements.

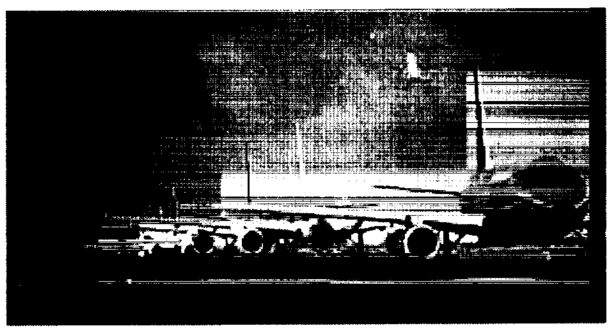


Figure 34: Aircraft Lined up for Takeoff [Ref. 42]

Models Developed

Modeling efforts have been under way for various components of the NAS for years. Codes resulting from such modeling efforts were identified and selected for this comprehensive simulation effort. However, certain areas were still lacking suitable models, or the models existing in these areas could not be obtained. Therefore, certain simplified models were developed. It should be noted that, were other more detailed codes to become available, the codes described herein should be easy to replace while maintaining the same types of interactions thanks to the modularity obtained by using the Model Center toolbox for their integration.

Airline Decision Making

Airlines dictate how passenger demand is served, and hence what kind of traffic each airport sees, as well as the distribution of that traffic in terms of fleet mix and times of day. These inputs to the LMI models can be varied and their effect on capacity can be assessed. However, if the motivation behind those policies is not captured somehow, the feedback of those capacity changes to the airline revenues will not be represented. For example, an airline could chose to serve demand with two smaller aircraft, or one large jet. The large jet will result in lower costs per passenger, and have a positive effect on the congestion problem, but the airline may choose to use two smaller aircraft because of the marketing potential. Such a decision could not be captured if the airline decision making process is not modeled.

Airline decisions are based on a delicate balance of profit and market share, their product is the schedule they offer which involves selecting aircraft types and flight times. The fleet mix feeds into the LMI capacity model, the flight times feed into the delay model. This product is driven by demand, and costs. The costs, including the cost of delays, are captured by ALCCA. Demand can be based on customer satisfaction partly dictated by the curve shown in Figure 33.

A simple knowledge-based system representing market share as a function of number of flights available during the day, the ticket price and the delays incurred was created. This knowledge-based system also generates recommended actions given the calculated market share and ROI. Thus, as a change in any of the components of the NAS is implemented its effect on airline policy, and the likely airline actions taken by the airline are captured. For example, slot pricing of peak arrival times could force the airline to use larger aircraft to serve its demand, but that may increase the separation required between incoming aircraft, reducing the overall capacity of the airport and resulting in delays, whether those delays are more or less than before the slot pricing is implemented will determine whether the airline continues that course of action or not. This is patterned in part after the ACSEM model which was not accessible for this task, however, the model generated is not agent-based in nature, and the iterative process is not automatic. The model only generates recommended actions; it does not execute them.

Infrastructure Costs

The influence of landing and other airport fees on airline profitability has been increasing in recent years, therefore, an estimate of how new infrastructure proposals will affect the behavior of airlines is needed. In order to do this a model representative of airline behavior must be combined with reasonable estimates of the costs related to technology implementation.

The costs of technology implementation in terms of new navigation aids and new runway layouts can affect airline costs in two ways. By increasing the landing fees the airline is required to pay, and by increasing the costs of aircraft equipment. An attempt was made to capture the cost of new navigation equipment to be installed in aircraft. Unfortunately, the data available in this area was either at a high level of aggregation, such as the total avionics costs defined in ALCCA, or in very detailed terms such as the specific part number that would be required from a Rockwell Collins parts catalog. Neither level seemed very adequate, the technologies proposed are not described in terms of part numbers, and the total avionics cost is a very coarse measure since only certain portions of the avionics would be affected by each technology. As such, technologies relating to avionics equipment are only captured by an increase in avionics cost and could not be modeled in detail.

The other aspect of airport and ATC improvements is reflected in infrastructure investments such as new runways. Such costs are propagated to the airlines using those airports through increased costs ranging from landing and rental fees to ticket taxes and PFC's. Landing fees are included in the costs estimated by ALCCA and can be increased as appropriate. PFC's are approved by the FAA and applied across the board to all airlines using the airport, so their effect is equal for all airlines and will not affect their competitiveness, with the exception of connecting flights where an airline with a different airport hub may have an advantage.

The first step in estimating airline costs due to airport improvements is to obtain a reasonable estimate of the actual costs that need to be covered by the increase in fees. This is not an easy task given the number of factors that determine runway construction costs, from the location of the airport to the type of landing aids incorporated. Estimates for the cost of constructing Atlanta's fifth runway were obtained from the Environmental Impact Statement (EIS) required by the FAA to approve the project [Ref. 43]. This report also contained date regarding what portion of those costs would be covered by Airport Improvement grants, vs. what percentage would have to be covered by an increase in airline fees. A more generalized estimate could be created taking data for several airport runways and establishing a correlation between runway characteristics and runway costs. Unfortunately, cost data, even for the few runways that are currently planned is not easily accessible. The data for ATL was available only because the library at Georgia Tech was selected as a repository, but the EIS report was not listed in the library catalog and required the help of several librarians to locate it.

Delay Propagation

Another aspect that is often overlooked in the estimating of delays is the interdependency of airline schedules in terms of equipment and crews. This type of scheduling policy practiced by most hub-and-spoke airlines sets up itineraries where an aircraft or its crew is expected to be at a certain location at a certain time to continue on to another destination or perform a return trip. If the first flight is delayed, then all subsequent flight that relied on that aircraft or crew are also delayed. Attempts have been made to capture such effects by modeling entire airline schedules, including the itineraries followed by each of the resources, aircraft and crew, throughout the day. Unfortunately, this is a very time consuming, complex task that requires in depth knowledge of schedule recovery procedures. Such a study was performed on a typical American Airlines schedule and delay multipliers as a function of the time of day and length of delay were calculated in reference 44. The delay multiplier is defined as

$$\text{Delay Multiplier} = (\text{Initial Delay} + \text{Downline Delay}) / \text{Initial Delay}$$

Thus, assuming another hub-and-spoke airline is going to have a similar degree of connectivity, the initial delay calculated by the LMI models can be tracked, including the time of day at which it occurred, and then multiplied by the appropriate delay multiplier to estimate the true delay experienced and its associated costs.

Interactions Captured

The goal of creating a modeling and simulation environment of the NAS was to capture the interactions between the various areas that are generally modeled independently. The basis for this goal was to capture true effects, both positive and negative, of technology implementation. Hence, special attention was paid to the affordability aspects of the NAS.

Thus, economics are modeled as the driving factor behind air travel demand, especially in terms of future demand growth. Airline operating costs, especially the costs related to delays and loss of customer satisfaction, are also considered as a contributing factor to that demand insofar as they affect ticket price. The behavior of those airlines is included in the model to represent the link between the passenger demand and the fleet mix and flight schedules required to execute the LMI capacity and delay models. Furthermore, economics play an essential part in the estimation of technology effects when one considers the cost of expanding infrastructure in terms of increased landing fees or increased avionics costs for new navigation equipment.

The model developed considers economics to be the puppet master pulling the strings and driving passenger, airline and airport decisions. Thus, the economic relationship between passenger demand and airline service, in terms of market share and ticket price, is considered of outmost importance, as is the symbiotic love-hate relationship existing between airports and the airlines using them.

Subtask 3: Technology Assessment

A modeling and simulation environment capable of capturing the interaction between components of the NAS has been developed enabling a technology assessment that considers the effect of technology programs in a broad sense, rather than the typical studies focused on establishing the benefits a particular technology can foster.

Technology Identification, Evaluation and Selection

The TIES methodology as developed at ASDL consists of eight steps, taking the designer from the problem definition to the selection of the best technological alternative. These eight steps, shown in Figure 35 are summarized below.

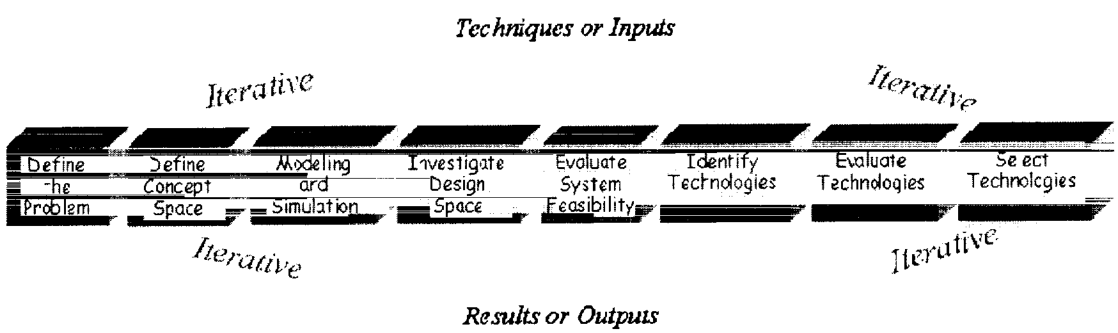


Figure 35: Ties Steps [Ref. 45]

Define the Problem

Generally by using management tools such as Quality Function Deployment to define customer requirements, and map those to system requirements. In this case the traveling public could be identified as the customer who desires a convenient, safe and timely air transportation service. This step should also generate a description of the system in terms of its main characteristics, as well as a means to measure system performance and customer satisfaction.

System Characteristics

The National Airspace System has been described in detail in the process of developing a suitable modeling and simulation environment for this task. Suffice it to say here that it is made up of four key players: the airline, the airplane, the airport and ATC and that these components are deeply intertwined with very complex interactions. It was also noted that economics are a pervading influence throughout the system and that government pressures and safety were additional influences in the rules established for the regulation of the system.

The Problem: Congestion and Delay

The cost and inconvenience of delays have caused much of the current attention the capacity problem has been receiving. Congestion is often blamed as the sole cause of those delays; however, the relationship between these two concepts is more subtle.

Congestion occurs when demand approaches or exceeds capacity. This can be due to a planning or an operational problem. The planning problem reflects scheduling policies such as non-uniform distribution of operations and the smaller-more-frequent approach to serving demand. Congestion due to this type of problem is present in normal operating conditions and it is not transient, but will remain as long as policies are not changed. The second type of congestion to be considered is operational in nature, and therefore harder to predict and prevent. This type of congestion is due to temporarily reduced capacities, as in the case of adverse weather conditions or malfunctioning equipment [Ref. 46]

Planning congestion can often only be addressed through direct methods that target the source of the problem, such as the number and time of flights, the seats served per departure, or the number of runways. Operational congestion, however, is often addressed through lest costly indirect methods by redistributing the excess demand to less congested and less expensive portions of the system. An example of such an approach is the FAA's Ground Delay Program which transfers airborne congestion to the ground. Ground congestion is preferable because of the reduced cost involved since fuel usage is higher in the air. Ground congestion is also preferable to airborne congestion from a safety standpoint since a stationary aircraft on the ground is less likely to create a safety hazard than one circling in the air unable to stop. Metering aircraft through a control point or rerouting them around a point of reduced capacity are other examples of indirect congestion reduction approaches. It should be noted that these approaches reduce congestion, and improve safety, but they may also increase delay [Ref. 47].

The Ground Delay Program yields a system-wide delay minimum provided uncertainty is ignored, en-route capacities are infinite and the arrival airport is always the final destination of an aircraft. The reason this congestion alleviation procedure can result in additional delays is these assumptions are not truly representative of the system. Flights are generally not independent so that an aircraft flying to New York City may then proceed to Chicago before returning to its original departure airport. Although airports represent the main bottleneck in the US airspace, en-route capacities are in fact limited by the ATC equipment and controllers in the sector. The NAS and its congestion are definitely not deterministic. Scheduled flights do not represent a constant demand, end even if that were the case, travel time is never fully deterministic, influenced by many factors like traffic volume or weather. Capacity is also not deterministic, since it depends on many unknown factors such as weather, the controller on duty, and the homogeneity of the traffic in the sector [Ref. 48]. In fact, capacity can be considered to have both an stochastic and a dynamic element. Stochastic in so far as it depends on weather which has a stochastic nature, and dynamic in so far as weather reports become increasingly accurate and can better predict capacity as a given time approaches [Ref. 49].

Thus, delays are a consequence of congestion, but the relationship may not be entirely direct. Furthermore, planned congestion and its associated delays are often built into airline schedules. Delays are only recorded when aircraft exceed their scheduled time by at least 15 minutes. Therefore, to improve customer satisfaction and obtain positive timeliness reports, airlines inflate the scheduled arrival time to include a certain delay margin [Ref. 40]. Consequently delays may be a biased metric, underestimating congestion and making other responses, such as throughput during peak periods, better predictors of system performance.

System Metrics

The purpose of this research is to assess the impact of capacity and throughput technologies and select those with the most promising returns. However, in order to compare the performance of the various technologies within the NAS, a series of metrics representative of the system are needed.

<u>Capacity</u>

The most obvious metric is capacity, which is defined as the maximum number of operations that can be performed during a fixed time interval. Airspace capacity depends on many factors such as meteorological conditions, runway configurations, arrival/departure ratio and fleet mix. However, capacity cannot be treated as a deterministic value since it is also influenced by the variability in flight speed and ROT even within a particular aircraft type. Furthermore, capacity can also affected by airspace factors so that, if the surrounding airspace is heavily loaded, maximum capacity may not be achieved. Human factors, such as controller workload, are also a source of variability in the capacity attainable. [Ref. 50].

<u>Demand</u>

Demand in excess of capacity is the other ingredient of the congestion that needs to be alleviated. Air travel demand is generally measured in RPM or RPK, or in the case of cargo, measured in RTK. As mentioned earlier, demand is driven mainly by GDP, fares and schedule convenience. Fares and schedules can be affected by technology infusion as scheduling policies change or technology costs are passed on to the customers. Furthermore, demand can be severely affected by the perception of safety which could easily be altered with technology infusion. Therefore, demand must be tracked not only as a factor to costly delays, but also independently to assess the impact of technologies.

<u>Delay</u>

As mentioned earlier, capacity is more representative of system performance than the often quoted delays which are only a consequence of congestion. However, obtaining a measure of delay becomes important when considering economic concerns, since there is a cost associated with the extra time expenditure. In fact, what phase of flight and what time of day that delay is accumulated would also be of interest given the different costs associated with airborne, ground and gate holds and the propagation of delays throughout the day.

<u>Cost</u>

Required average yield per RPM is an adequate measure of economic impact insofar as it contains the total operating costs of the airline per trip. The total operating costs include costs associated with delays, which they wish to minimize, as well as any increases in landing fees or aircraft purchase costs that may result from technology infusion. However, appropriate estimates of those costs that need to be accounted are also necessary.

<u>Noise and Emissions</u>

Noise reduction is a major thrust by airports and the administration. The intention is to reduce noise impact on airport communities, therefore noise regulations can restrict capacity, while noise reduction technologies can open up currently unavailable approach paths, and therefore can be considered within the capacity enhancing technologies. Noise is generally measured in EPNL (Effective Perceived Noise Levels) which account both for the noise level and the time of exposure to it or in DNL (Day-night Noise Level). Noise foot prints and the number of people affected by the noise could also be tracked.

Emissions represent another concern for the airport community, especially as air travel continues to grow. Emissions are generally measured in terms of CO_2 and NO_x lbs released per ASM (available seat mile) and are directly related to the amount of fuel used. As such the effect of aircraft operations on the air quality of the surrounding areas could be another factor to consider when assessing the consequences of delays.

<u>Safety</u>

Typically safety is measured in terms of fatalities or damage both of which occur only rarely. Safety is also often measured in terms of accident and incident rates. However, customer confidence, and therefore demand, is most often based on 'perceived safety' an entirely qualitative measure that may not have any relationship with the quantitative measures mentioned.

Other

Other metrics, such as predictability and flexibility, have been proposed as more suitable to capture system performance. Predictability focuses on the variable nature of the system and the desire to reduce uncertainty in flight time and arrival rates. Flexibility attempts to capture user intent, such as an airline's desire to give priority to a particular flight regardless on the effect on the total delay [Ref. 51].

Define Concept Space

This step is intended to decompose the system into its components, and identify the potential alternatives for each component. The result of this step can be displayed in the form of a Morphological Matrix, where each component of the system is displayed on the left hand side, with its potential alternatives listed in the same row. This Morphological Matrix can then be used to identify a baseline and potential technological alternatives. In this case the NAS is composed of the aircraft, the airline, the airport, and the air traffic control system. Each of these components can be further decomposed to a level where technological alternatives can be described. For example, the aircraft could be described in terms of its cruise, landing and takeoff speeds, number of passengers carried, etc...A sample morphological matrix can be seen in Figure 36.

		Alternatives			
Attributes	Aircraft	Propeller	Small	Large	Very Large
	Airline	Hub-and-spoke	Point-to-Point	Charter	
	Airport	International	Regional	Local	GA
	ATC	Centralized	Shared	Free-flight	

Figure 36: Sample Morphological Matrix of the NAS

Modeling and Simulation

This is possibly one of the most difficult steps to implement for a complex system. Striking a balance between detail captured and ease of execution can be extremely challenging when the system is composed of tightly interacting components. In the case of the NAS, models exist for individual components, but they tend to consider each component in isolation, not accounting for the interactions among the pieces of the puzzle. Furthermore, the models available for each of these components are varied in nature, ranging from purely analytical, to continuous time, to knowledge based, to agent-based. However, a simulation environment was created in Subtask 2 to generate a what-if environment where future technologies could be tested.

Investigate Design Space

With this step a better understanding of the system is desired. Identifying the major drivers behind the metrics of interest, recognizing trends and determining how uncertainty is propagated through the system are some of the goals behind the design space exploration. If the model lends itself well to Response Surface Methodology, a design of experiments can be used to screen out those inputs that do not contribute significantly to the change in the response, using the remaining values to create a Response Surface Equation, of the form shown in below, representative of the model [Ref. 4 and 52].

$$Metric = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} b_{ii} x_i^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} b_{ij} x_i x_j$$

This RSE can then be used within a Monte Carlo simulation to estimate the metric values an their associated probability of occurrence. An additional advantage of this approach is the creation of a dynamic environment called a prediction profile within the software package JMP [Ref. 53]. This environment, an example of which is shown in Figure 37, allows the designer to assess what-if scenarios very quickly. Unfortunately, RSE's do not estimate metric values correctly when internal constraints, which cause metric discontinuities, are present. The metric values and their associated probability of occurrence can also be obtained by applying a Monte Carlo simulation to the model directly, if the speed of execution is fast enough, or by using Fast Probability Integration Techniques [Ref. 54]. These techniques, though less restrictive than the RSE approach, do not yield a prediction profile environment.

