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An Application of a Technology Impact Forecasting (TIF) Method to an Uninhabited Combat Aerial Vehicle

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ABSTRACT

In today's atmosphere of lower U.S. defense spending and reduced research budgets, determining how to allocate resources for research and design has become a critical and challenging task. In the area of aircraft design there are many promising technologies to be explored, yet limited funds with which to explore them. In addition, issues concerning uncertainty in technology readiness as well as the quantification of the impact of a technology (or combinations of technologies), are of key importance during the design process. The methodology presented in this paper details a comprehensive and structured process in which to explore the effects of technology for a given baseline aircraft. This process, called Technology Impact Forecasting (TIF), involves the creation of a forecasting environment for use in conjunction with defined technology scenarios. The advantages and limitations of the method will be discussed, as well its place in an overall methodology used for technology infusion. In addition, the example TIF application used in this paper, that of an Uninhabited Combat Aerial Vehicle, serves to illustrate the applicability of this methodology to a military system.

MOTIVATION

In the past, military aircraft design has been characterized by an emphasis to design for optimum performance. Aircraft success was defined in terms of the aircraft's ability to perform at least as well as the requirements to which it was designed, including adaptability to rapidly changing threat environments. Recent imperatives, however, have shifted the emphasis from performance to overall system effectiveness as a key measure of merit for the aircraft. *Design for affordability* is defined as the design and evaluation of a system that is no longer dictated solely by mission capability or selected product characteristics. It is instead a robust decision-making process that balances the **benefits** and **costs** of these design decisions while reducing and mitigating the risk associated with them.

Furthermore, in traditional aircraft design, most design decisions are made relatively early in the process, when the designer (or design team) has the least available knowledge about the proposed new aircraft. Design decisions lock in financial commitments, so the bulk of the cost is committed early in the design process. As these decisions are made, design freedom falls off rapidly. A paradigm shift, founded on the notion of Integrated Product and Process Design (IPPD), is now widely accepted. IPPD seeks to bring more knowledge about the system life cycle to an earlier stage of the design process, in an attempt to delay cost commitments and also keep design freedom open [1]. In other words, the designer needs to understand and quantify the implications of his/her decisions earlier in the design process in order to effectively reduce cost.

This need for more information earlier in the design process implies the need for a comprehensive and robust forecasting environment. This environment must be able to predict the technical feasibility and economic viability of the aircraft for a given probability of success. But since this economic viability is a direct result of design decisions made early in the design process, and because these design decisions increasingly involve the addition of a new technology or combinations of technologies, this forecasting environment must necessarily include the ability to quantify the impact of technology infusion decisions.

The difficulty in creating such an environment lies with the modeling of the technologies being considered. A new technology or improvement concept may or may not be completely defined, and is often identified in the context of some constraint that is being violated or an objective to be satisfied. In addition, it is often more desirable to understand the impact of a new technology long before committing to the expense and risk of its full development. Thus, a way to assess new or proposed technologies is to model them as the changes they cause to key disciplinary metrics. These metrics are then linked, through the physics of the problem, to all pertinent system responses.

In this paper the authors present a methodology called Technology Impact Forecasting (TIF) that allows the preliminary aircraft designer to quantify the effects and impacts of new technologies on a given baseline aircraft. TIF is described in a step-by-step fashion and includes an overview of the tools and concepts necessary to create the TIF environment. The definition and use of technology scenarios are explained, as well as the benefits and limitations to the method. Finally, although some civil aircraft examples of TIF have been demonstrated [2,3,4,5] the method is also applicable to military systems, and is demonstrated here for an Uninhabited Combat Air Vehicle (UCAV) concept provided by Lockheed Martin Tactical Aircraft Systems.

OVERALL METHODOLOGY

In order to discuss the TIF methodology, it is first necessary to describe the overall technology infusion methodology. Developed at the Aerospace Systems Design Lab at Georgia Institute of Technology, this methodology is a process that enables the designer to identify, evaluate the impact of, and select technologies to be applied to a given aircraft or system. This robust process outlines the steps that need to be taken, yet allows for a variety of analytical procedures to be used. TIF, then, becomes one specific path taken through a part of the overall process, and begins with the assumption of a realistic baseline, which may or may not be feasible or economically viable, and that generic technologies are to be explored. The complete flowchart is shown in Figure 1, with the TIF component clearly labeled. For a more complete explanation of other components of the process, the reader is referred to References [3,6,7].