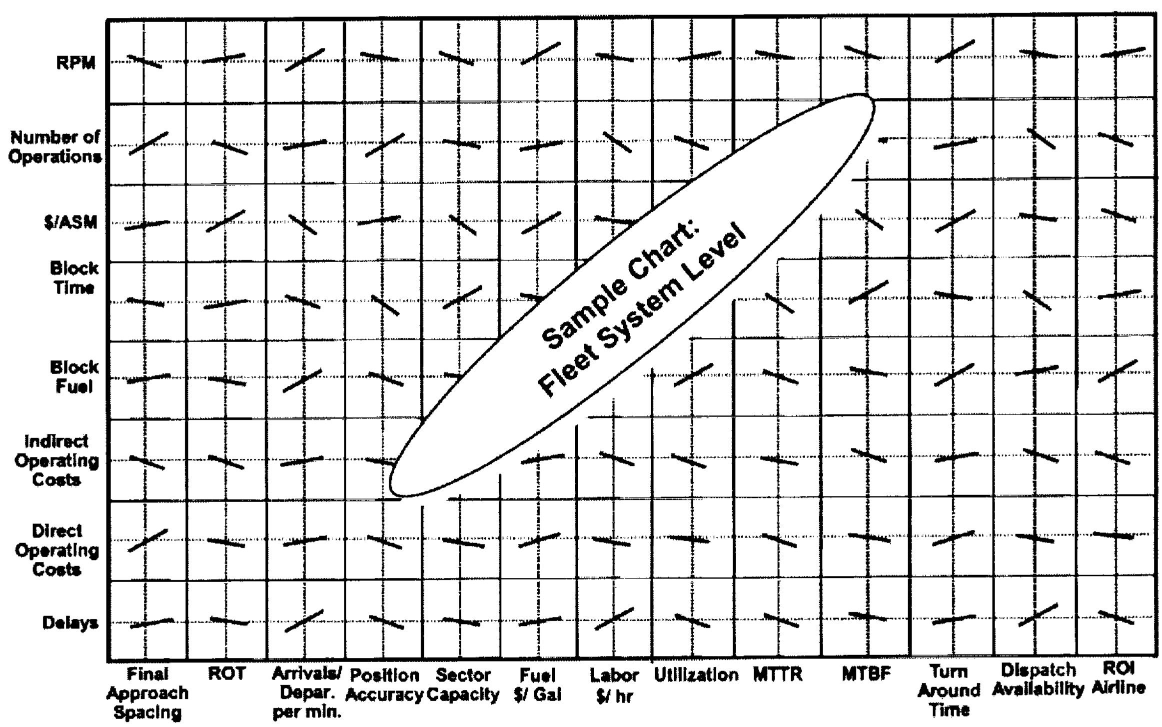


Figure 37: Sample Prediction Profile

Evaluate System Feasibility

Here the metric probability distributions obtained in the previous step are compared to the customer dictated constraints. Thus recognizing which customer desires are not satisfied, or how much confidence can be attached to achieving them. This information can then be used to establish what metrics require technology infusion, thus narrowing the search for suitable technologies.

The customer demands in this case could be as broad as safe and efficient service from point A to point B, or as specific as the goals NASA has set to reduce the aircraft accident rate by a factor of five and double the aviation system capacity within 10 years. Regardless, the system is not operating as efficiently as desired and as delays increase customer satisfaction will continue to deteriorate.

Identify Technologies

Potential technologies can be identified using the Morphological Matrix previously defined. The impacts, in terms of both benefits and drawbacks, of these technologies must also be identified. A probability distribution may be attached to these impacts to reflect technology readiness levels, the closer a technology is to being fielded, the less uncertain its impacts will be. Furthermore, there may be a set of technologies that are incompatible with each other. Identifying these technologies early on may reduce the size of the problem, since those technology combinations need not be tested.

Technologies Proposed

The nature of the technologies proposed to improve capacity and throughput is as varied as the components of the NAS. However, they can be loosely grouped as follows.

Demand Management

These technologies focus on managing the flows within the existing system to take full advantage of whatever capacity is currently available. They include procedures to redistribute the traffic flow to avoid overloading congested areas such as the Ground Delay Program. The use of slots with higher prices at the peak hours of the day to make demand more uniform would be another example. From a more innovative point of view the redistribution of demand with other types of aircraft could be included within this category also. Large aircraft such as the projected A380 could alleviate some of the congestion problem by carrying more passengers per operation, however, they would not alleviate terminal congestion. Tilt Rotors and runway independent aircraft have also been proposed as an alternative to regular transports provided they could operate without disturbing current traffic flow and their noise production could be minimized. Taking this idea of serving demand without altering exiting capacity further is the SATS program which would not affect major airport capacity, but rather would attempt to make use of the thousands of General Aviation (GA) airports currently underutilized. However, this program would have to overcome the perceived lack of safety of GA aircraft, and the infrastructure issues of serving large traffic and passenger volumes at those additional airports.

Capacity Enhancement

Beyond the management of demand within current capacity constraints there are also efforts underway to increase capacity at major airports by enabling more operations per runway, and expanding the number of runways available at airports. Perhaps the first step to accomplish this is to reduce the lead time required to allow construction of new runways which can be as much as 10 years. The FAA is taking steps to expedite the process, however, community pressures and availability of land may be unavoidable constraints at some airports.

In addition to accelerating the airport expansion process, a number of initiatives have been taken to increase the number of operations possible per runway regardless of weather conditions, and to minimize the separation required between parallel runways to maintain independent operations. These initiatives are currently being investigated by NASA, under their TAP program, with the intention of eliminating built in separation buffers currently necessary to account for reaction and communication time, as well as positional uncertainty and wake turbulence. The TAP program is developing aids in four main areas to include only the separation that is strictly necessary. These areas as described in the program objectives are:

- *Reduced Spacing Operations:* To reduce lateral and longitudinal spacing in non-visual conditions. AVOSS (Aircraft VOrtex Sensing System) and AILS (Airborne Information for Lateral Spacing) are some of the enabling technologies under consideration.
- *Air Traffic Management:* To enhance CTAS (Center-TRACON Automation System), integrating it with the FMS (Flight Management System) to reduce spacing and position uncertainty.
- *Low Visibility Landing and Surface Operations:* To expedite airport surface operations in adverse weather through sensor and display technologies such as ROTO (Roll Out and Turn Off), TNASA (Taxi Navigation And Situational Awareness system) or DROM (Dynamic Runway Occupancy Measurement).
- *Aircraft-ATC Systems Integration:* To enable clear weather operations in instrument-weather conditions. Cost, safety and technology demonstrations are the main focus of this research area.

With all these technologies the TAP is attempting to address inefficiencies in the arrival stream at an airport, currently in place to maintain safety in an uncertain environment. Should these technologies achieve full development they would contribute to a significant reduction in the uncertainty intrinsic to airport arrival operations [Ref. 36]. Figure 38 illustrates these inefficiencies and the technologies that target them.

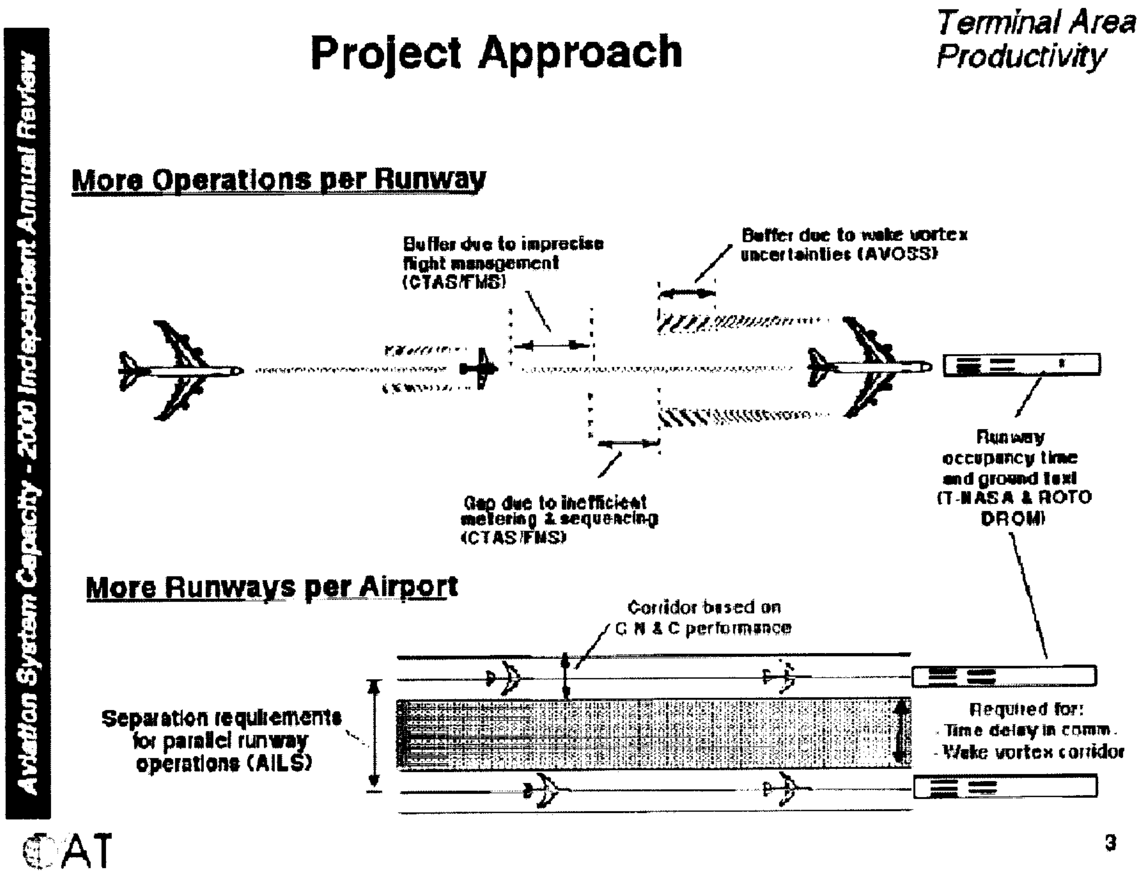


Figure 38: TAP Project Approach

<u>Innovative Concepts</u>

The concept of "Free Flight", which is also currently being explored by NASA and the FAA, signifies a radical change in air traffic management policy. The goal is to eliminate the constraints imposed by a centralized ATC system, transferring the responsibility for safety and efficiency to the airplane operators. Such a leap in air traffic practices requires development of numerous tools to maintain a guarantee of safety, especially during the technology transition phase. Most of these tools are intended to provide decision support and task-automation for controllers and pilots. The first step toward a free-flight environment involves the testing of those tools within the existing ATC system with hopes of dividing the ATM (Air Traffic Management) tasks between pilots and controllers at a later date.

Thus far, certain technologies developed by NASA under their AATT (Advanced Air Transportation Technologies) initiative, such as pFAST (Passive Final Approach Spacing Tool), SMA (Surface Movement Advisor) and TMA (Traffic Management Advisor), have already been field tested. These technologies will continue to mature and additional technologies will come online as Free Flight phase 2 develops.

But innovative concepts are not limited to a new ATC paradigm. The decentralizing approach to congestion relief could be taken to the extreme moving away from the concept of airport-to-airport travel entirely. NASA's mobility goal is aimed at reducing doorstep-to-destination travel time, but whenever a change of transportation modes is required waiting time is inevitable. Thus, Personal Air Vehicle concepts could be considered as a long-term solution to lengthy travel times and terminal area congestion. Though congestion in the airways may then be inevitable, at least airways can be laid in three dimensions, whereas the highway system is limited to two.

Evaluate Technologies

If appropriate factors exist within the model to capture technology discontinuities a procedure similar to the one used to investigate the design space can be used to estimate the effect of technologies and their combinations yielding results in terms of the metric values that can be obtained with a particular confidence level.

Select Technologies

The results from the previous step can now be used to select the most promising technologies in terms of their effects on the system, and the resources required to implement them.

Case Study

The modeling environment developed and the methodology proposed can now be tested on a sample case. This case study utilizes technologies applied in different components of the NAS to demonstrate the new capability of capturing aircraft and airspace technologies simultaneously. It also focuses attention on the affordability issues related to technology implementation.

Atlanta Hartsfield International Airport

The Atlanta International airport was chosen as a good site for this case study given its large operation volume, the largest in the nation in terms of passengers in the year 2000, as well as projects currently underway to add a runway and continue testing of free-flight related technologies such as SMA.

The Logistics Management Institute provided capacity and delay models for this airport with subsequent modifications to capture runway configurations not previously considered. These models were also modified to take advantage of the potential for increased capacity in the future through the addition of a third Cat III runway at the Atlanta airport. This fifth runway would also be available for departures thanks to its 9,000 ft length, increased from the initially approved commuter runway. Construction of this runway at the Atlanta airport will be especially challenging due to space constraints. The Atlanta airport is set at the intersection of three interstate highways, I-85, I-75 and I-285, and the projected runway which will open in 2005 along with its servicing taxiway will be required to cross over I-285 [Ref. 55].

Another reason this airport was chosen was the availability of its Environmental Impacts Statement which contains information regarding runway costs and projected demand for the area.

Terminal Area Productivity Program

The terminal area productivity program comprises a set of air traffic control technologies aimed at improving the existing system, whereas the technologies developed under AATT are aimed at developing the decision support aids for a completely different ATC paradigm. The TAP technologies, especially those relating to closely-spaced parallel runways are specially applicable in this case since the Atlanta airport currently contains two pairs of runways separated by the terminal building. In normal operations, the two outer runways are used for independent approaches, and the two inner runways are used for independent departures. However, during departure or arrival pushes each pair of runways could be used simultaneously if the technologies to make such a proposition safe existed. Furthermore, the fifth runway, though nearly 4,000ft south of the existing runways, is still too close to enable independent operations in bad weather. In addition, detailed information regarding the TAP technologies is available from a previous study carried out at LMI and described in Reference 56 which makes validation of this technique possible.

The Surface Management Advisor, though technically developed under the AATT program, will also be modeled in this task since it is already in testing at the Atlanta airport.

Delta: A Hub-and-Spoke Airline

In the modeling effort a simulation of airline decision-making procedures was developed based on the typical behavior of U. S. hub-and-spoke airlines. ATL is the main hub for one such airline: Delta. Some contacts were established with that airline in efforts to leverage their expertise in the area. Those efforts have thus far been unfruitful, but demand estimates for this airline specifically, as well as the airport as a whole have been obtained from OAG data. Additionally, Delta recently restructured its schedule to alleviate delay related problems. The study of such a behavior in the model, compared to the actual steps taken, would also be of interest.

A380: The Aircraft of the Future?

The goal for this task was to enable selection of technologies at the infrastructure as well as the aircraft level. The aircraft technology considered in this case is a new aircraft concept carrying far more passengers than ever before. The Boeing company abandoned its efforts to develop such an aircraft with the firm conviction that the tendency to serve demand with smaller aircraft would continue, and therefore the market for such large airliners would not exist. Airbus, however, continued its development of the aircraft and has recently released preliminary data regarding its airport compatibility [Ref. 57]. It is a gamble for the aircraft manufacturer, similar to that taken by Boeing in the seventies with the development of the B747. If the market is not there, the investment made in developing and manufacturing the aircraft will be lost and the company many not be able to withstand such a financial setback. However, if the project succeeds and the airlines that have ordered the craft are joined by others that have expressed interest, but no firm orders, Airbus will have a corner on the market. Its main market is likely to be in the still regulated markets of the Asia-Pacific region where land constraints make airport expansion prohibitive. Therefore, one of its main advantages, its ability to alleviate congestion, cannot be truly captured unless an approach such as the one developed in this task is taken.

Results and Conclusions

The results of this case study will be forthcoming. Technical difficulties in obtaining the modified capacity and delay models from the Logistics Management Institute caused an unexpected delay in this portion of the task. An updated copy of that code was finally obtained in March of 2002 and current efforts are underway to modify that version in order to include the fifth runway and reintegrate it with the rest of the modeling environment.

ACKNOWLEDGEMENTS

This report was prepared by Ms. Elena Garcia. However, a number of people contributed to the work involved in accomplishing the tasks described herein. Dr. Michelle Kirby led Task Three, and Ms. Carrie Nottingham and Mr. Samson Lim undertook the majority of the effort for Task Four. Furthermore, the capacity focus task would not have been possible without the help of the Logistics Management Institute and, specifically, Mr. Robert Hemm.

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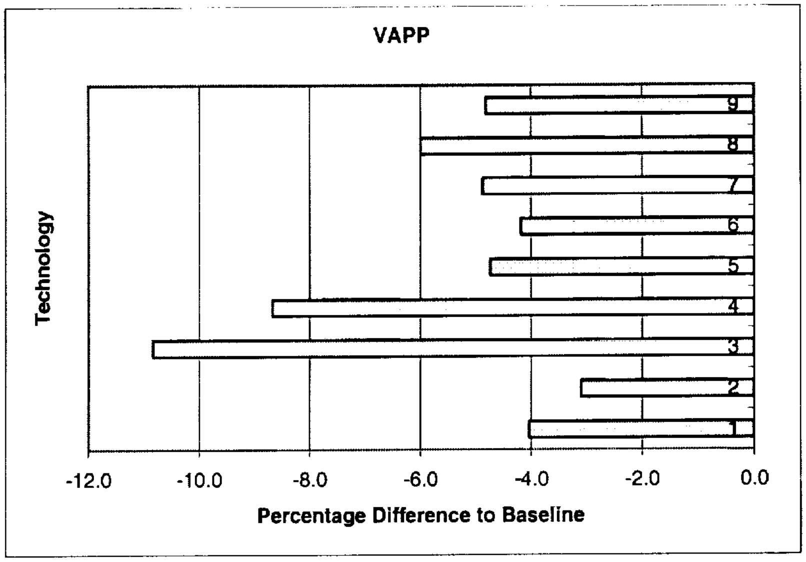
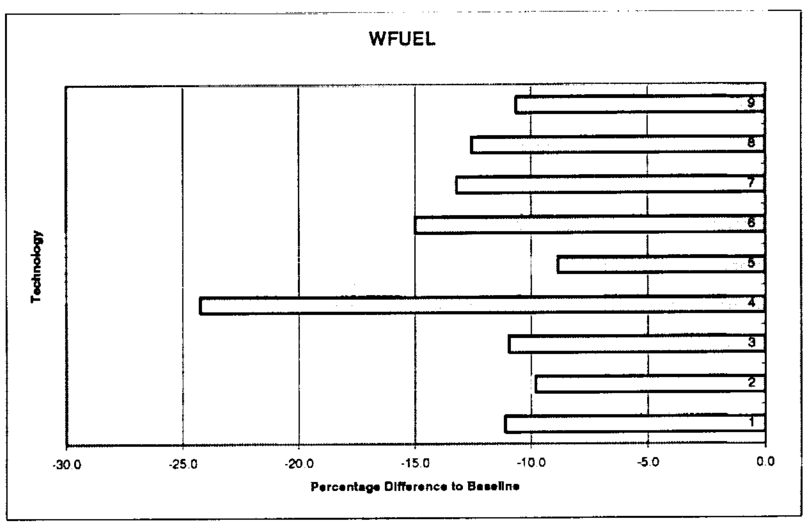
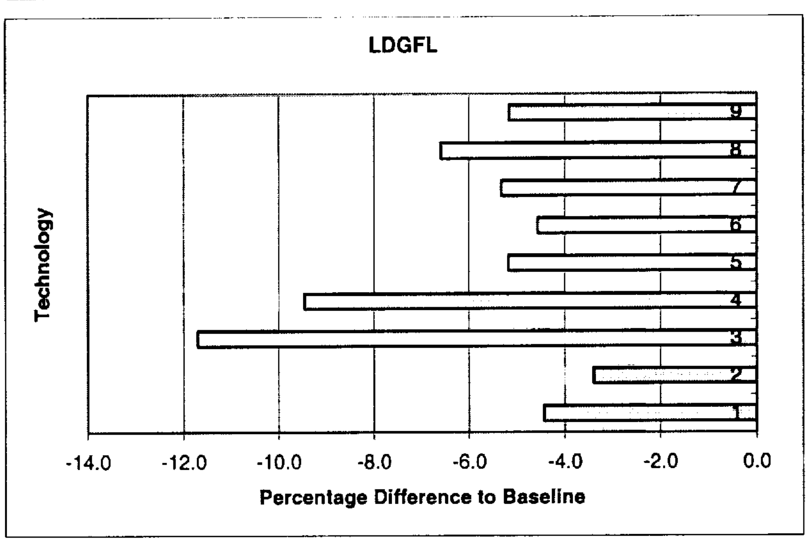
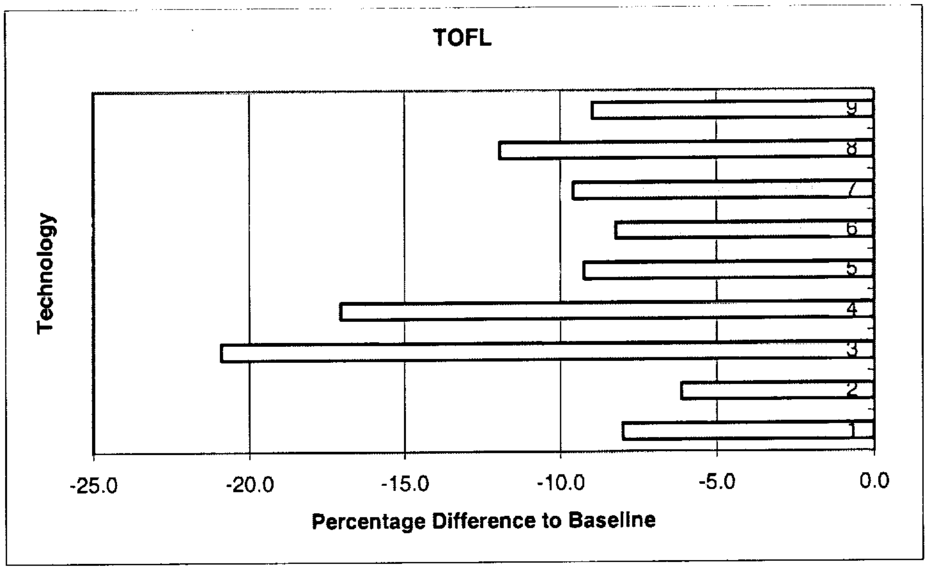
APPENDIX A: PARETO CHARTS