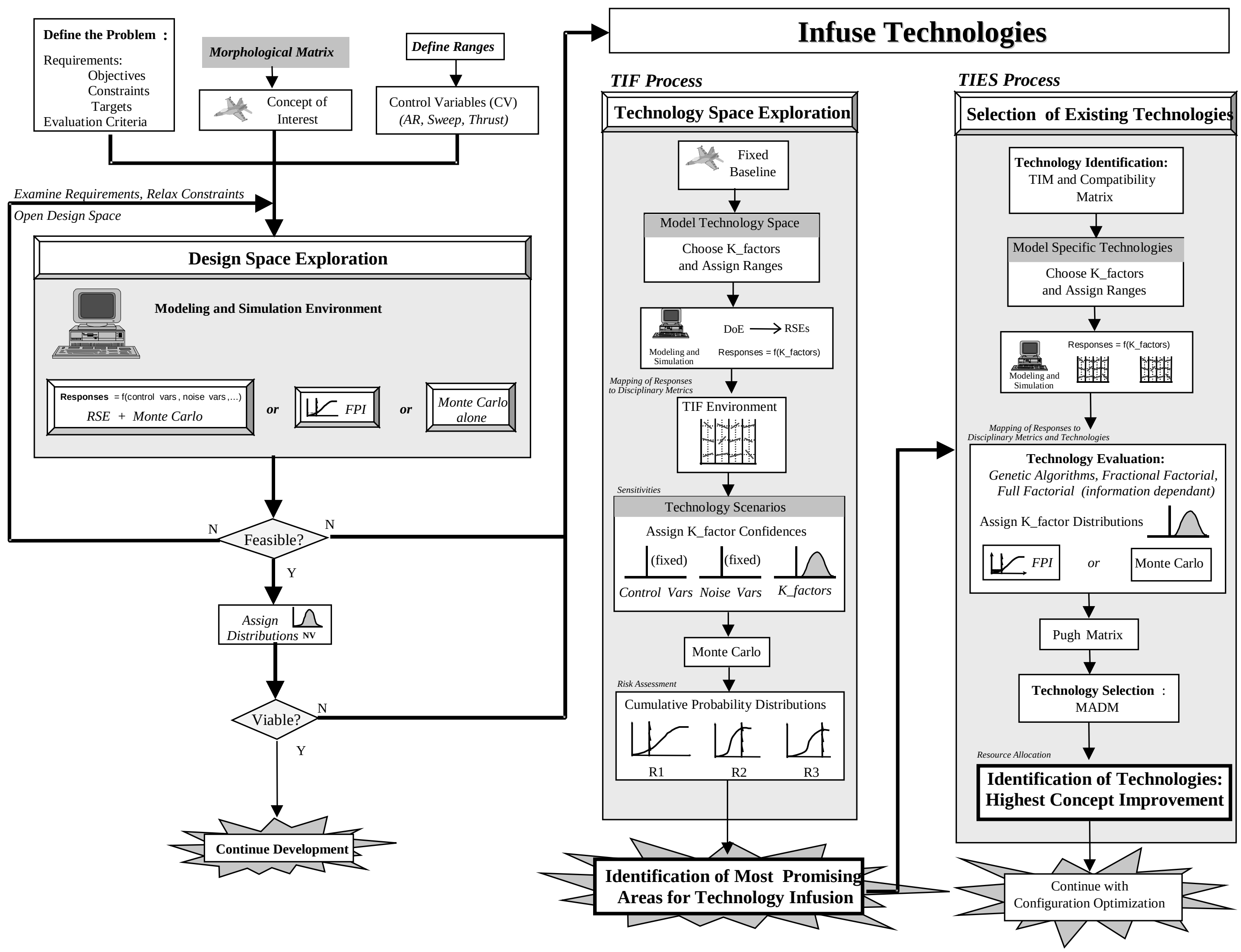


Figure 1- Technology Assessment Process

CONCEPTS AND TOOLS

The TIF methodology links together several tools and concepts to produce a cohesive process. A basic knowledge of these tools is helpful in understanding the overall process, and thus brief summaries of these tools are presented here. For more detailed explanations and examples of these tools the reader is referred to References [8,9,10,11,12].

DESIGN OF EXPERIMENTS AND RESPONSE SURFACE METHODOLOGY

The Response Surface Methodology (RSM) is an efficient, multivariate approach to modeling that defines clear cause-and-effect relationships between design variables and system responses. It is based on a statistical approach to building and rapidly assessing empirical models [8,9]. In general, in order to thoroughly establish a cause-and-effect relationship between given system variables and system responses, there must exist a complete set of knowledge about the system. Because this complete knowledge is difficult (and often impossible) to obtain and identify, this knowledge can be approximated with an empirically-generated deterministic relationship. The RSM methodology, employing a Design of Experiments (DOE) strategy, aids in this by selecting a subset of combinations of variables to run which will guarantee orthogonality (i.e. the independence of the various design variables) and will allow for the creation of a statistically representative model. This technique allows the maximum amount of information to be gained from the fewest number of experiment executions, and thus provide trade study results in a more cost-effective manner.

A Design of Experiments is chosen that is suitable for the problem being analyzed. This DOE is expressed as a table of experimental cases, specifying the values of the variables to be used for each case. These values are usually normalized to a low, high, or midpoint value of the variable (represented by a –1, 1, and 0 to aid in the statistical analysis). An example DOE table is shown in Table 1. Typically, the response is first modeled using a second order quadratic equation of the form:

$$R = b_o + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} b_{ij} x_i x_j$$

R is the desired response term
b_0 is the intercept term
bi are regression coefficients for the first order terms
bii are coefficients for the pure quadratic terms
bij are the coefficients for the cross-product terms
x_i and x_j are the independent variables
k is the total number of variables considered

Other forms of the equation may be used. If the non-linearities of the problem are not sufficiently captured using this form of the equation, then transformations of the variables and/or the responses need to be found which improve the fidelity/accuracy of the model.

These Response Surface Equations (RSEs) are created by running the variable combinations as defined by the DOE table. The resulting responses for each run are then added to the table (the blank columns in Table 1). A statistical analysis package (in this case, JMP [13]) provides the ability to take this data and perform a regression analysis to create these polynomial representations (Analysis of Variance or ANOVA) to determine these sensitivities, relative importance, fidelity, etc. JMP also aids in providing the experimental setup, as well as facilitating visualization of the results. The resulting RSEs, thus, are in actuality meta-models of the synthesis code used in their creation. The equations represent a quick, accurate way of determining a response for given values of variables (as long as these values are within the range of variables for which the RSE is defined).

Table 1- Example Design of Experiments Table

CASE	Wing Area	Sweep	Engine Scale Factor	Response 1 (R_1)	…Response n (R_n)
1	-1	-1	-1		
2	-1	-1	1		
3	-1	1	-1		
4	-1	1	1		
5	1	-1	-1		
6	1	-1	-1		
7	1	1	-1		
8	1	1	1		
9	-1	0	0		
10	1	0	0		
11	0	-1	0		
12	0	1	0		
13	0	0	-1		
14	0	0	1		
15	0	0	0		

The Response Surface Methodology is comprised of two basic steps, facilitated by the program JMP. The first is referred to as the effect screening. It creates a linear model which is used to determine the sensitivity of a response to various inputs and to screen out, using a Pareto analysis, those variables that do not contribute significantly to the response. The second step is called surface fitting, and yields a polynomial representation that gives the response as a function of the most important input parameters. These steps are illustrated in Figure 2.