TOFL
Technology
9
8
7
6
5
4
3
2
1
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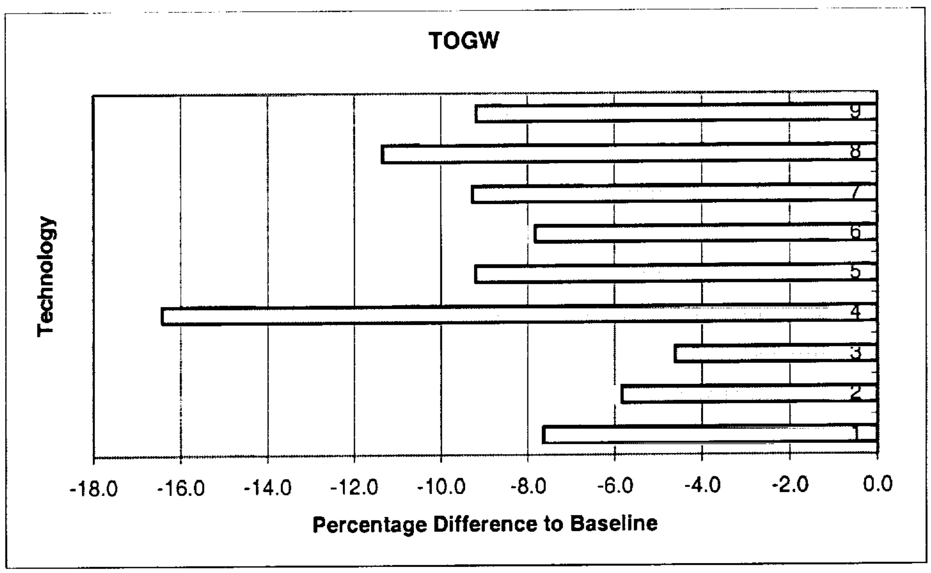
-20.0
-15.0
-10.0
-5.0
0.0
Percentage Difference to Baseline


TOGW
Technology
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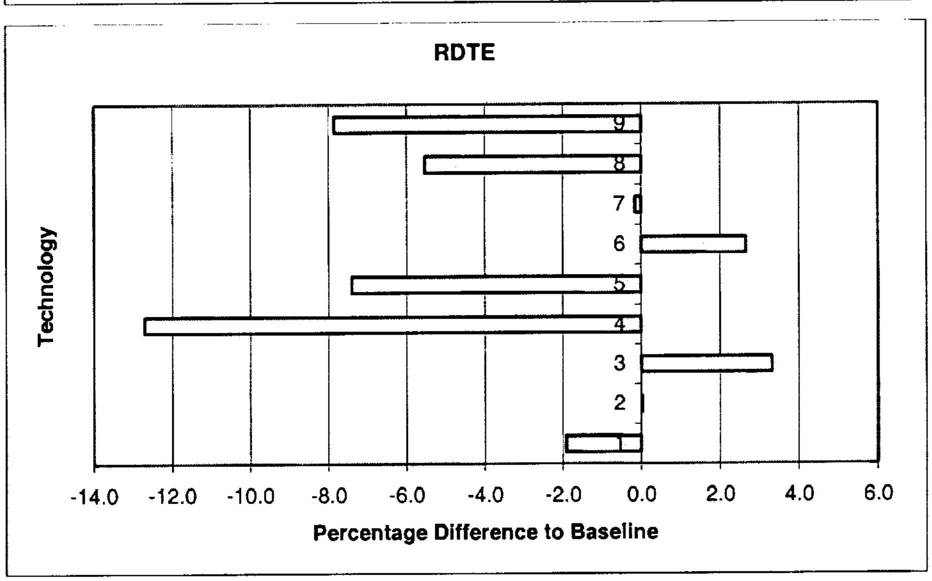
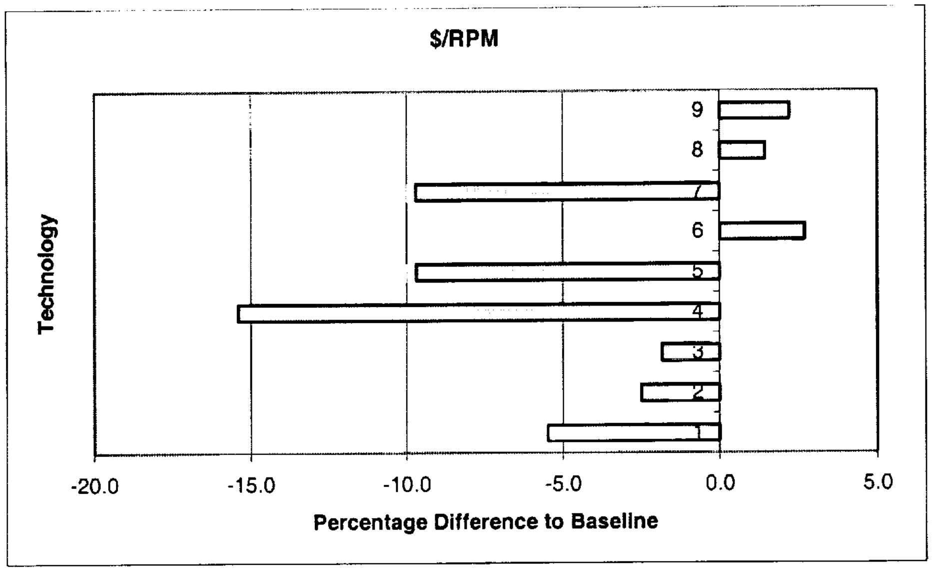
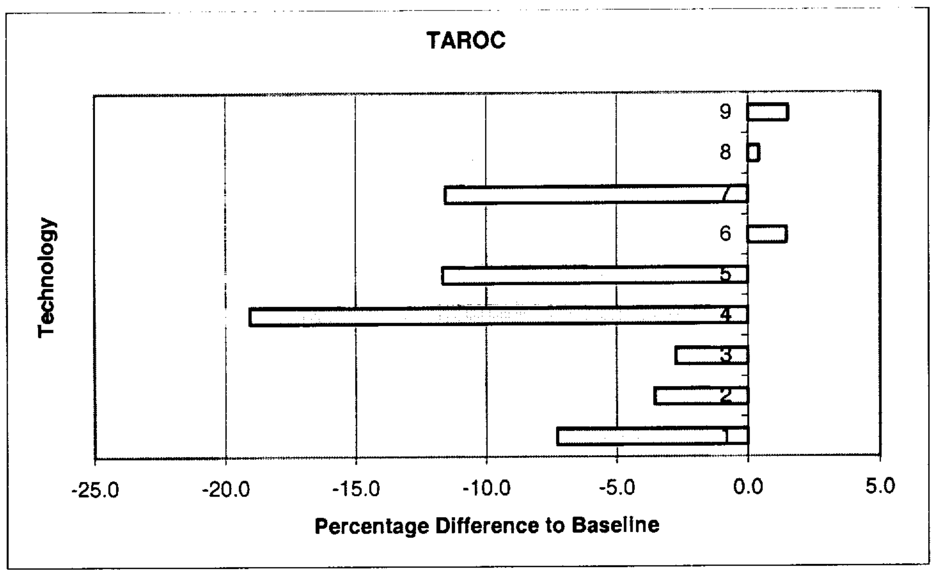
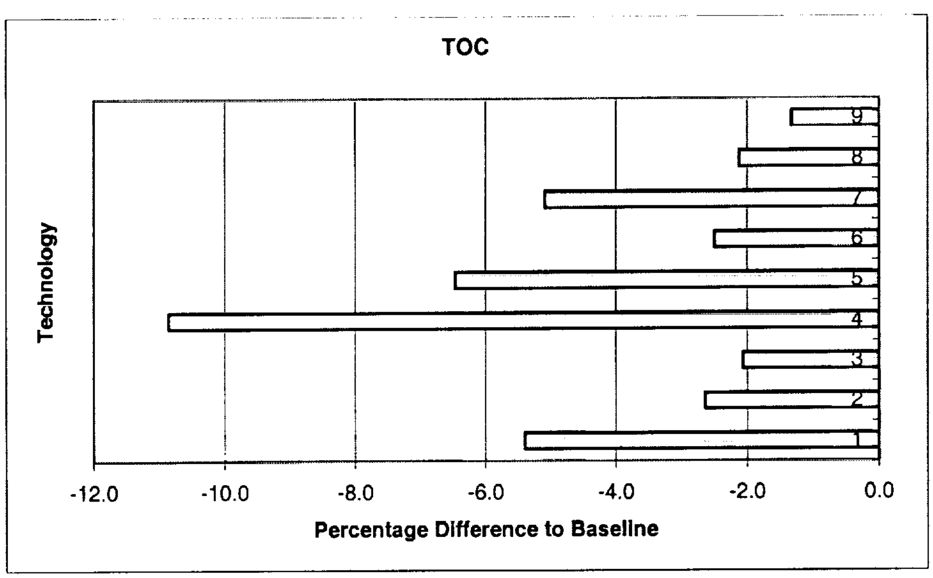
8
7
6
5
4
3
2
1
-18.0
-16.0
-14.0
-12.0
-10.0
-8.0
-6.0
-4.0
-2.0
0.0
Percentage Difference to Baseline


RDTE
Technology
9
8
7
6
5
4
3
2
-14.0
-12.0
-10.0
-8.0
-6.0
-4.0
-2.0
0.0
2.0
4.0
6.0
Percentage Difference to Baseline


$/RPM
Technology
9
8
7
6
5
4
3
2
1
-20.0
-15.0
-10.0
-5.0
0.0
5.0
Percentage Difference to Baseline


TAROC
Technology
9
8
7
6
5
4
3
2
1
-25.0
-20.0
-15.0
-10.0
-5.0
0.0
5.0
Percentage Difference to Baseline


TOC
Technology
9
8
7
6
5
4
3
2
1
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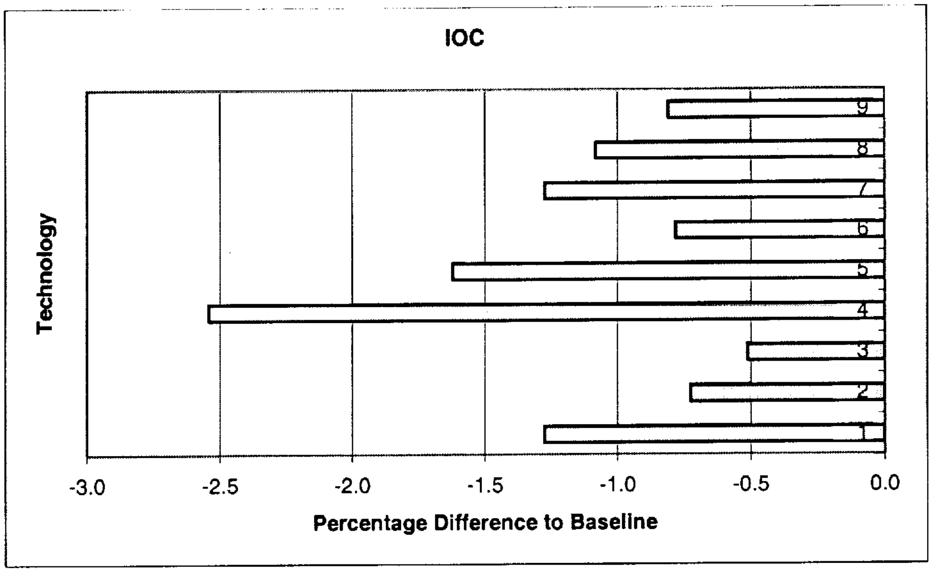
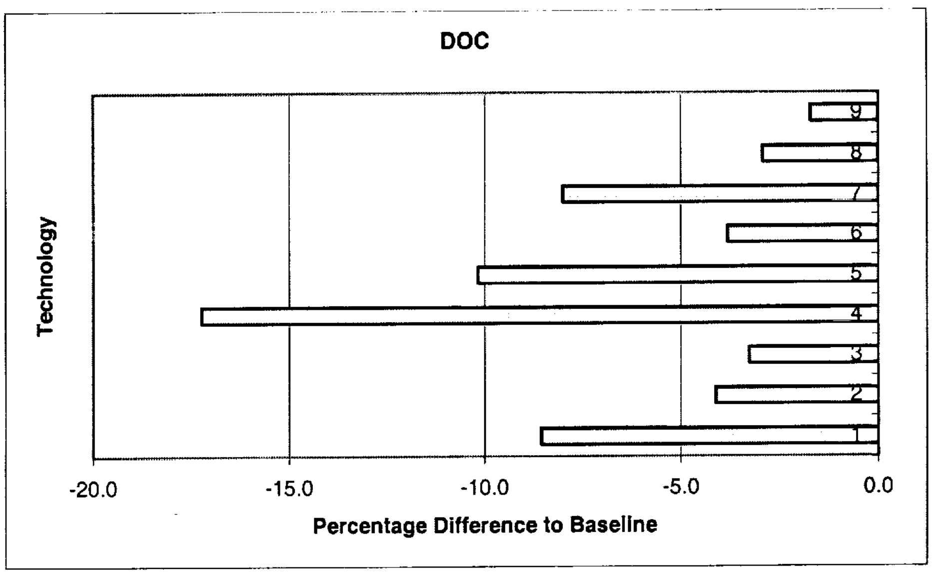
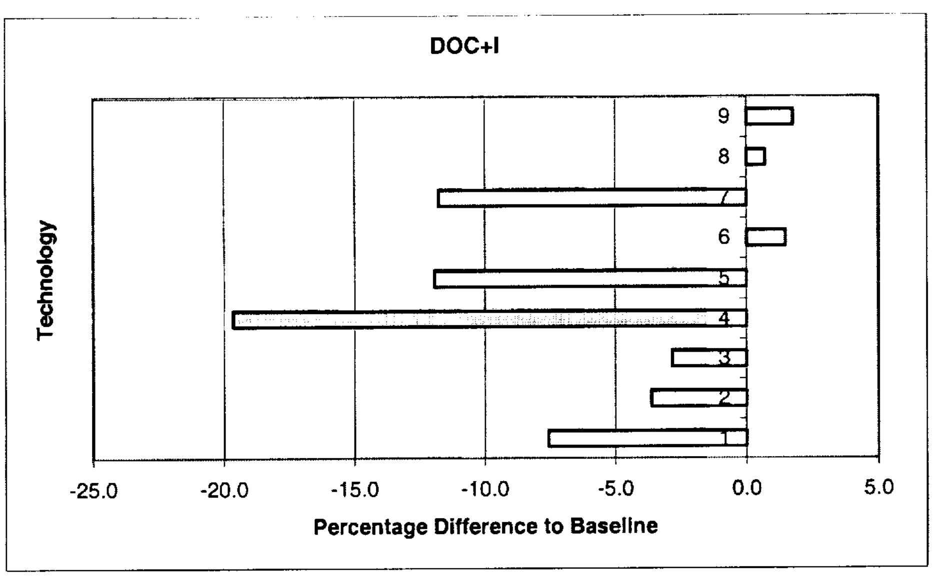
-8.0
-6.0
-4.0
-2.0
0.0
Percentage Difference to Baseline


IOC
Technology
9
8
7
6
5
4
3
2
1
-3.0
-2.5
-2.0
-1.5
-1.0
-0.5
0.0
Percentage Difference to Baseline


DOC
Technology
9
8
7
6
5
4
3
2
1
-20.0
-15.0
-10.0
-5.0
0.0
Percentage Difference to Baseline