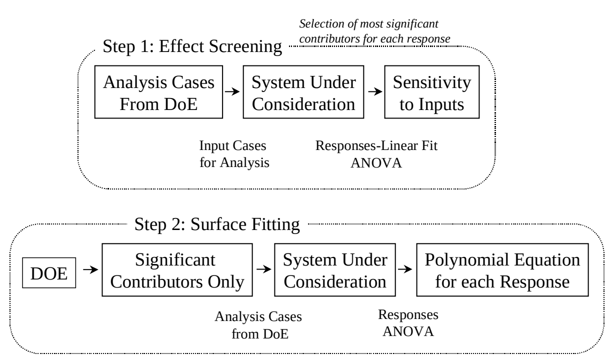


Figure 2-Basic Steps of Response Surface Methodology

The benefit of RSM is that it provides an almost instantaneous evaluation time. The equations are portable and can be run in a spreadsheet, a computer code, or even by hand. Within the variable ranges given, the results can be highly accurate. Caution should be exercised as to the ranges of applicability of these equations since they do not, as all polynomials, extrapolate well. If variable values are needed outside the range of the RSEs generated, a new DOE experiment must be created and run. In addition, the equations are continuous, and thus cannot account for discontinuities or higher order effects.

PREDICTION PROFILES

Once the RSEs are created, JMP can then be used to create prediction profiles. These profiles allow the designer to see graphically how the responses vary with respect to changes in each of the variables. Figure 3 shows a sample prediction profile. The lines in Figure 3 denote the sensitivity of the response with respect to each variable. So, in essence, they are the partial derivatives of the response with respect to the variable with all other variables set at a given value. A flat or barely sloped line indicates that the variable does not have much impact on that response.

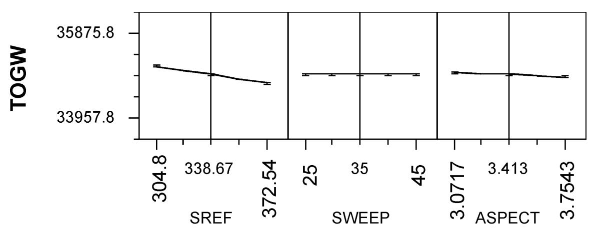


Figure 3- Example of a Prediction Profile

When using the prediction profile tool while in JMP (as opposed to a hard copy printout of the graph), the program allows the designer to change the value of the variables by using a click and drag technique. Using the RSEs, the graph is then updated in real time to show the new values of the responses. In this way the designer can manipulate the equations to gain insight into the problem and also to seek optimal configurations.

PROBABILISTIC ANALYSIS

Technology Mappings and K_factors

A new technology concept is characterized by ambiguity and uncertainty with regards to its performance, cost, etc. This uncertainty is directly proportional to its development status and the uncertainty is at its greatest in the early phases of the technology's development. In order to introduce these uncertainties into the model, variability must be added to each input variable. When applied to new technologies, the variability is introduced through the use of technology factors (in other words, a disciplinarian metric multiplier) referred to here as K_factors. A technology is mapped against a vector of K_factors representing primary and secondary effects. For example, Figure 4 shows an example shape distribution for the K_factor associated with wing weight. This particular shape distribution would be appropriate for a technology that is expected to give a 7.5% decrease in wing weight, yet recognizes, through the use of a skewed distribution, that there is some chance of achieving either a greater or lesser change in wing weight. Other distribution shapes that may be used include a uniform distribution, used for when each value is as likely as another value, or a normal distribution which is used when there is an equal uncertainty around a particular value.

Once defined, the K_factors become the variables used in the DOE table and subsequent RSE generation. The responses, in the form of the response surface equations, are functions of the individual K_factors. Each technology concept then, becomes a vector of these variables. In essence, a K_factor becomes a "technology dial". The methodology establishes a direct relationship between the technology dials and the responses of interest. By examining the prediction profile, created by varying the K_factors in the DOE instead of design variables, the designer can identify their sensitivities to the responses. Remembering that the K_factors directly represent parts of technology concepts, the designer can clearly identify those factors which have a significant impact on the responses. Later, these sectional technology concepts, represented by their K_factors, can be grouped together (to create a vector) to form "technology scenarios", with each scenario representing a complete technology concept. In this way, the designer can analyze both the benefits and the risks associated with a technology concept.

A final advantage to use the K_factors is that they represent a smooth relationship between the K_factors and the system responses, based on the shape distributions given. This allows the designer to select not only the endpoints of the technology (in other words, having the technology "on" or "off") but also lets him/her select an intermediate value of a technology improvement and assess its impact on the design. For example, if a K_factor represents a technology that impacts aircraft L/D ratio, the designer could "dial" in a maximum value of, say, 15% improvement and quantify this impact. However, the designer could also explore a 10% improvement, a 5% improvement, or any other value that is contained in the range of the K_factor that was used to produce its RSE.

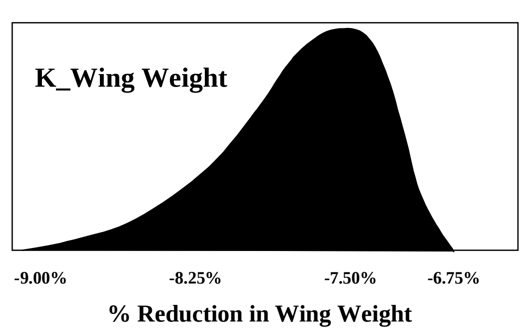
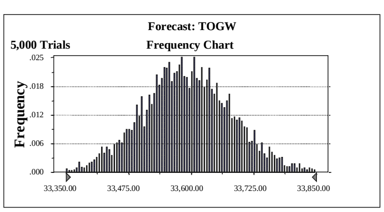


Figure 4- Notional Shape Function for a Wing Weight Reduction Technology Dial

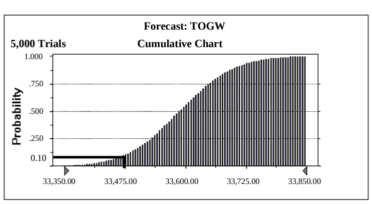
Monte Carlo Simulation

After determining shape distributions for all of the variables, a Monte Carlo simulation, utilizing the Crystal Ball [14] software, is run. The program achieves this by randomly choosing variable values based on the shape distributions given. The responses are then calculated through the use of the RSEs. The results are probability distributions that indicate the likeliness of achieving a certain result. Figure 5 shows examples of the two ways that the probabilistic results can be presented. The first is the probability density function (PDF), which depicts the frequency that a certain value is observed in the simulation. The second is the integral of the PDF, called the cumulative distribution function (CDF), which shows the probability or confidence of achieving a certain value. By examining the CDF in Figure 5, the designer can see that there is about a 10% chance of achieving a takeoff gross weight of 33,475 pounds or less, but a 100% chance of achieving a takeoff gross weight of less than 33,850 pounds (find 33,475 on the horizontal axis, follow it up to where it hits the curve, and read the corresponding probability from the vertical axis).

The designer can interpret information from the probability distributions in a number of ways. If the distribution has quite a bit of variability, but some or most of it fulfills the requirement being examined, this would suggest the benefit of investing more resources into that technology concept. This addition of resources could have the effect of narrowing the uncertainty associated with the technology. On the other hand, if the distribution indicates that the probability of meeting the requirement is low, then it might be more provident to examine other technology options before investing money into a technology that might not be sufficient to solve the problem. This kind of system-level investigation can also show how much the detrimental effects of the technology are penalizing the system. This information, shared with the disciplinary experts that engage in the development of the technologies, could be investigated to see how resources need to be allocated towards reducing the penalties, as opposed to improving benefits.



Example of a Probability Density Function



Example of a Cumulative Distribution Function

Figure 5- Examples of a Probability Density Function and a Cumulative Probability Function

TIF METHODOLOGY

The Technology Impact Forecasting method is a technique that generates an environment that allows the quantitative exploration, including sensitivities, of aircraft goals and constraints (such as weight, performance, and economics) of new technology concepts. The overall methodology is represented by Figure 6. The following steps and tools are linked together to create the TIF process and are described below.

In order to start the TIF process, it is assumed that a baseline aircraft is given, and that this aircraft is realistic but not necessarily feasible (i.e. satisfying all design constraints) or economically viable (i.e. satisfying all economic targets).

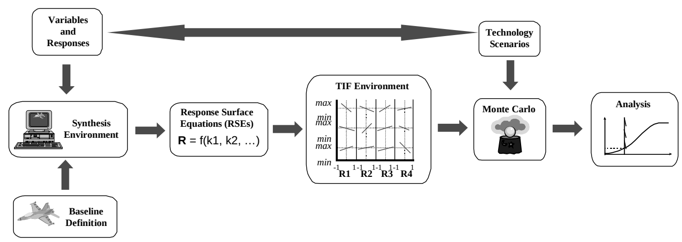


Figure 6- Process to Create TIF Environment and Assess Technology Scenarios

1) *Define the Synthesis and Sizing Environment*- a synthesis code must be available that adequately models and sizes the vehicle under consideration. Typically the code will have as inputs the geometric definition of the aircraft, aerodynamic, propulsion, and structural (weights) data, and a mission profile. The code must also be capable of resizing the aircraft subject to a list of performance related constraints (i.e. sizing points). An economics package must be included or linked to provide the necessary economic analysis. Ideally the code will be user-friendly and lend itself to quickly changing inputs and multiple runs. Normally a shell script is created to facilitate the multiple runs and changing variables.

2) *Define the Baseline*- in order to quantify the effects of changing variables or added technologies, a baseline configuration must be generated. This baseline should be a representative configuration usually before any candidate advanced technologies are added. It must have the ability to be easily modified, and care should be taken that the aircraft can still be sized with reasonable accuracy at the extremes of the variable ranges.

3) *Define Variables and Responses*- variables need to be selected that can model changes in technology and are also represented in the synthesis code. For example, an improvement in aerodynamic technology would most probably impact aircraft L/D. If there exists in the synthesis code a way to increment or decrement L/D, then L/D is a viable variable. If, however, the code does not

have an explicit variable for L/D but does allow the user to change total aircraft drag, then drag becomes the variable. Once the variables have been selected, ranges need to be defined for which the RSEs will be created. Using the aerodynamic example, the designer may wish to explore a technology that could theoretically provide up to a 15% improvement in L/D. But other technologies under consideration may have a detrimental effect on L/D, say, 5%. In order to capture technologies representing both an improvement to L/D and a decrement, the range for the K_factor associated with L/D would be, in this case, -15% to +5%. Finally, responses need to be selected that provide useful information to the designer. Usually these are measures of aircraft size (takeoff gross weight, fuel weight), performance (load factors, excess power), and economics (first unit acquisition cost, life cycle cost).

4) <u>*Create a Design of Experiments*</u>- utilizing the statistical analysis package JMP, the variables and their ranges are entered and a design of experiments is selected that represents a compromise between model accuracy and number of code executions. The DOE table generated will provide the settings of the variables and the number of cases that will be run experimentally in the synthesis code. The table generated will be an orthogonal array, guaranteeing that each variable can be varied independently. While the actual values of the K_factors may be used, statistically it is more accurate to convert the table into -1, 0, and 1s (in other words, normalizing the variables) to reflect the lowest, midpoint, and highest values of the variables.

5) <u>*Run the Cases*</u>- using the generated DOE table, multiple runs of the synthesis code are conducted, corresponding to one execution for each DOE case. Often a shell script is useful at this step for substituting in different values of the variables, running the cases, and parsing out the responses. The scripts are simply used to automate the process.