DOC+I
Technology
9
8
7
6
5
4
3
2
1
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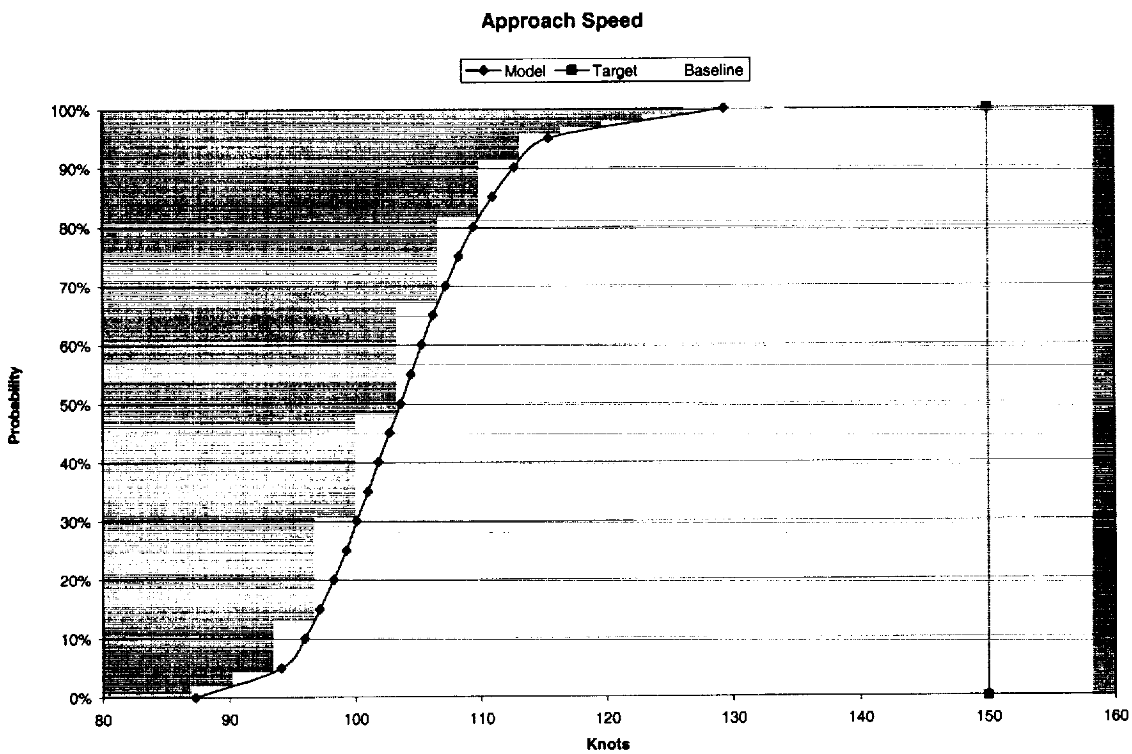
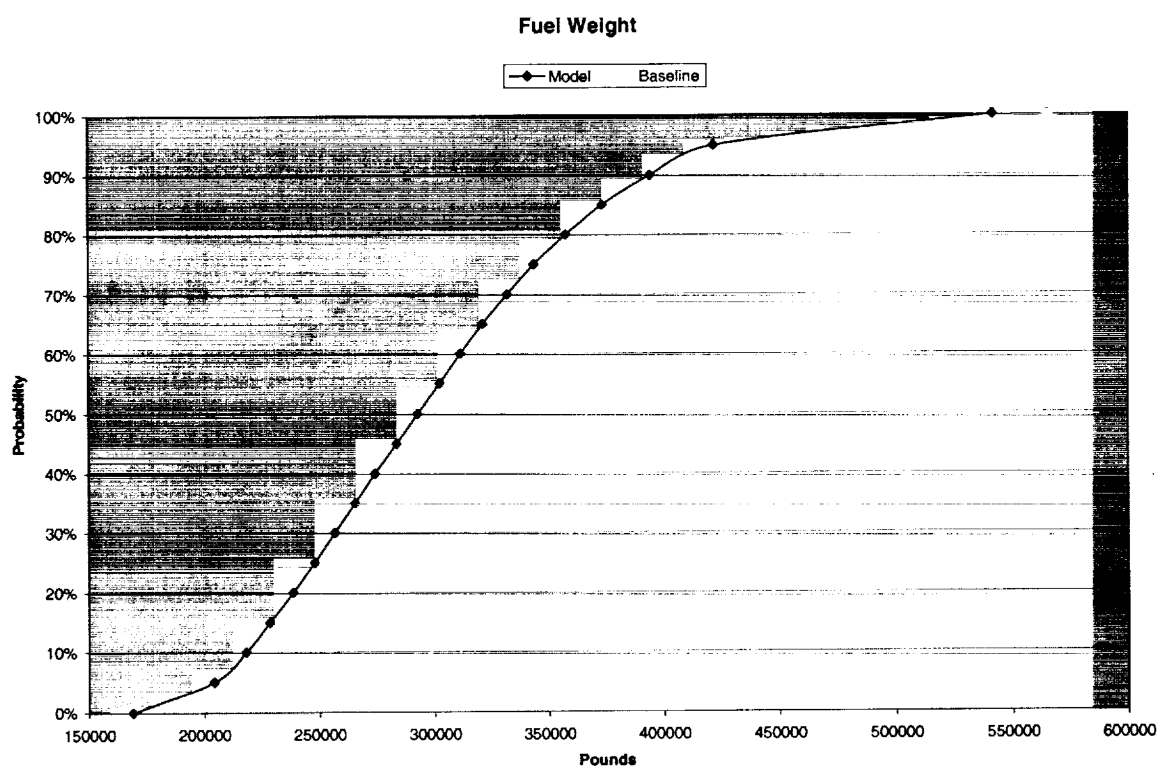
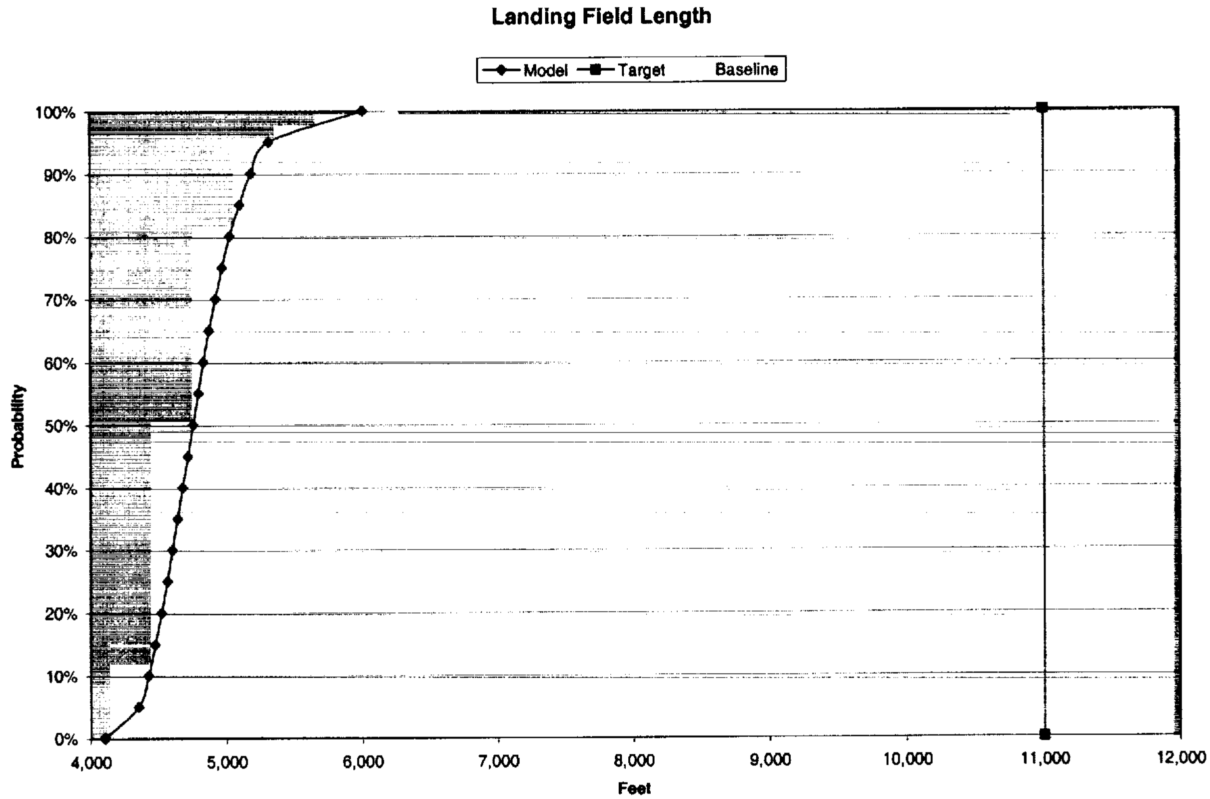
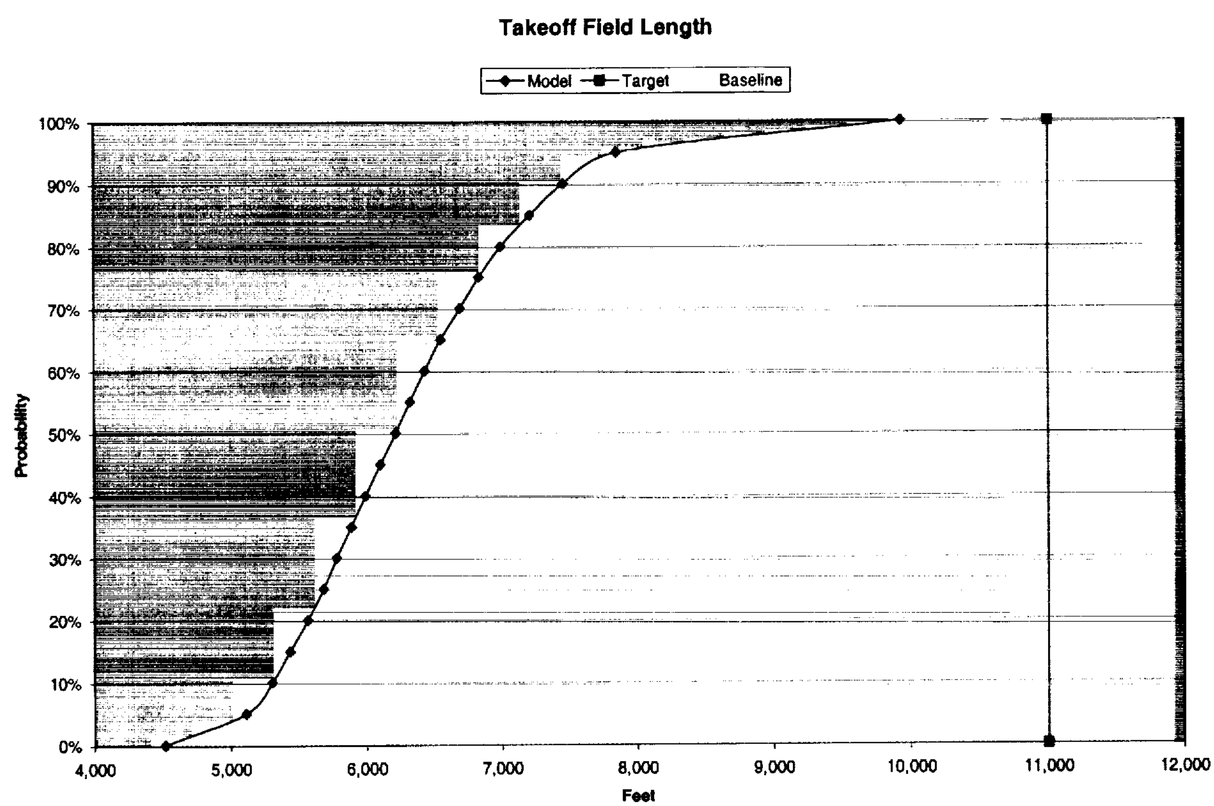
0.0
5.0
Percentage Difference to Baseline