6) <u>*Create the Response Surface Equations*</u>- after all of the runs have been completed, the results are imported back into JMP. A screening test can be conducted, which is a lower level design of experiments, designed to identify only first order effects. Next, Pareto plots can be created, which show the rankings of variables according to how much they contribute to the variability of a specific response. This tool is useful in identifying the most significant contributing variables. This is a useful step if the designer has too many variables before starting the TIF process and needs to eliminate the variables that contribute less to the overall response. Next, the response surface equations are generated and saved for use in the next few steps. Several analysis options exist at this point, all providing useful information to the designer. The first is the generation of the prediction profile. This tool is a graphical aid showing the designer which variables affect which responses and to what degree.

7) <u>*Examine the TIF Environment*</u>- The TIF environment is comprised of the prediction profile generated in JMP that relates the technology K_factors to the system responses. Examination and analysis of this environment provides the designer with information concerning the nature of the relationships between the K_factors and the responses. This environment also allows the designer to select different values of the K_factors and see their immediate effects on the values of the responses. The TIF environment is also useful in conducting sensitivity analyses. It allows the identification of those disciplinary metrics that have the most significant effect on the various responses and constraints. Finally, the environment is used to quantify the impact of the K_factors, set targets for each of them, and identify which areas need improvement.

8) <u>*Define the Technology Scenarios*</u>- A technology scenario is created as follows. For each candidate technology, identify the key disciplinary metrics (represented by K_factors) that will be affected by that technology and decide by what amounts they will be affected. For example, an advanced aerodynamics scenario might affect, either positively or negatively (representing *both* benefits and drawbacks), the following variables: overall aircraft drag (an improvement), engine specific fuel consumption (a degradation due to possible increased engine bleed to power, say, a blown wing), and the systems learning curve (increased due to increased system complexity). Together, this group of variables represents one technology scenario. (Realize that each of the variables selected must have been used as a variable in the creation of the RSEs.) This step will be based on data provided by the discipline experts, empirical or historical databases, and the configuration designer's own knowledge and intuition.

9) <u>*Create the Analysis Environment*</u>- the next step is to import the RSEs into the Monte Carlo analysis package called Crystal Ball in order to conduct the analysis. Excel spreadsheet templates were created to allow the user to easily import the RSEs in the format they are provided by JMP. A new input file is created for each technology scenario to be explored, based on the above technology scenarios. A shape function must be assigned to each variable affected by the scenario. These shape functions will determine the probability of achieving certain values of variables. Because the actual shape functions are subjectively selected and can heavily influence the results, it is up to the designer to use his/her database of knowledge and expertise to ensure the shape distributions are appropriate and reasonable. Variables that are not affected by the technology scenario are set at their most probable, or baseline, values.

10) <u>*Run the Monte Carlo Simulation*</u>- Crystal Ball is called to run the simulations. After shape distributions have been determined for each variable, the program will randomly select variable values based on the shape distributions defined earlier. The RSEs will then be utilized for each response, and the probability distributions of the

responses determined. In order to get a good statistical analysis, it is suggested that the number of runs be on the order of 10,000 cases. This will provide an approximate 1% confidence level of accuracy. Because the RSEs are fairly straightforward equations, they require little computational power, and running thousands of cases is a timely and feasible task. (Compare this to running the same number of cases through the synthesis code and the computational beauty of the RSEs becomes apparent.)

11) *Analyze the Cumulative Probability Distribution Functions*- the final products of the methodology are the CDFs for each response. These functions will give the probability of achieving a certain response given a certain confidence level. By examining these graphs, the designer can quantify the confidence of risk associated with these new technologies, represented by the defined technology scenarios, upon the system responses chosen.

At this point the environment is complete and the tool is ready for further analysis and use. If a response represents a design constraint and the CDFs show a low probability of achieving that response, the designer has a few options. One is to manipulate the shape functions to give a better probability of success. Realize, however, that this represents a potentially higher level of technology that must be achieved. For example, if an advanced aerodynamics scenario is created and the designer, based on information from his/her discipline experts, can expect a 10% improvement in L/D, but the CDF shows a low probability of success, the designer can rerun the simulation and see how much a 15% improvement will do. If it is determined that there is a high probability of success with the 15% improvement, the designer will need to go back to his/her discipline experts and have them determine whether such levels are realizable or even possible. Other options include redefining or reducing the constraint, or continuing to look at alternative technologies. Either way, the designer has gained valuable knowledge concerning the effect of integrating a technology on a vehicle system.

The environment that has been created represents a specific class of aircraft with a specific range of variables. The tool, therefore, may be used to conduct studies on similar aircraft without having to recreate a new environment.

ADVANTAGES AND CAUTIONS

The TIF environment was created to explore the infusion of new technologies on a baseline aircraft. This implies that the new technologies under consideration have been theorized and may, in fact, exist at a certain technology readiness level. The method, however, may also be used to help define requirements for technologies that have not yet been identified or developed. Remember that the key to the method is modeling the technologies as K_factors, or "technology dials". One can go straight to selecting K_factors even if a specific technology is not in mind. For example, a general improvement in the discipline of structures may be explored. To do this, the designer merely assigns K_factors to associated structural variables, such as component weights, manufacturing learning curves, and materials, and then runs an analysis. By examining the results, the designer may optimize the improvements needed in order to achieve a certain overall improvement in life cycle cost. For example, the designer may conclude that a 5% decrease in life cycle cost could be obtained with an 80% confidence if wing weight could be decreased by 10% and manufacturing learning curves could be increases by 2%. These then become requirements for the discipline experts as they explore potential technology improvements.