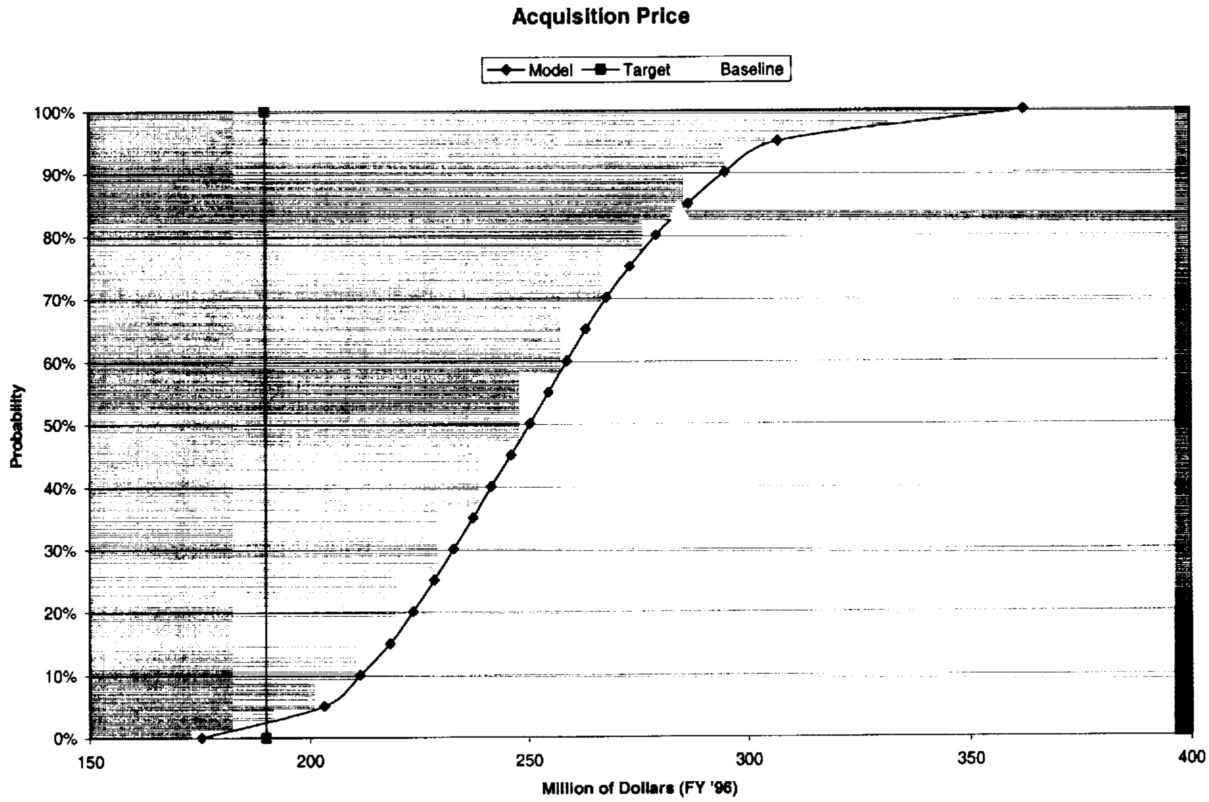
APPENDIX B: CDF OF TECHNOLOGY SPACE

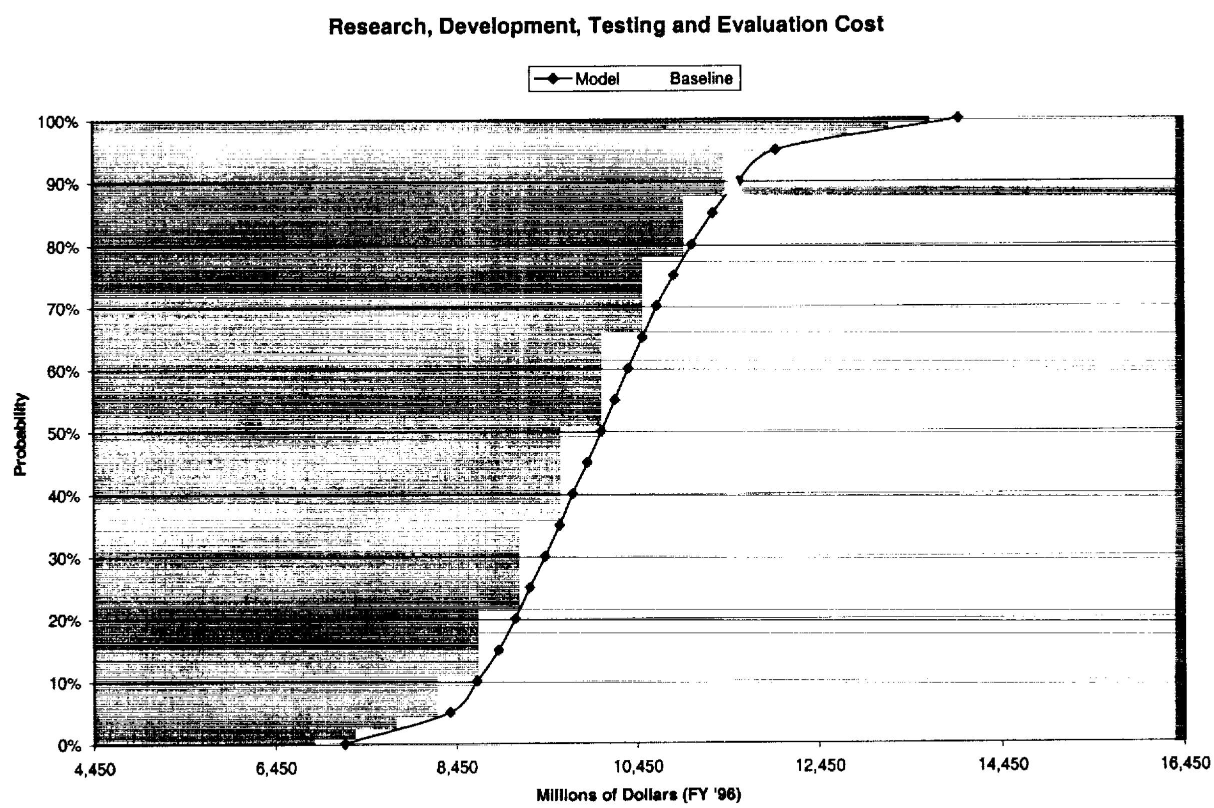


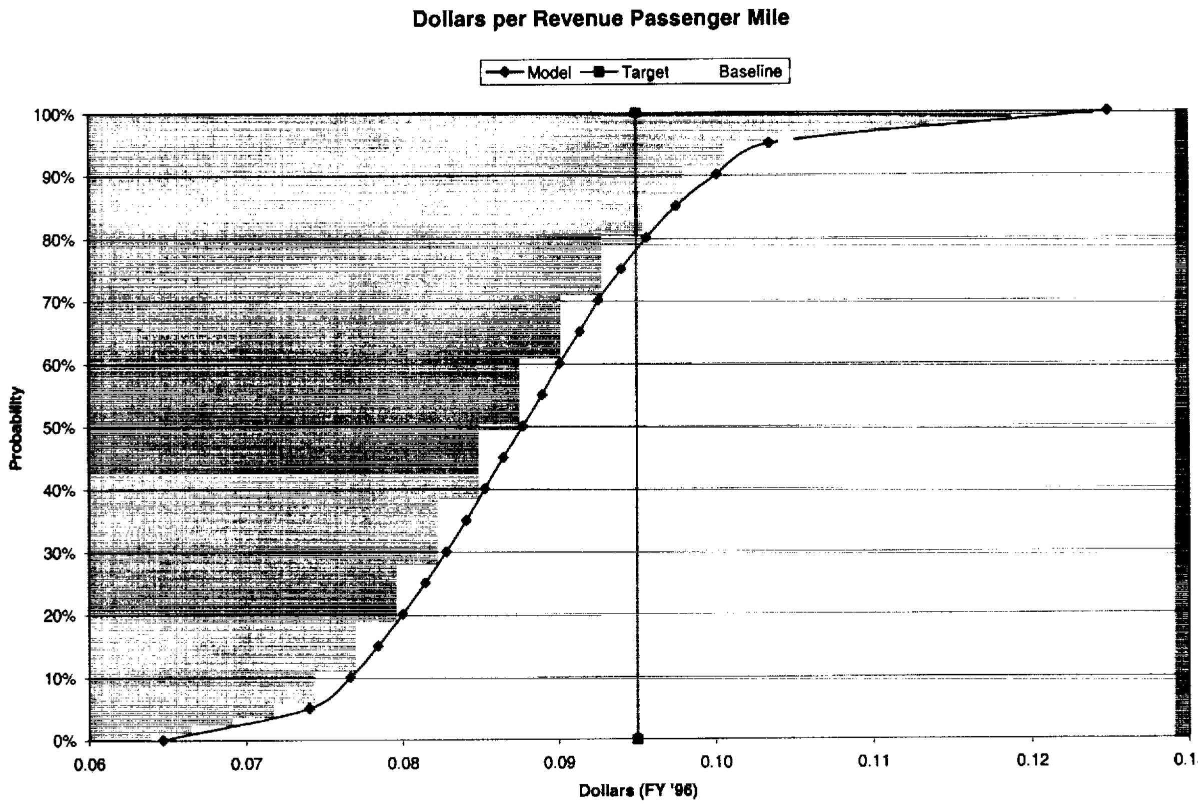


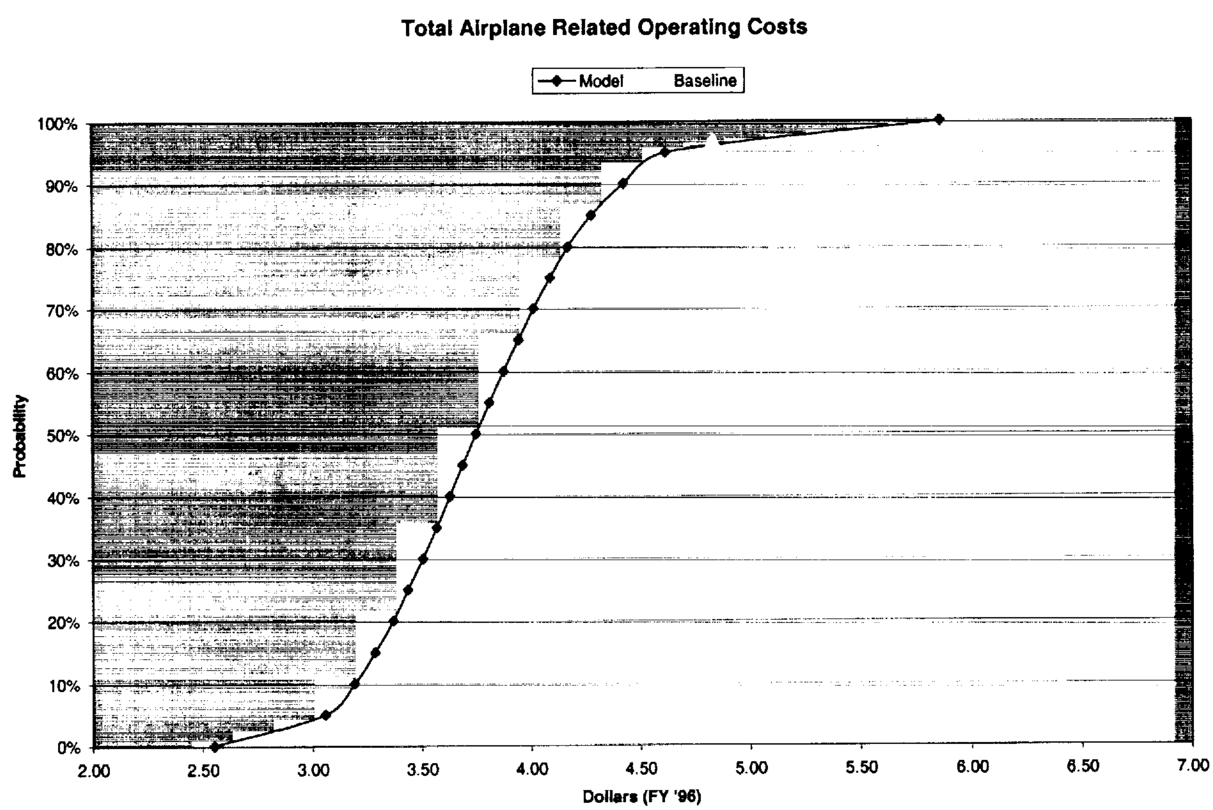

Landing Field Length
Model
Target
Baseline
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Probability
4,000
5,000
6,000
7,000
8,000
9,000
10,000
11,000
12,000
Feet

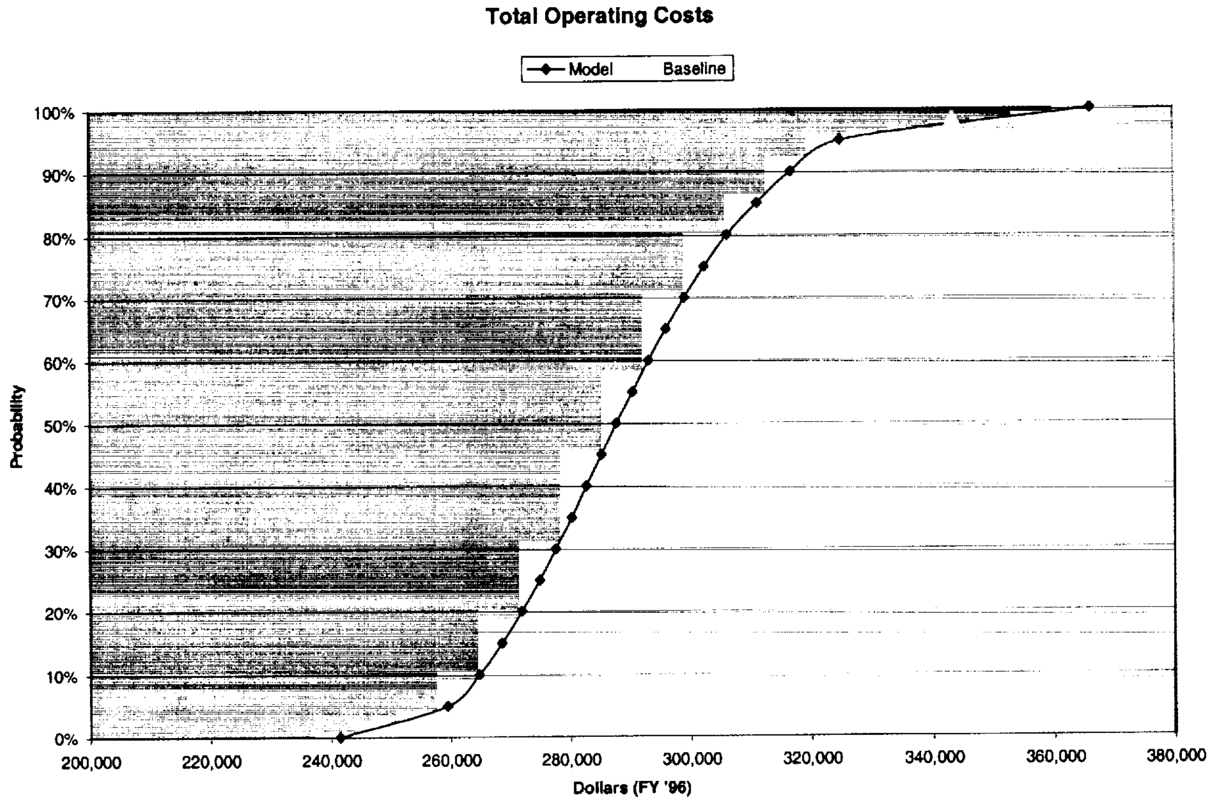

Takeoff Field Length
Model
Target
Baseline
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Probability
4,000
5,000
6,000
7,000
8,000
9,000
10,000
11,000
12,000
Feet

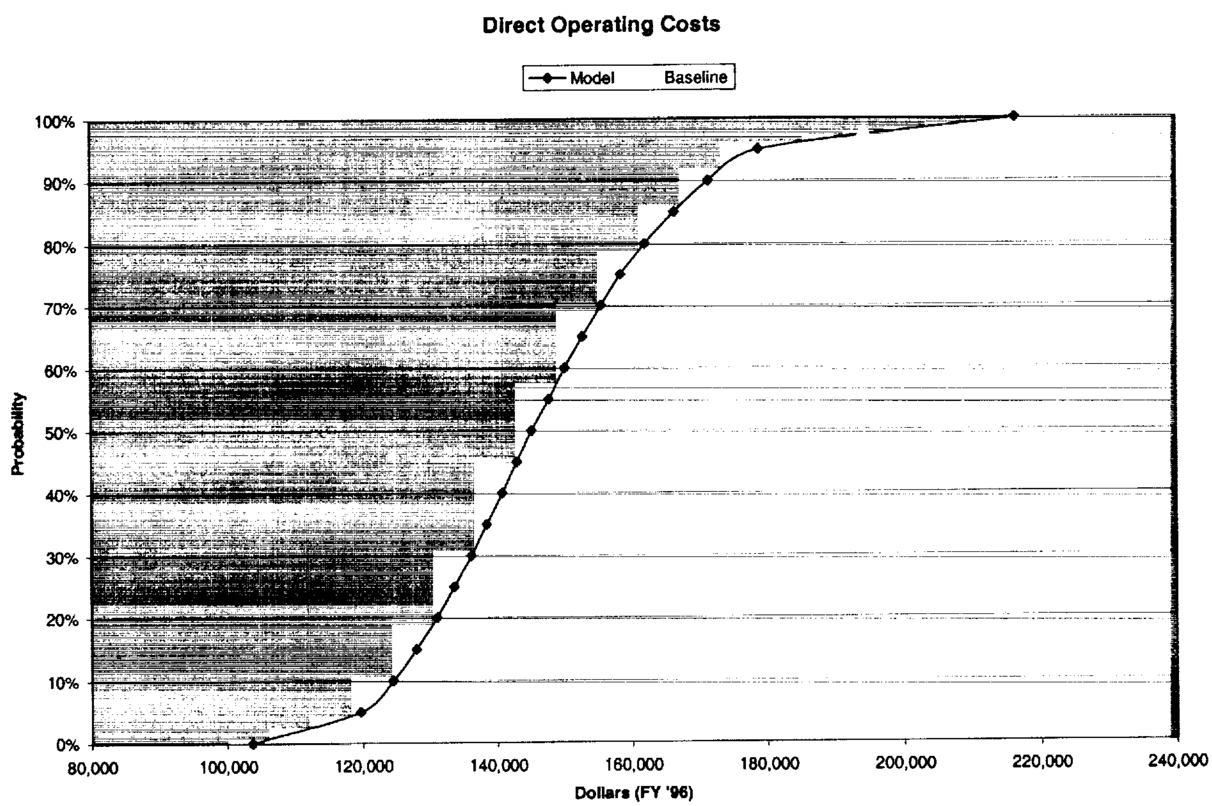

Acquisition Price
Model
Target
Baseline
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Probability
150
200
250
300
350
400
Million of Dollars (FY '96)


Research, Development, Testing and Evaluation Cost
Model
Baseline
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Probability
4,450
6,450
8,450
10,450
12,450
14,450
16,450
Millions of Dollars (FY '96)

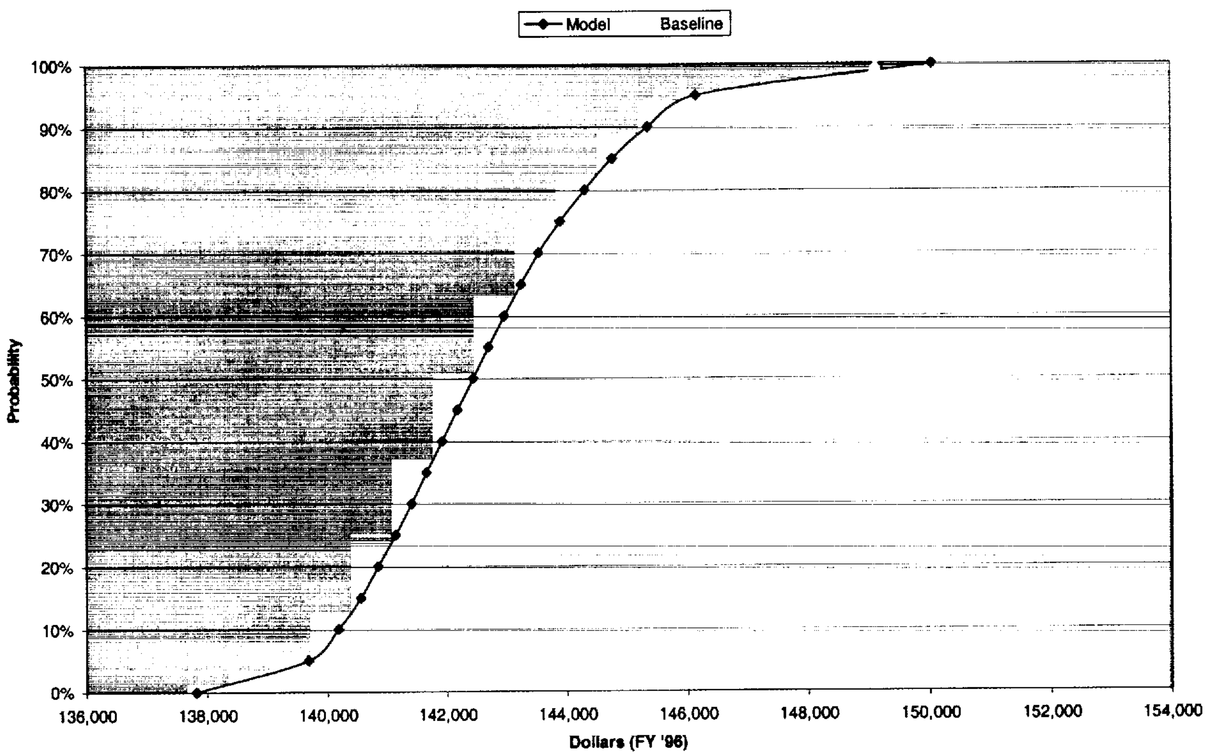

Dollars per Revenue Passenger Mile
Model
Target
Baseline
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Probability
0.06
0.07
0.08
0.09
0.10
0.11
0.12
0.13
Dollars (FY '96)


Total Airplane Related Operating Costs
Model
Baseline
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Probability
2.00
2.50
3.00
3.50
4.00
4.50
5.00
5.50
6.00
6.50
7.00
Dollars (FY '96)

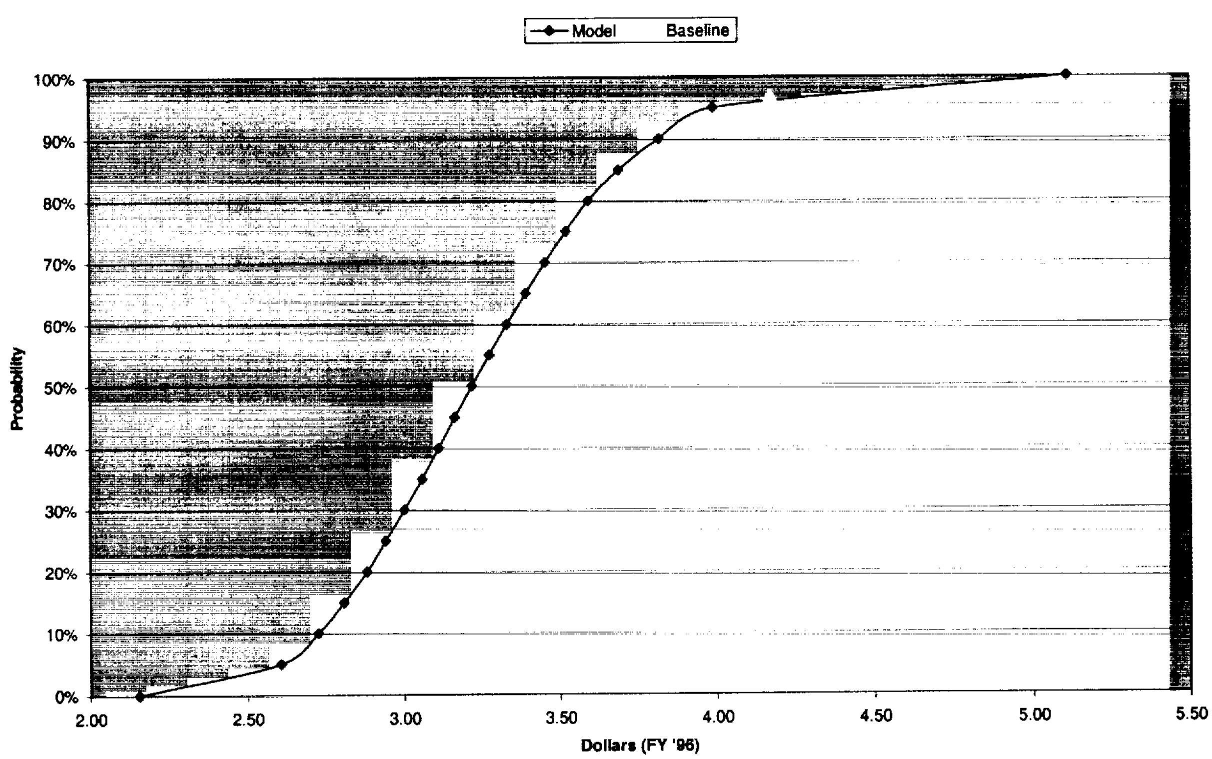

Total Operating Costs
Model
Baseline
Probability
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
200,000
220,000
240,000
260,000
280,000
300,000
320,000
340,000
360,000
380,000
Dollars (FY '96)


Direct Operating Costs
Model
Baseline
Probability
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
80,000
100,000
120,000
140,000
160,000
180,000
200,000
220,000
240,000
Dollars (FY '96)

Indirect Operating Costs



Direct Operating Costs + Interest



APPENDIX C: FPI DETAILS

FPI COMPONENT ANALYSIS KEYWORD SUMMARY

PARAMETER DATA	Input Options: Alphanumeric	Input Options: No.	Allowable ANALTYPE	Description	MODEL DATA	Required Data
*FPI						
Title				Problem title (one line)		
*RVNUM				Number of random variables (n)	*DEFRANVR	Mean, Std., Distribution[1]
*GFUNCTION	LINE	1	0,1,2	Z = LINEar (least-squares)	*DATASETS	Data (m > n + 1)
	QUAD	2	0,1,2	Z = QUADratic (least-squares)	*DATASETS	Data (m > 2n + 1)
	R-S	5	1	Z = X1 - X2 (g = R-S)		
	USER	6	0,1,2	Z = f(X_1,..X_n) in {RESPON}	*EXACTPRM	Eq. no. and parameters
	URES	7	01,2	Z = f(X_1,..X_n) in {USERES} by using "PREFPI"		
	UEQN	8	01,2	Z = f(X_1,..X_n). Fortran statement defined in input deck		
*DATASETNM				Number of data sets (m) (For GFUNCTION = 1 or 2)	*DATASETS	
*METHOD	FORM	0	0,1,2	First-Order Reliability Method		
	FPI	1	0,1,2	Fast Prob. Integration method (3 para. normal)		
	CONVX	2	1	Fast CONVolution method (X-space)		
	CONVU	3	1	Fast CONVolution method (U-space)		
	SORM	4	1	Second-Order Reliability Method (Breitung)		
	ISAMF	5	1	Importance SAMpling method (Factor)	*MONTE	Samp. no., Seed, User factor
	MONTE	6	0,1	Standard MONTE carlo method	*MONTE	Samp. no., Seed, 0.
	ISAMR	7	1	Importance SAMpling method (Radius)	*MONTE	Samp. no., Seed, User radius
	AIS1	8	1	Adaptive Imp. Samp. method (1st-order)	*ITOL	Error(%), confidence(%)
	AIS2	9	1	Adaptive Imp. Samp. method (2nd-order)	*ITOL	Error(%), confidence(%)
	MV	10	0,1,2	Mean Value Method		
	AMV	11	0,1,2	Advanced Mean Value Method		
	AMV+	12	0,1,2	AMV +(plus) iterations	*ITER	max. iteration number
*ANALTYPE	CDF	0		Automated full CDF analysis		
	ZLEV	1		User specified Z_o LEVel	*ZLEVELS	No. and Z_o values
	PLEV	2		User specified P (cdf) LEVel	*PLEVELS	No. and P values
*CONFINT	NO	0		No confidence interval analysis		
	YES	1	1	YES, compute random mean and std. (For GFUNCTION = 1 or 2)	*CONFINTVL	COVs. for mean and std.
*PRINTOPT	SHORT	0		SHORT print-out		
	LONG	1		LONG print-out		
*END				End of parameter data	*END	End of model data

[1] Distribution input options (alphanumeric input in parenthesis) = 1 (WEIB), 2 (NORM), 3 (EVD1), 4 (LOGN), 5 (CHIS), 6 (MAXE), 7 (CFIT), 8 (FREC), 9 (TWEI), 10 (TNOR)

"manuf.dat": Sample FPI Input

```
*FPI
Input for ALCCA Manufacturing fidelity study
*RVNUM 30
*GFUNCTION 6
*METHOD AMV
*PRINTOPT 0
*ANALTYP 2
*END
*PLEVELS 9
0.01 0.05 0.1 0.3 0.5 0.7 0.9 0.95 0.99
*EXACTPRM
1,0,0
*DEFRANVR
CFWINGAL
     1.0  0.1  2.0
CFWINGTI
     1.0  0.1  2.0
CFWINGCO
     1.0  0.1  2.0
CFEMPAL
     1.0  0.1  2.0
CFEMPTI
     1.0  0.1  2.0
CFEMPCO
     1.0  0.1  2.0
CFBODYAL
     1.0  0.1  2.0
CFBODYTI
     1.0  0.1  2.0
CFBODYCO
     1.0  0.1  2.0
CFLGAL
     1.0  0.1  2.0
CFLGTI
     1.0  0.1  2.0
CFLGCO
     1.0  0.1  2.0
CFNACAL
     1.0  0.1  2.0
CFNACTI
     1.0  0.1  2.0
CFNACCO
     1.0  0.1  2.0
CFENG
     1.0  0.1  2.0
CFTREV
     1.0  0.1  2.0
CFENAC
     1.0  0.1  2.0
CFFUSY
     1.0  0.1  2.0
CFAERO
     1.0  0.1  2.0
CFHYCD
     1.0  0.1  2.0
CFELCD
     1.0  0.1  2.0
CFPNCD
     1.0  0.1  2.0
CFACS
     1.0  0.1  2.0
CFANTC
     1.0  0.1  2.0
CFPOW
     1.0  0.1  2.0
CFPACC
     1.0  0.1  2.0
CFINST
     1.0  0.1  2.0
CFAVON
     1.0  0.1  2.0
CFHNDL
     1.0  0.1  2.0
*END
```

"RESPON.f": Addendum to Nessus code to automate its connection to the analysis code

```
      FUNCTION RESPON(XSTAR)
C
C  Created: B Roth and N Macsotai, Oct 1997
C  Version: 1.0
C  Modified:
C
C  This is a generic "RESPON.f" subroutine created for use with the FPI
C  analysis code created by the Southwest Research Institute.   Every
C  attempt has been made to make this subroutine as easy and convienent
C  to use as possible, however, it is necessary for the user to make a
few
C  modifications in order to adapt the subroutine to their specific
problem.
C  In order to assist in this process, a step-by-step set of
instructions has
C  been provided in the code of this subroutine.  To set up the RESPON
file
C  for your application, simply follow the instructions embedded in the
code.
C
C  INFORMATION ON GENERAL USE
C  The RESPON.f subroutine creates two sets of files when executed.  The
first
C  set is called "XSTAR", "XSTAR2", etc.  These file contain the values
of the
C  variables which FPI ran to obtain the CDF.  The second set of files
are called
C  "respon", "respon2", etc.  These files contain the values of all the
responses
C  which were tracked by FPI.  The user can define up to 100 responses
to be
C  tracked.  All that is required is that they are placed in a file
named "response"
C  with one response value per line.  Note that the input file must
contain the
C  "*EXACTPRM" namelist.  This namelist looks like:
C   *EXACTPRM
C   10,0,0
C  where the 10 represents the response on which FPI will conduct the
probabilistic
C  analysis.
C
C  INFORMATION ON RESPON.f FILE SET-UP
C  To set up the RESPON.f subroutine for you application, follow the
steps outlined
C  in the source code below.
C
      IMPLICIT INTEGER(I-N)
      IMPLICIT DOUBLE PRECISION(A-H,O-Z)
      DIMENSION XSTAR(100),R(100)
      DOUBLE PRECISION RESPON
C   COMMON /MENU/ IEQ,NCOEF,NPOW,COEF(100),POW(100)
C  COMMON /FLAGS/ IERROR,NSI(100)
C  COMMON /COUNTERS/ NRUNS,NVARS
C
C  COMMON BLOCK "FLAGS" IS USED FOR ERROR TRAPPING AND STATUS UPDATES
C  COMMON BLOCK "COUNTERS" IS USED FOR COUNTING THE NUMBER OF FUNCTION
C          CALLS THAT FPI MAKES.
C
C  IERROR = GENERAL ERROR FLAG; 1=ERROR, 0=NO ERROR
C  NSI    = VECTOR OF NUMERICAL STATUS INDICATOR REFERENCES (USER
DEFINED)
C
C  NRUNS  = COUNTER FOR NUMBER OF TIMES FPI CALLS RESPON.F
C  N      = NUMBER OF RESPONSES IN THE R VECTOR
C  NVARS  = FLAG INDICATING THAT MORE THAN 15 VARIABLES ARE BEING USED
C
C  XSTAR  = Vector of input variables generated by FPI
C  R      = Vector of response Variables Generated by scripts
C
C  Set Up Counters and flags
C
      NRUNS=NRUNS+1
      N=1
      IERROR=0
      print*,' '
      print*,'PROCESSING FPI SUB-CASE ',NRUNS
      print*,' '
C
C  Zero out the R vector
C
      DO j=1,100
           R(j)=0
      ENDDO
C
C  Trap error if IEQ is <1 or >100.
C
      IF (IEQ.lt.1) THEN
           PRINT*,'ERROR: Response # specified in EXACTPRM is <1.'
           STOP
      ELSEIF (IEQ.gt.100) THEN
           PRINT*,'ERROR: Response # specified in EXACTPRM is >100.'
           STOP
      ENDIF
C------------------------------------------------------------------
C  STEP1: Variable Assignments
C         Modify the following lines of code so that they use the
C         variable names (in the order that they appear in the .dat
C         file).  Note that you must modify the format statement as
```

```
C         as well as the variable assignment statement.  Also, change
C         the file name for unit 98 to whatever is appropriate.
C
      CFWINGAL = XSTAR(1)
      CFWINGTI = XSTAR(2)
      CFWINGCO = XSTAR(3)
      CFEMPAL = XSTAR(4)
      CFEMPTI = XSTAR(5)
      CFEMPCO = XSTAR(6)
      CFBODYAL = XSTAR(7)
      CFBODYTI = XSTAR(8)
      CFBODYTI = XSTAR(9)
      CFLGAL = XSTAR(10)
      CFLGTI = XSTAR(11)
      CFLGCO = XSTAR(12)
      CFNACAL = XSTAR(13)
      CFNACTI = XSTAR(14)
      CFNACCO = XSTAR(15)
      CFENG = XSTAR(16)
      CFTREV = XSTAR(17)
      CFENAC = XSTAR(18)
      CFFUSY = XSTAR(19)
      CFAERO = XSTAR(20)
      CFHYCD = XSTAR(21)
      CFELCD = XSTAR(22)
      CFPNCD = XSTAR(23)
      CFACS = XSTAR(24)
      CFANTC = XSTAR(25)
      CFPOW = XSTAR(26)
      CFPACC = XSTAR(27)
      CFINST = XSTAR(28)
      CFAVON = XSTAR(29)
      CFHNDL = XSTAR(30)
C
C       CREATE THE CONTENTS OF varfile
C       Varfile looks like:
C               namelist variable value
C               namelist variable value
C               ...
C
        OPEN(UNIT=98,FILE="manuf.var",STATUS="UNKNOWN")
        WRITE(98,123) CFWINGAL
123     FORMAT("CMAN   CFWINGAL ",F10.4)
        WRITE(98,124) CFWINGTI
124     FORMAT("CMAN   CFWINGTI ",F10.4)
        WRITE(98,125) CFWINGCO
125     FORMAT("CMAN   CFWINGCO ",F10.4)
        WRITE(98,126) CFEMPAL
126     FORMAT("CMAN   CFEMPAL ",F10.4)
        WRITE(98,127) CFEMPTI
127     FORMAT("CMAN   CFEMPTI ",F10.4)
        WRITE(98,128) CFEMPCO
128     FORMAT("CMAN   CFEMPCO ",F10.4)
        WRITE(98,129) CFBODYAL
129     FORMAT("CMAN   CFBODYAL ",F10.4)
        WRITE(98,130) CFBODYTI
130     FORMAT("CMAN   CFBODYTI ",F10.4)
        WRITE(98,131) CFBODYCO
131     FORMAT("CMAN   CFBODYCO ",F10.4)
        WRITE(98,132) CFLGAL
132     FORMAT("CMAN   CFLGAL ",F10.4)
        WRITE(98,133) CFLGTI
133     FORMAT("CMAN   CFLGTI ",F10.4)
        WRITE(98,134) CFLGCO
134     FORMAT("CMAN   CFLGCO ",F10.4)
        WRITE(98,135) CFNACAL
135     FORMAT("CMAN   CFNACAL ",F10.4)
        WRITE(98,136) CFNACTI
136     FORMAT("CMAN   CFNACTI ",F10.4)
        WRITE(98,137) CFNACCO
137     FORMAT("CMAN   CFNACCO ",F10.4)
        WRITE(98,138) CFENG
138     FORMAT("CMAN   CFENG ",F10.4)
        WRITE(98,139) CFTREV
139     FORMAT("CMAN   CFTREV ",F10.4)
        WRITE(98,140) CFENAC
140     FORMAT("CMAN   CFENAC ",F10.4)
        WRITE(98,141) CFFUSY
141     FORMAT("CMAN   CFFUSY ",F10.4)
        WRITE(98,142) CFAERO
142     FORMAT("CMAN   CFAERO ",F10.4)
        WRITE(98,143) CFHYCD
143     FORMAT("CMAN   CFHYCD ",F10.4)
        WRITE(98,144) CFELCD
144     FORMAT("CMAN   CFELCD ",F10.4)
        WRITE(98,145) CFPNCD
145     FORMAT("CMAN   CFPNCD ",F10.4)
        WRITE(98,146) CFACS
146     FORMAT("CMAN   CFACS ",F10.4)
        WRITE(98,147) CFANTC
147     FORMAT("CMAN   CFANTC ",F10.4)
        WRITE(98,148) CFPOW
148     FORMAT("CMAN   CFPOW ",F10.4)
        WRITE(98,149) CFPACC
149     FORMAT("CMAN   CFPACC ",F10.4)
        WRITE(98,150) CFINST
150     FORMAT("CMAN   CFINST ",F10.4)
        WRITE(98,151) CFAVON
151     FORMAT("CMAN   CFAVON ",F10.4)
        WRITE(98,152) CFHNDL
152     FORMAT("CMAN   CFHNDL ",F10.4)
      GOTO 49
48    PRINT*,'ERROR: Couldn''t create varfile'
      STOP
49    CLOSE(UNIT=98)
C-------------------------------------------------------------
C  STEP 2: Set-up Run Script
C         Change the following statement so that it issues the
```

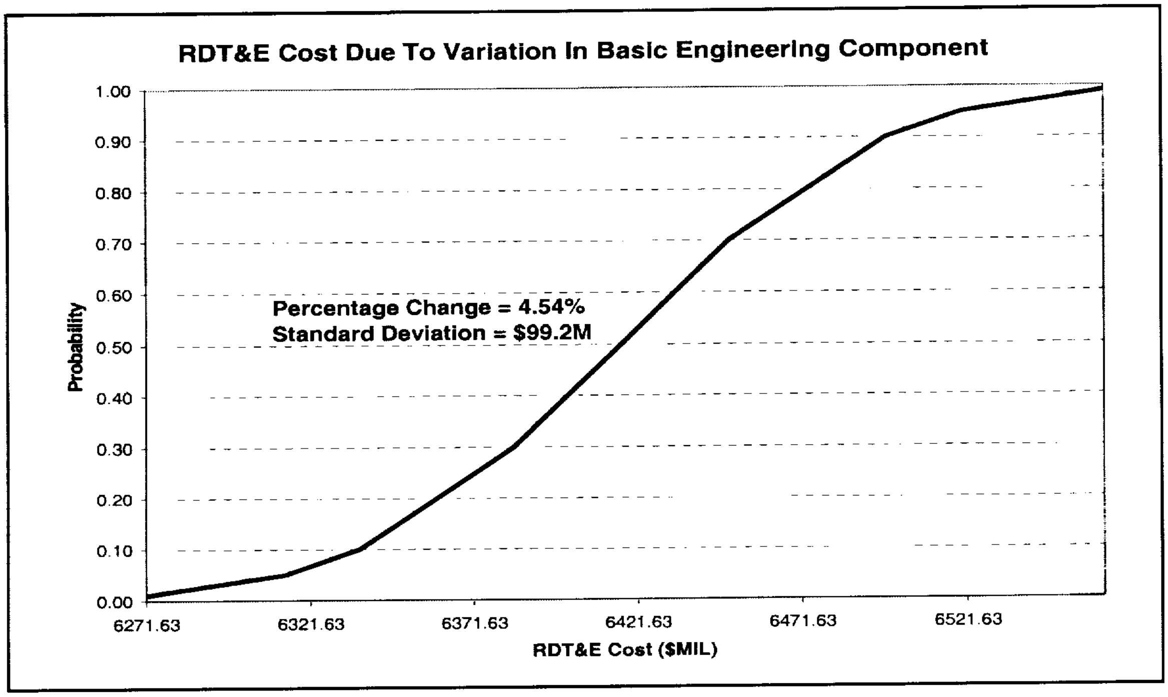
```
C          appropriate unix command to call you shell script
C
        CALL SYSTEM("./run.all")
C
C  run.all puts the response function in a file
C  named 'response'; response file looks like:
C                            response1
C                            response2
C                            response3
C                            ...
C
      OPEN(UNIT=98,FILE="response",STATUS="OLD",ERR=52)
50    READ(UNIT=98,FMT=*,END=51) R(N)
      N=N+1
C-------------------------------------------------------------
C
C  error trapping
C
      IF (N.eq.101) THEN
          PRINT*,'WARNING: > 100 responses in response file'
          N=100
          GOTO 51
      ENDIF
      GOTO 50
51    CLOSE(UNIT=98)
      RESPON=R(IEQ)
C
C  Error Trapping
C
      GOTO 60
52    print*,'ERROR: Response file does not exist.'
      STOP
60    IF (IERROR.ne.0) THEN
          PRINT*,'ERROR DETECTED- ABORTING!!'
          STOP
      ENDIF
C
C  Write Results Out to a Data File
C  Unit 96 = 'respon'= File containing all responses for 1-10
C  Unit 88= 'respon2'=File containing all responses for 11-20
C  Unit 99 = 'XSTAR' = Output file for XSTAR(1-9) + RESPON
C  Unit 97 = 'XSTAR2'= Output data file for XSTAR(10-18)
C  Unit 89= 'XSTAR3'= Output file for XSTAR(19-27) + RESPON
C  Unit 90= 'respon3'=File containing all responses for 21-30
C  Unit 91= 'XSTAR4'= Output file for XSTAR(28-36) + RESPON
C  Note: XSTAR2 is automatically created if XSTAR(10).ne.0
C  Note: respon2 is automatically created if n.gt.10
C
       IF (NRUNS.EQ.1) THEN
           OPEN(UNIT=99,FILE='XSTAR',STATUS='UNKNOWN')
           OPEN(UNIT=96,FILE='respon',STATUS='UNKNOWN')
           WRITE(99,5)
           WRITE(96,7)
           If (XSTAR(9).ne.0.) THEN
               OPEN(UNIT=97,FILE='XSTAR2',STATUS='UNKNOWN')
               WRITE(97,6)
               NVARS=1
           ENDIF
           If (XSTAR(19).ne.0.) THEN
               OPEN(UNIT=89,FILE='XSTAR3',STATUS='UNKNOWN')
               WRITE(89,9)
               NVARS=2
           ENDIF
           If (XSTAR(28).ne.0.) THEN
               OPEN(UNIT=91,FILE='XSTAR4',STATUS='UNKNOWN')
               WRITE(91,11)
               NVARS=3
           ENDIF
           IF (N.GT.10) THEN
               OPEN(UNIT=88,FILE='respon2',STATUS='UNKNOWN')
               WRITE(88,8)
           ENDIF
           IF (N.GT.20) THEN
               OPEN(UNIT=90,FILE='respon3',STATUS='UNKNOWN')
               WRITE(90,10)
           ENDIF
       ENDIF
       WRITE(96,12) NRUNS,R(1),R(2),R(3),R(4),R(5),R(6),R(7),
      +R(8),R(9),R(10)
       IF (N.GT.10) THEN
           WRITE(88,12) NRUNS, R(11),R(12),R(13),R(14),R(15),
      +R(16),R(17),R(18),R(19),R(20)
       ENDIF
       IF (N.GT.20) THEN
           WRITE(90,12) NRUNS, R(21),R(22),R(23),R(24),R(25),
      +R(26),R(27),R(28),R(29),R(30)
       ENDIF
       WRITE(99,12) NRUNS,XSTAR(1),XSTAR(2),XSTAR(3),XSTAR(4),
      +XSTAR(5),XSTAR(6),XSTAR(7),XSTAR(8),XSTAR(9),RESPON
       IF (NVARS.GE.1) THEN
           WRITE(97,12) NRUNS,XSTAR(10),XSTAR(11),XSTAR(12),
      +        XSTAR(13),XSTAR(14),XSTAR(15),XSTAR(16),XSTAR(17),
      +        XSTAR(18),RESPON
       ENDIF
       IF (NVARS.GE.2) THEN
           WRITE(89,12) NRUNS,XSTAR(19),XSTAR(20),XSTAR(21),
      +        XSTAR(22),XSTAR(23),XSTAR(24),XSTAR(25),XSTAR(26),
      +        XSTAR(27),RESPON
       ENDIF
       IF (NVARS.GE.3) THEN
           WRITE(91,12) NRUNS,XSTAR(28),XSTAR(29),XSTAR(30),
      +        XSTAR(31),XSTAR(32),XSTAR(33),XSTAR(34),XSTAR(35),
      +        XSTAR(36),RESPON
       ENDIF
         RETURN
C
C  Formatting for Output Files
C
```