Because the CDFs are entirely dependant on the shape distributions assigned and the technology scenarios defined, care needs to be taken that the shape functions are not inadvertently used to determine specific desired results. It is entirely possible to manipulate the data in such a way as to produce very favorable results. Like all tools, the designer needs to be aware of how the tool works and how his/her inputs affect the output in order to produce meaningful and insightful results. To this end, it is imperative that the designer be able to justify all assumptions based on empirical data, expert opinion and justification from disciplinarians, and the designer's own experience and common sense.

Finally, the designer needs to be aware of the capabilities and limitations of the synthesis code used in the creation of the RSEs. In order to gain meaningful results, variables and modeling must exist in the synthesis code that adequately capture both the advantages and the disadvantages of a particular technology. For example, if the designer wishes to explore increasing engine thrust, and the synthesis code contains a variable that allows the thrust to be scaled, but does not correspondingly increase engine weight, then only the beneficial effect of the increased thrust could be assessed, without the penalty and associated risk of this new technology. An example of this limitation is presented in the UCAV example below.

MILITARY APPLICATION OF TIF: UNINHABITED COMBAT AIR VEHICLE (UCAV)

In order to validate the TIF methodology for a military system, the authors collaborated with Lockheed Martin Tactical Aircraft Systems (LMTAS) in Ft. Worth, Texas. The baseline aircraft and synthesis code were provided by LMTAS, allowing the method to be applied using a new and different synthesis environment. The baseline aircraft selected by LMTAS for the study was an Uninhabited Combat Aerial Vehicle (UCAV). Because of its unique configuration, unpiloted status, and revolutionary concept, this baseline aircraft became an ideal testbed for investigating technology infusion.

SYNTHESIS ENVIRONMENT

Adaptable Design Synthesis Tool (ADST)

The in-house aircraft synthesis tool used by Lockheed Martin is called the Adaptable Design Synthesis Tool (ADST). In this code, a baseline aircraft is defined by specifying geometry, propulsion, aerodynamics, and a mission. The aircraft design may then be perturbed by changing any of the inputs and the aircraft is then fuel sized to meet the design mission. Results are presented in the form of an output file of varying degrees of detail (depending on the input flags) from which specific data of interest may be parsed.

In other synthesis codes, it is most common that the sizing routine will scale the baseline aircraft by holding thrust to weight and wing loading constant. In the ADST code, however, sizing of the aircraft may be accomplished by adding both fuselage length and volume to accommodate fuel volume needed due to a change in other input parameters. The fuselage size may be limited to a minimum or maximum size. This allowed for a unique opportunity to track thrust and weight and wing loading as sizing results, rather than inputs.

MALCCA

An ASDL in-house military aircraft economics tool was developed at Georgia Tech and is called Military Aircraft Life Cycle Cost Analysis (MALCCA). The cost estimating relationships used in MALCCA are weight-based regressions of a military life cycle cost historical database. Inputs include component weights (provided directly by the aircraft synthesis code), learning curves, production rates, complexity and technology factors, and crew salaries and training. Outputs are in the form of detailed cost breakdowns, including life cycle cost, RDT&E cost, production and operation, and support costs.

Overall Environment

The overall synthesis environment used for this study is shown in Figure 7. The ADST aircraft synthesis tool has as its inputs the baseline aircraft geometry, aerodynamics, propulsion, and mission. The aircraft is then sized and the outputs include detailed weights, performance, and the sizing parameters of the aircraft.

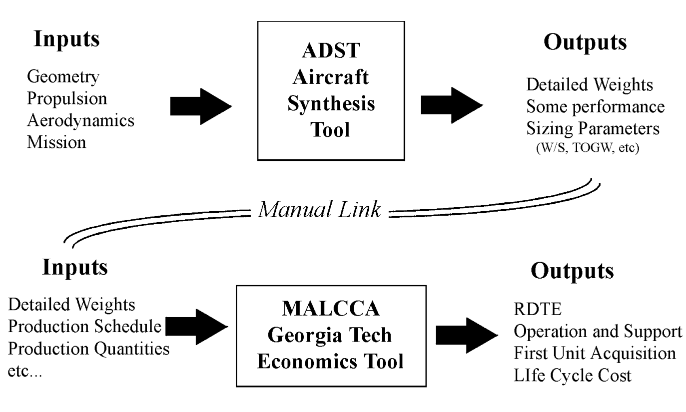


Figure 7- Synthesis and Economic Analysis Environment Used for the UCAV Study

Since ADST was not yet linked to a detailed economics code, the Georgia Tech military economics tool MALCCA was used in the analysis. Because this tool was located at Georgia Tech, a manual link between the two codes was created. In other words, the necessary output data are saved to a file, transported electronically to Georgia Tech, where it became the input file for MALCCA. The outputs from MALCCA were then combined with the necessary outputs from ADST and the analysis conducted. Several shell scripts were created around ADST and MALCCA for the purpose of defining, running, and parsing the output of the cases needed to create the TIF environment. This serves to illustrate the flexibility of the method; as long as a cohesive analysis path exists that can relate the inputs to the outputs, the TIF methodology can be employed.

BASELINE AIRCRAFT

The reference UCAV baseline, as developed by LMTAS, is a unique configuration that emphasizes payload/sensor modularity and flexibility combined in a survivable design. The aircraft, as shown in Figure 8, is distinguished by a blended wing-body and highly swept V-tail. The payload-carrying sections are podded and interchangeable, each with the ability to be configured for weapons, sensors, or additional fuel. The modular nose sections of each pod allow them to be independently configured for radar, infrared, or other capabilities [15].

Another unique feature of this LMTAS UCAV concept is its ability to host a manned version. This is accomplished through utilization of the extra volume afforded by the diverterless inlet compression surface. A manned version could perform several missions, including air-to-air combat, airborne battle management, and "on-the-scene" control of unmanned versions. Note that only the unmanned version was modeled for this study.