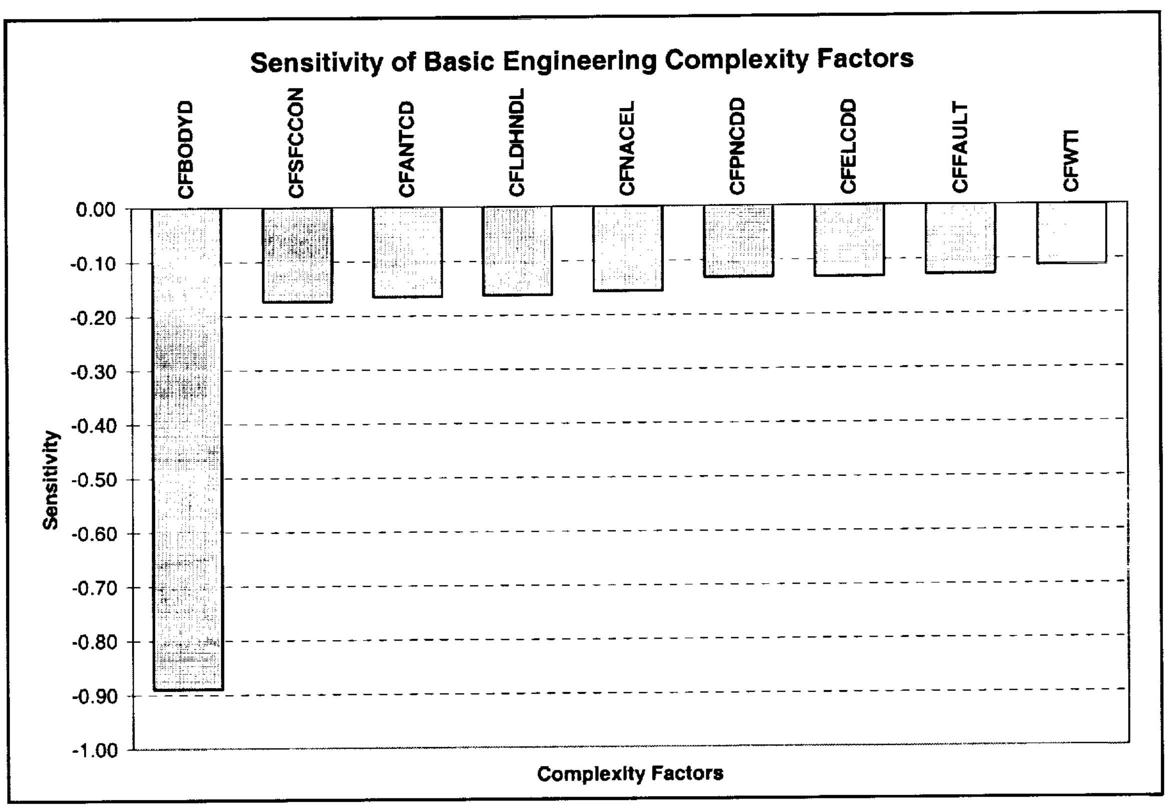
```
5     FORMAT('CASE     X1          X2          X3          X4          ',
     +' X5       X6          X7          X8          X9          ',
     +'RESPON')
6     FORMAT('CASE     X10         X11         X12         X13         ',
     +' X14      X15         X16         X17         X18         ',
     +'RESPON')
7     FORMAT('CASE     R1          R2          R3          R4          ',
     +' R5       R6          R7          R8          R9          ',
     +' R10  ')
12    FORMAT(I3,1x,E11.5,1x,E11.5,1x,E11.5,1x,E11.5,1x,E11.5,1x,E11.5,
     +1x,E11.5,1x,E11.5,1x,E11.5,1x,E11.5)
8     FORMAT('CASE     R11         R12         R13         R14         ',
     +' R15      R16         R17         R18         R19         ',
     +' R20  ')
9     FORMAT('CASE     X19         X20         X21         X22         ',
     +' X23      X24         X25         X26         X27         ',
     +'RESPON')
10    FORMAT('CASE     R21         R22         R23         R24         ',
     +' R25      R26         R27         R28         R29         ',
     +' R30  ')
11    FORMAT('CASE     X28         X29         X30         X31         ',
     +' X32      X33         X34         X35         X36         ',
     +'RESPON')
      END
```

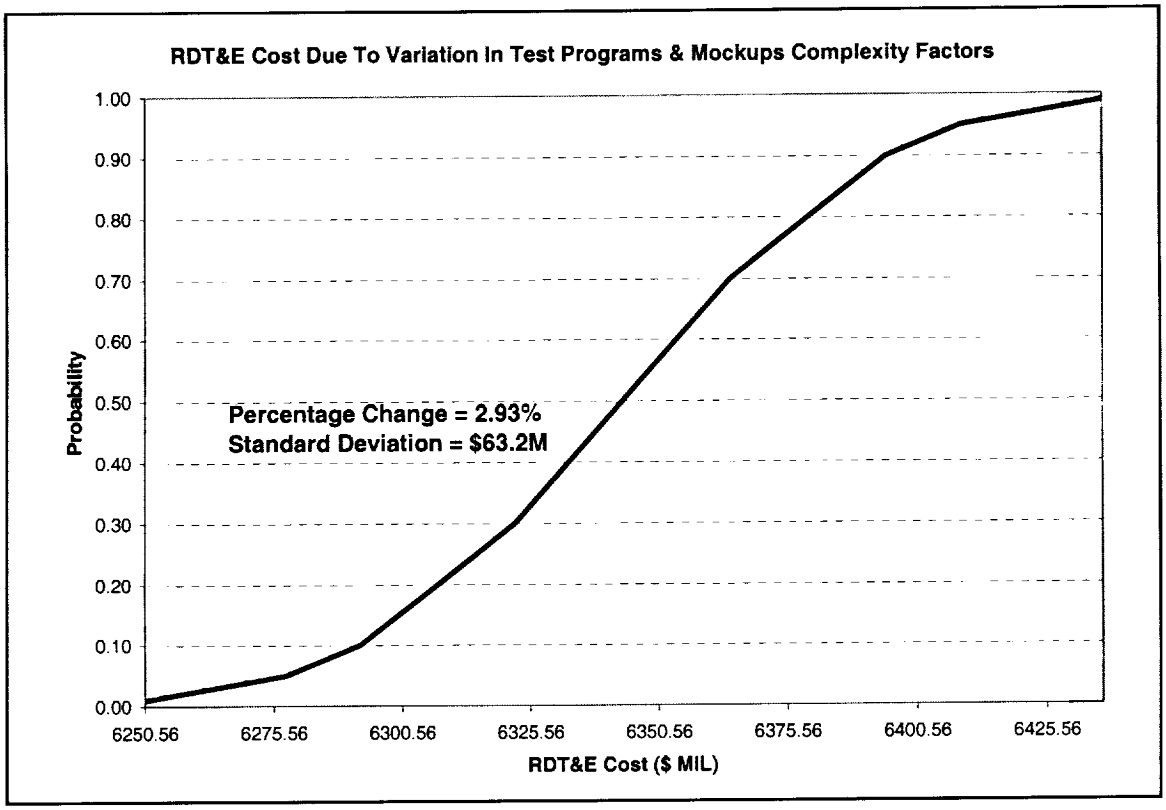
"run.all": Shellscrip executed by RESPON.f to automate writing of input files and their execution.

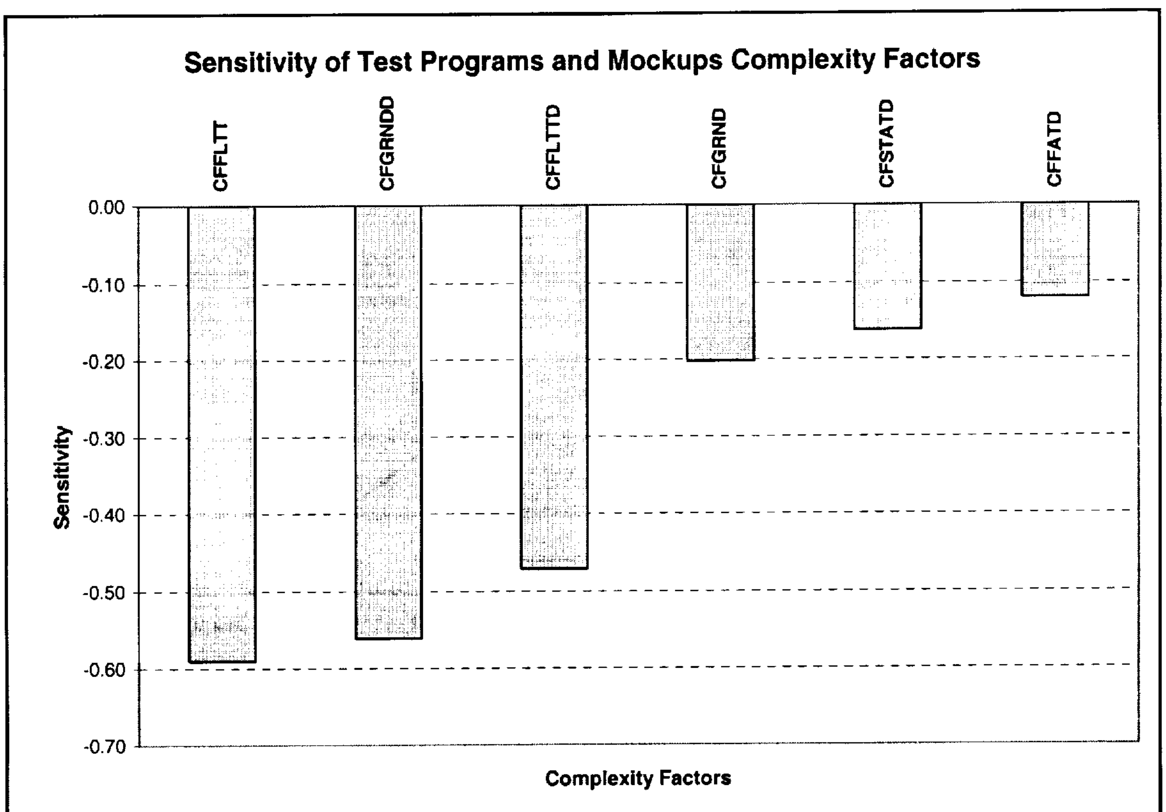
```
#!/bin/ksh
echo "*** Running the shell script ***"
tsw -input alcca.in -output case.in manuf.var
2>/dev/null
echo "*** Running  alcca***"
../alcca case.in case.out
parse -search "Price" -read 3 -occurance 25 -
offset 0 case.out > response 2>/dev/null
#tail -15 case.out >> cases
echo "" >> cases
cat response >> response.log
rm manuf.var
```

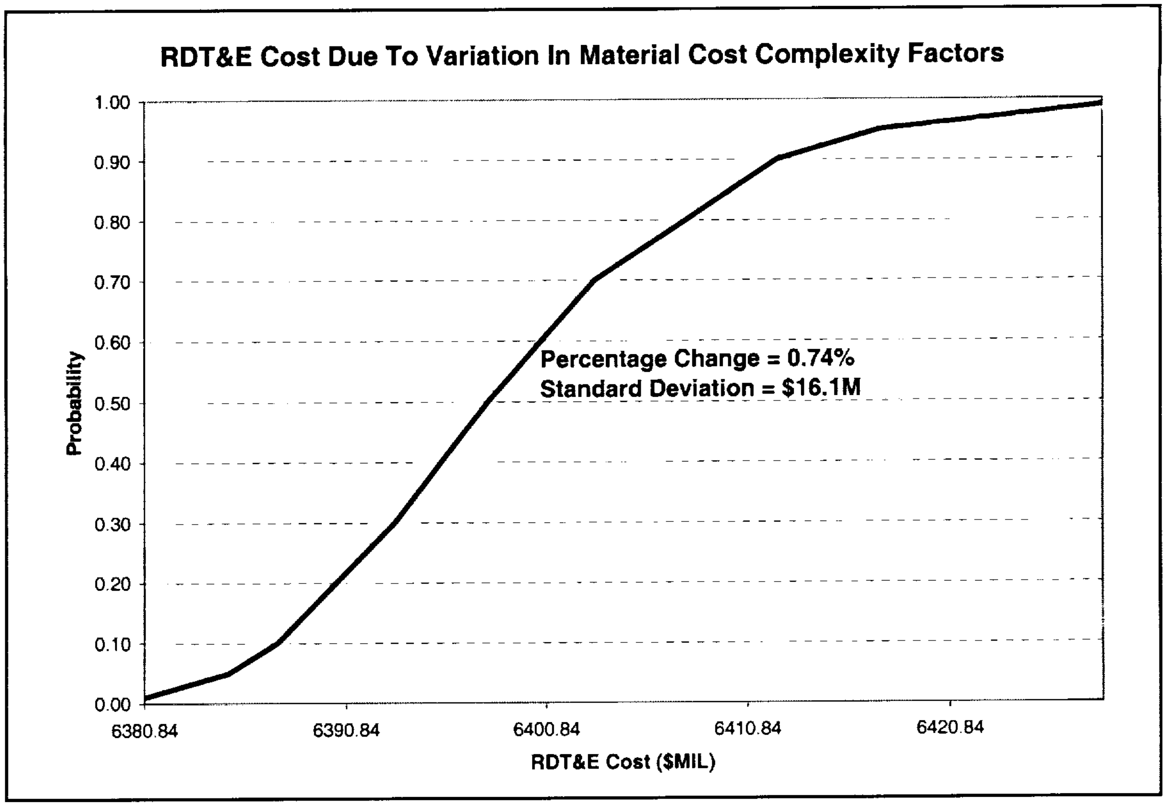
APPENDIX D: RDT&E CODE FIDELITY FIGURES

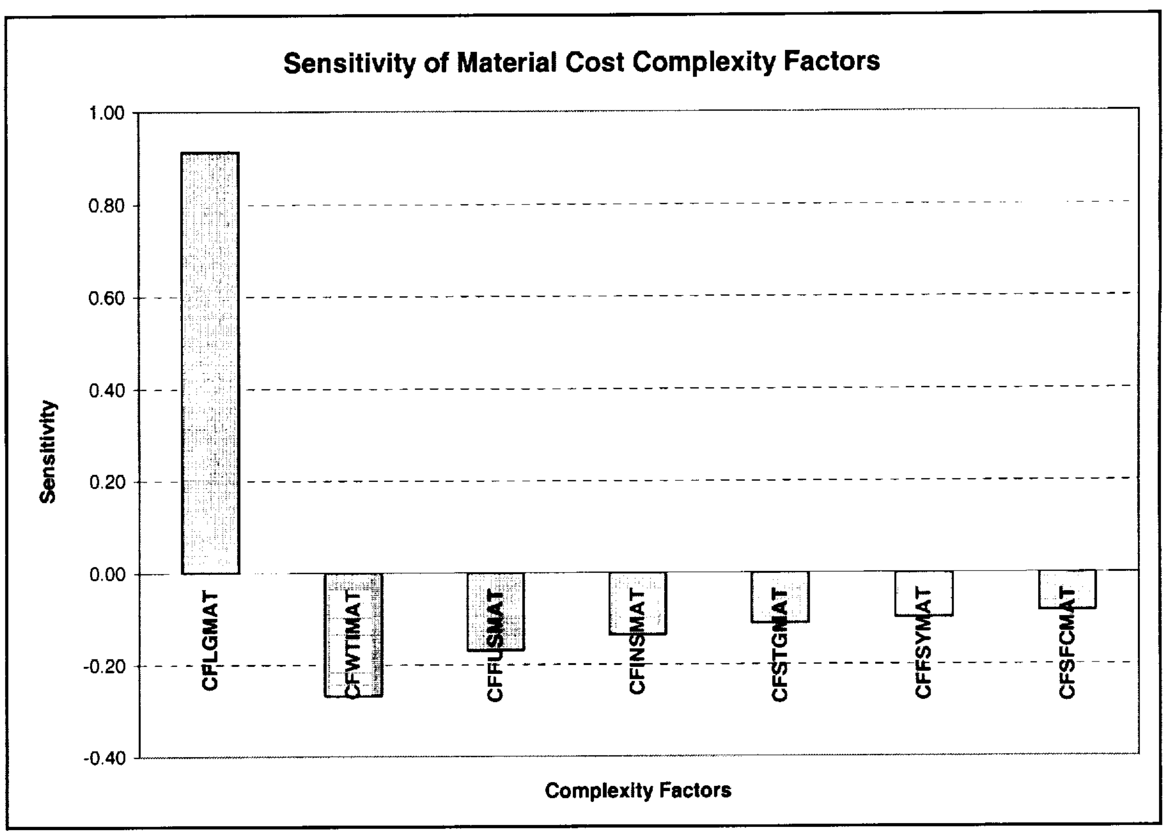


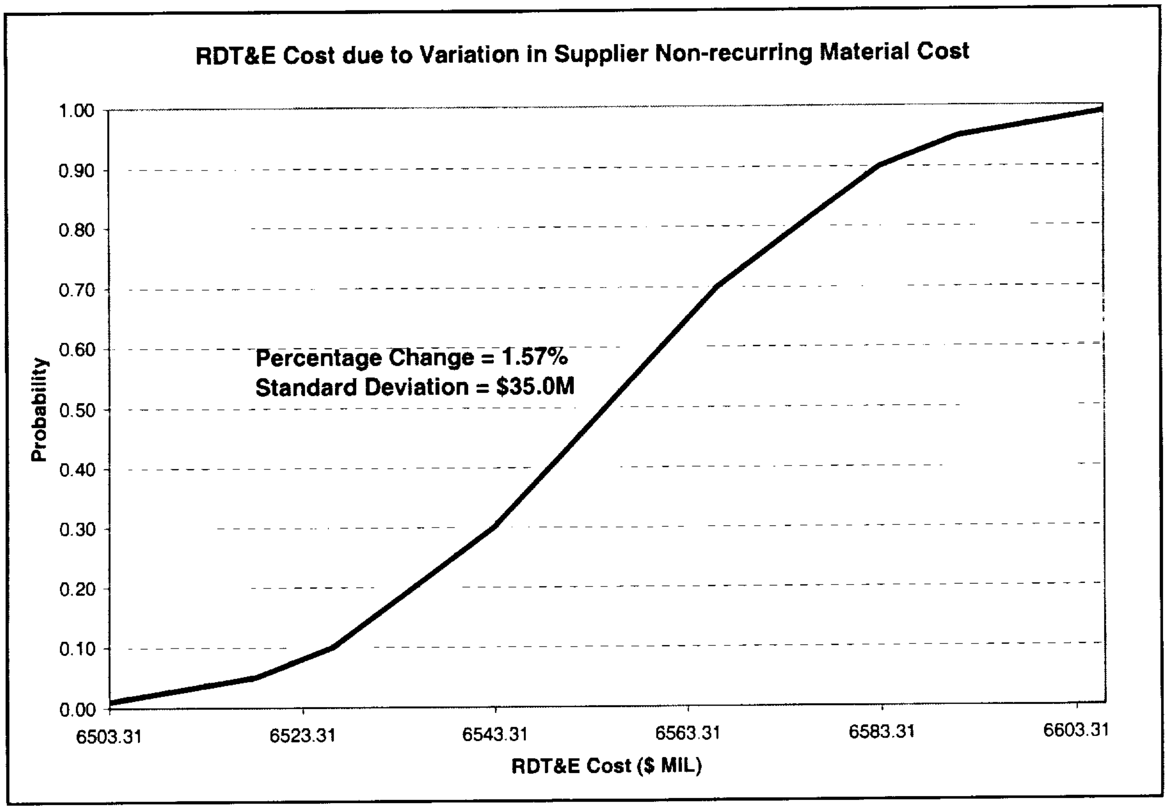


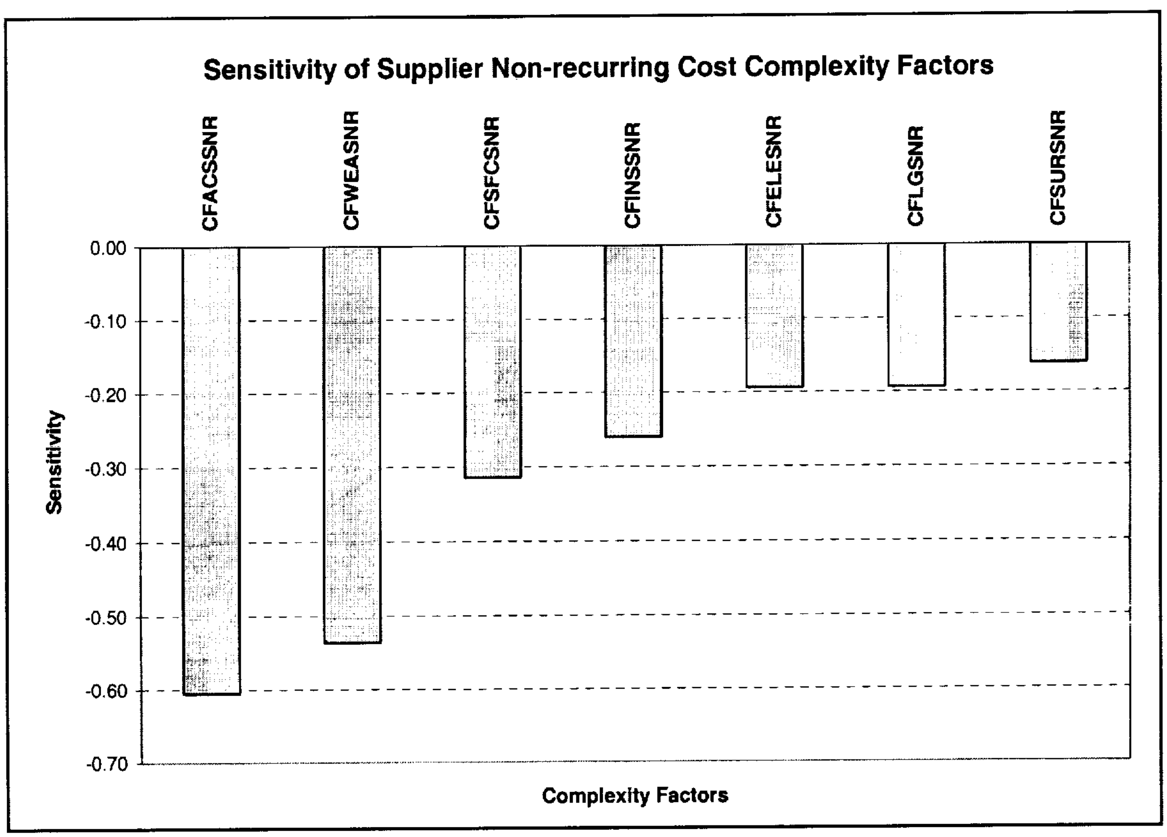

RDT&E Cost Due To Variation In Test Programs & Mockups Complexity Factors
Probability
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Percentage Change = 2.93%
Standard Deviation = $63.2M
6250.56
6275.56
6300.56
6325.56
6350.56
6375.56
6400.56
6425.56
RDT&E Cost ($ MIL)

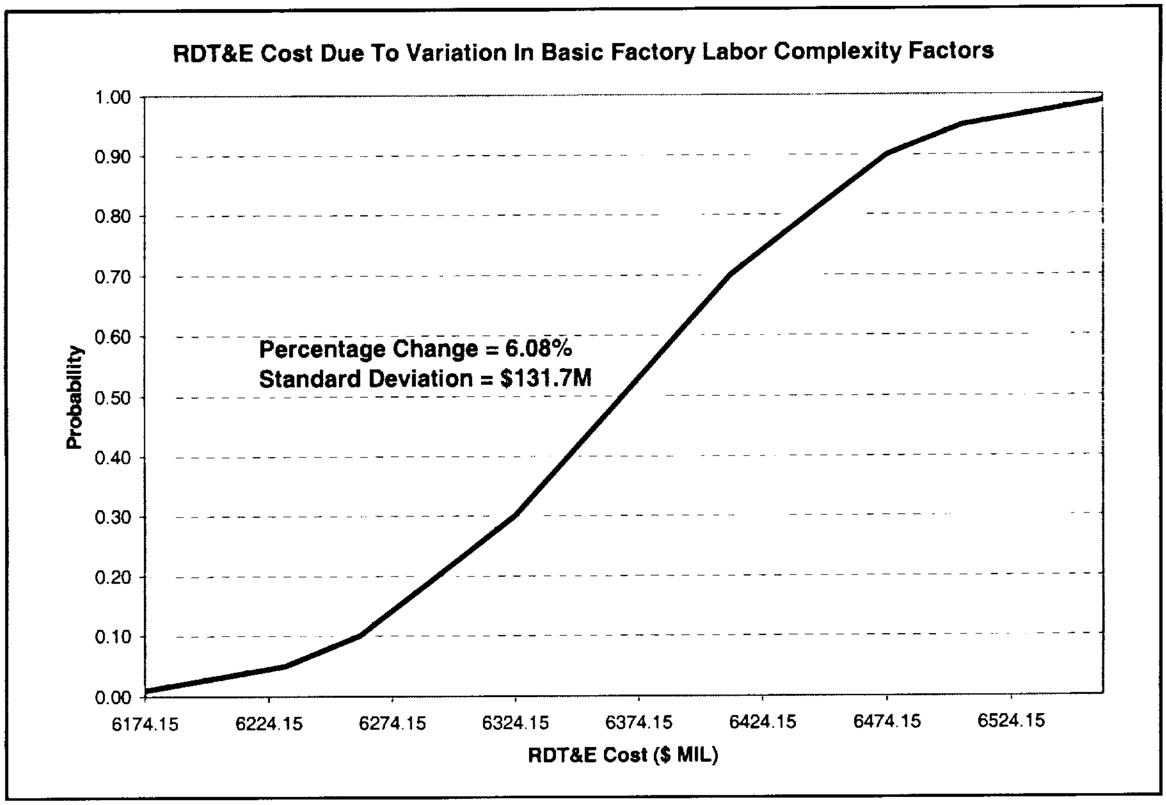

Sensitivity of Test Programs and Mockups Complexity Factors
CFFLTT
CFGRNDD
CFFLTTD
CFGRND
CFSTATD
CFFATD
Sensitivity
0.00
-0.10
-0.20
-0.30
-0.40
-0.50
-0.60
-0.70
Complexity Factors

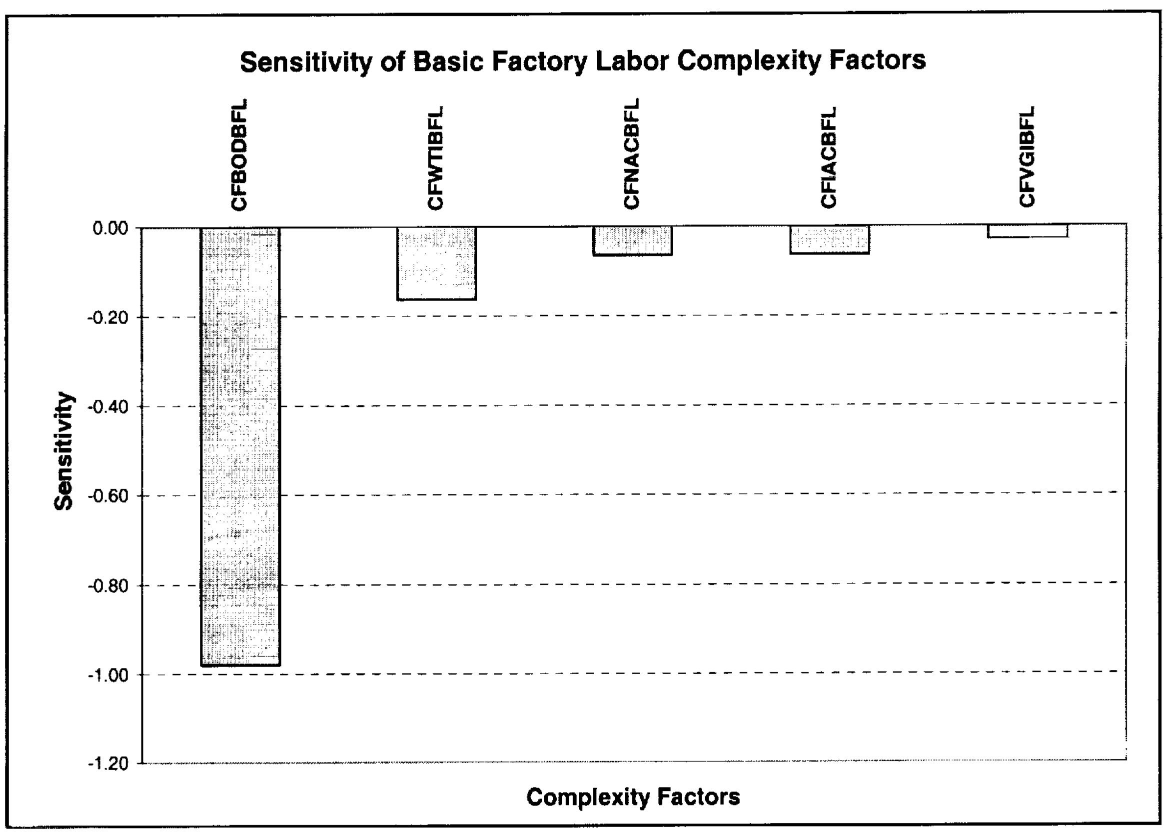

RDT&E Cost Due To Variation In Material Cost Complexity Factors
Probability
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Percentage Change = 0.74%
Standard Deviation = $16.1M
6380.84
6390.84
6400.84
6410.84
6420.84
RDT&E Cost ($MIL)

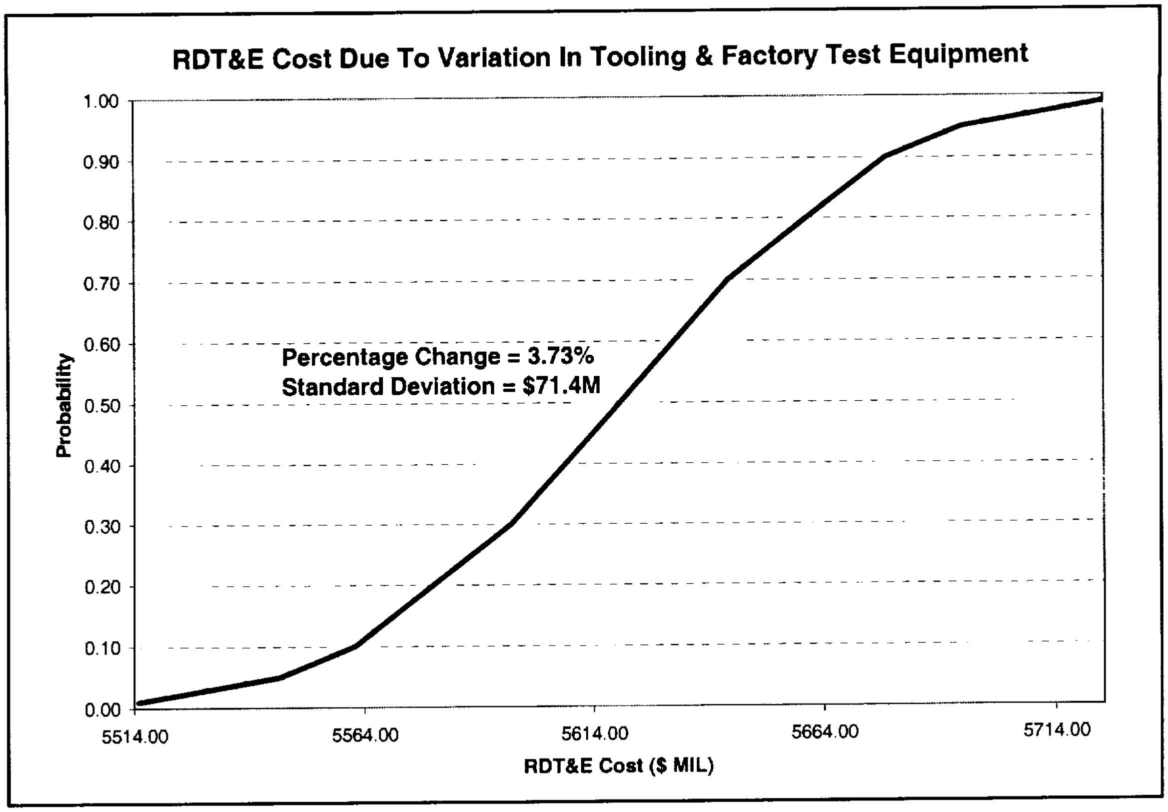

Sensitivity of Material Cost Complexity Factors
Sensitivity
1.00
0.80
0.60
0.40
0.20
0.00
-0.20
-0.40
CFLGMAT
CFWTIMAT
CFFUSMAT
CFINSMAT
CFSTGMAT
CFFSYMAT
CFSFCMAT
Complexity Factors

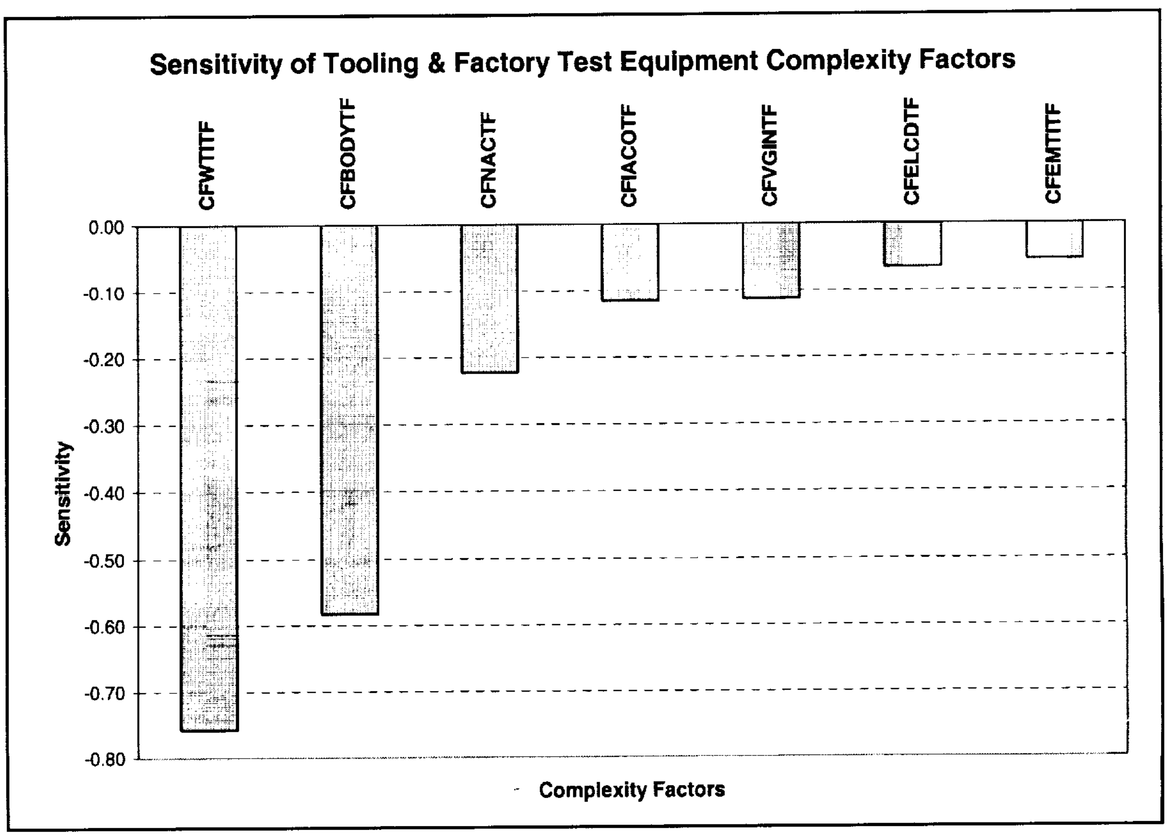

RDT&E Cost due to Variation in Supplier Non-recurring Material Cost
Percentage Change = 1.57%
Standard Deviation = $35.0M
Probability
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
6503.31
6523.31
6543.31
6563.31
6583.31
6603.31
RDT&E Cost ($ MIL)


Sensitivity of Supplier Non-recurring Cost Complexity Factors
CFACSSNR
CFWEASNR
CFSFCSNR
CFINSSNR
CFELESNR
CFLGSNR
CFSURSNR
Sensitivity
0.00
-0.10
-0.20
-0.30
-0.40
-0.50
-0.60
-0.70
Complexity Factors


RDT&E Cost Due To Variation In Basic Factory Labor Complexity Factors
Percentage Change = 6.08%
Standard Deviation = $131.7M
Probability
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
6174.15
6224.15
6274.15
6324.15
6374.15
6424.15
6474.15
6524.15
RDT&E Cost ($ MIL)


Sensitivity of Basic Factory Labor Complexity Factors
CFBODBFL
CFWTIBFL
CFNACBFL
CFIACBFL
CFVGIBFL
Sensitivity
0.00
-0.20
-0.40
-0.60
-0.80
-1.00
-1.20
Complexity Factors


RDT&E Cost Due To Variation In Tooling & Factory Test Equipment
Percentage Change = 3.73%
Standard Deviation = $71.4M
Probability
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
5514.00
5564.00
5614.00
5664.00
5714.00
RDT&E Cost ($ MIL)


Sensitivity of Tooling & Factory Test Equipment Complexity Factors
CFWTITF
CFBODYTF
CFNACTF
CFIACOTF
CFVGINTF
CFELCDTF
CFEMTITF
Sensitivity
0.00
-0.10
-0.20
-0.30
-0.40
-0.50
-0.60
-0.70
-0.80
Complexity Factors