The UCAV has a wing span of 34 ft, and an overall length of 45 feet. The TOGW is in the 30,000 lb. class. There are 3 possible weapons loadings listed for each payload module, either:

(1) 2000lb JDAM or
(2) AMRAAM or
(10) 250lb Small Smart Bombs

Instead of the weapons loads, the sensors-configured -payload module can include a Side-Looking Aperture Radar (SLAR). The baseline engine used in the concept is an afterburning F414-GE-400.

A typical mission profile for the aircraft is shown in Figure 9. This was the mission modeled and used for the study. Because of the proprietary nature of the aircraft, performance capabilities are not shown, but were modeled adequately.

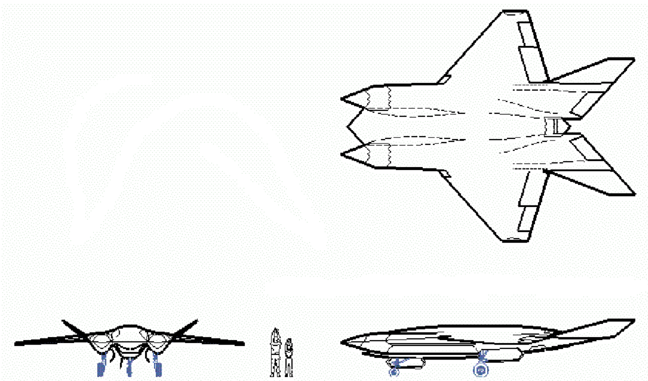


Figure 8- LMTAS UCAV Baseline

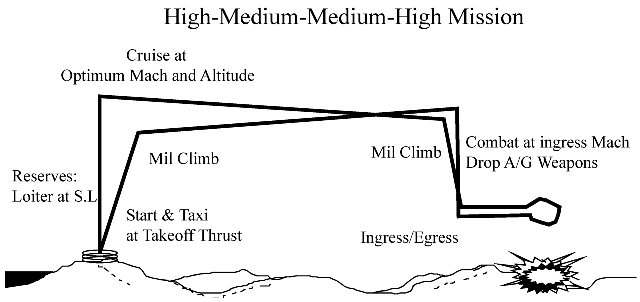


Figure 9- Mission Profile Used to Size LMTAS UCAV

The baseline ADST aircraft file for the UCAV was provided by LMTAS. The MALCCA economics baseline file was created with the aid of data provided by LMTAS and was created starting with defaults based on the military aircraft assumptions, which themselves were determined using data sourced from the F-15 and F-16 fighter aircraft. All variables associated with crew and cockpit were set to zero, including ejection seat weights, display complexity factors, and crew-associated weights. All ground testing complexity factors were increased by 10% and the flight test complexity factors increased by 20%. This was to account for the unique unmanned capabilities of the aircraft and recognizes the heavy ground support needed for the system. The model assumes a low radar cross-section treatment.

VARIABLES AND RESPONSES

Technology Scenarios and Variable Selection

There were four technology scenarios of interest in this study: advanced structures, advanced aerodynamics, advanced propulsion, and advanced stability and control. An advanced structures scenario implies technological advances in materials and manufacturing processes which primarily result in reductions of component weights. Because of the unique blended wing body of the notional UCAV baseline, both changes in wing weight and fuselage weight were considered important variables. The empennage consists of a canted combination horizontal/vertical stabilizer and was modeled as a single horizontal tail. Change in empennage weight was also considered a variable. Materials selection was modeled as percentage of composites for both wing and fuselage. Finally, a complexity factor was used to model increased complexity in structures technology. This was an economics factor.

The advanced aerodynamics scenario was modeled through changes in overall aircraft drag coefficient (thus affecting the lift-to-drag ratio). Advanced propulsion has as its variables changes in overall aircraft thrust, changes in the fuel flow, the percent of new engine development (an economic factor modeling engine complexity) and a technological factor on engine installation.

Due to limitations on the synthesis tool, advanced stability and control could not be modeled as explicitly as the other scenarios. A change in empennage size (modeled as weight) was used, and several economic factors utilized, such as a change in the complexity factor for flight software and technological factor for avionics.

Finally, for each of the four scenarios, economics were modeled primarily as changes in learning curves: engine learning curve, systems learning curve, assembly learning curve, and structures learning curve. Table 2 compiles all the variables used in this study, as well as indicating the range of the variables used. It must also be noted that there is some crossover in variables, even though they are grouped by disciplines for convenience. For example, the economic variable assembly learning curve was used to model "touchless" robotic manufacture for the advanced structures scenario.

Table 2- UCAV Technology Variables and Ranges of Variability Examined

		Percent Deviation from Baseline	
		Lower	Upper
Structures	Δ Wing Weight	-15%	+5%
	Δ Fuselage Weight	-15%	+5%
	Δ Empennage Weight	-15%	+5%
	% Wing Composites	75%	95%
	% Fuselage Composites	45%	80%
	Δ Tech Factor Fuselage	-5%	+15%
Aerodynamics	Δ Drag Coefficient	-13%	+5%
Propulsion	Δ Thrust	-5%	+15%
	Δ Fuel Flow	-15%	+5%
	% New Engine Development	0%	30%
	Δ Tech Factor Engine Installation	-5%	+15%
Stability and Control	Δ Tech Factor Flight Software	-5%	+15%
	Δ Tech Factor Avionics	-5%	+15%
Economics	Δ Engine Learning Curve	-5%	+5%
	Δ Systems Learning Curve	-5%	+10%
	Δ Assembly Learning Curve	-5%	+15%
	Δ Structures Learning Curve	-5%	+10%

Responses of Interest

Just as variables needed to be identified to model the system level effects of certain technologies, responses likewise need to be selected such that changes in the system level metrics produce useful changes in the responses. By quantifying the changes in the responses, the designer can identify the potential benefits and risks associated with a technology scenario. Table 3 lists the responses chosen. In the area of sizing, key weights were identified.

Thrust to weight and wing loading, while not commonly used as responses for studies of this nature, were tracked here specifically due to the unique sizing routine in ADST. Most aircraft synthesis codes will scale a baseline aircraft by keeping a fixed thrust to weight ratio and wing loading. ADST, however, grows the aircraft fuselage to accommodate needed fuel. Thus, thrust to weight and wing loading change and are therefore tracked as sizing responses.

Table 3- Tracked UCAV Responses

Vehicle Size	Takeoff Gross Weight
	Empty Weight
	Fuel Weight
	Thrust to Weight Ratio (T/W)
	Wing Loading (W/S)
Vehicle Performance	Acceleration: 200 ft, M=0.45 to 0.76, Max A/B
	Acceleration: 15k ft, M=0.6 to 0.90, Max A/B
	Turn Load Factor, 15k, M=0.8, Max A/B
	Excess Power, 15k ft, M=0.8, Mil Power
	Excess Power, 15k ft, M=0.8, Max A/B
Vehicle Cost	RDTE Cost
	First Unit Acquisition Cost
	Operation and Support Cost
	Life Cycle Cost

Performance responses were selected to show changes in certain acceleration capabilities of the aircraft, as well as turn load factor and excess power changes. Economic changes were identified through top-level responses such as Research, Development, Testing and Evaluation (RDTE), First Unit Acquisition Cost, Operation and Support Cost, and Life Cycle Cost.

Note that for top-level system work, the TIF methodology often employs these four economic responses also as system level variables. This is the case when the designer wishes to simply assess the changes influenced by the technology scenario at a system level. For example, for this particular study it was desired to know the effect of "touchless" robotic manufacturing on the economics for the advanced structures scenario. Another designer may not wish to go into such detail and simply model the changes for the advanced structures scenario as changes in RDTE or First Unit Acquisition Cost. The level of detail the designer wishes to use is dependant on study requirements and synthesis tools available.

SYSTEM LEVEL SCREENING TESTS

Screening tests were performed in order to identify primary drivers of vehicle size, performance, and cost. The screening tests are shown in the form of Pareto plots, which identify, through the use of bar charts, which variables contribute to each response, and by how much. An example screening test for aircraft size responses is shown in Figure 11. Table 4 lists the three primary variables that affect the responses. As can be seen, for those responses corresponding to aircraft size, dominant variables are fuel flow, drag, thrust, and fuselage weight. Fuselage weight is considered a major player because of the unique configuration of the vehicle. For most vehicles, wing weight is the significant structural weight. But the blended wing-body design of the UCAV necessitated modeling a large portion of the lifting surface as fuselage. In this design, a majority of the wing actually is the fuselage.

Table 4- Identification of Most Significant Contributors

	Primary Effect	Secondary Effect	Tertiary Effect
Takeoff Gross Weight	∆ Fuel Flow	∆ Drag Coefficient	∆ Fuselage Weight
Empty Weight	∆ Fuselage Weight	∆ Thrust	∆ Fuel Flow
Fuel Weight	∆ Fuel Flow	∆ Drag Coefficient	∆ Thrust
Thrust to Weight	∆ Thrust		∆ Drag Coefficient
Wing Loading	∆ Fuel Flow	∆ Drag Coefficient	∆ Fuselage Weight
Acceleration: 200 ft, M=0.45 to 0.76, Max A/B	∆ Thrust	∆ Fuel Flow	∆ Drag Coefficient
Acceleration: 15k ft, M=0.6 to 0.90, Max A/B	∆ Thrust	∆ Drag Coefficient	∆ Fuel Flow
Turn Load Factor, 15k, M=0.8, Max A/B	∆ Drag Coefficient	∆ Fuel Flow	∆ Fuselage Weight
Excess Power, 15k ft, M=0.8, Mil Power	∆ Thrust	∆ Drag Coefficient	∆ Fuel Flow
Excess Power, 15k ft, M=0.8, Max A/B	∆ Thrust	∆ Drag Coefficient	∆ Fuel Flow
RDTE Cost	% New Engine	% Fuselage Composites	∆ Fuselage Weight
First Unit Acquisition Cost	Structures Learning Curve	Assembly Learning Curve	∆ Fuselage Weight
Operation and Support Cost	∆ Fuel Flow	Structures Learning Curve	∆ Fuselage Weight
Life Cycle Cost	Structures Learning Curve	Assembly Learning Curve	∆ Fuselage Weight

It is no surprise that the key variables contributing to the performance responses are fuel flow, thrust, and drag. The tertiary effect for turn load factor is fuselage weight, which is appropriate. Finally, the key effects on cost are seen to be those variables that are associated with the manufacturing process (learning curves) of the vehicle, as well as materials themselves and weights.

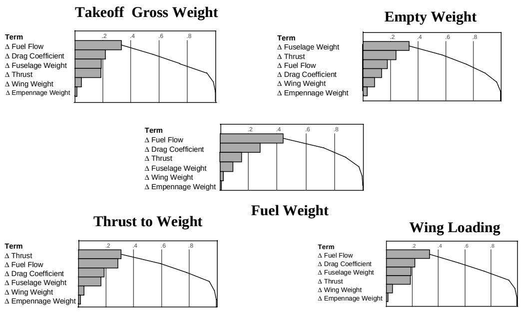


Figure 11- Typical Sample of the Pareto Plots Generated for UCAV Size

RESULTS

With the four technology scenarios defined and the variables and responses selected, the Design of Experiments was conducted, creating the Response Surface Equations. Figure 12 contains the entire prediction profile (technology impact environment), linking the variables, in the form of K_factors, to the responses. By examination of Figure 12, the designer can immediately identify the sensitivities of the responses to each K_factor. For example, it can be seen that the 1st Unit Acquisition Cost has the highest degree of sensitivity to the K_factor for the structures learning curve. The prediction profile is also useful in seeing the sensitivities of the responses to all of the K_factors in a single chart (i.e. it is easy to see the "big picture"). Note that the prediction profile is another way of presenting the information seen in Figure 11.

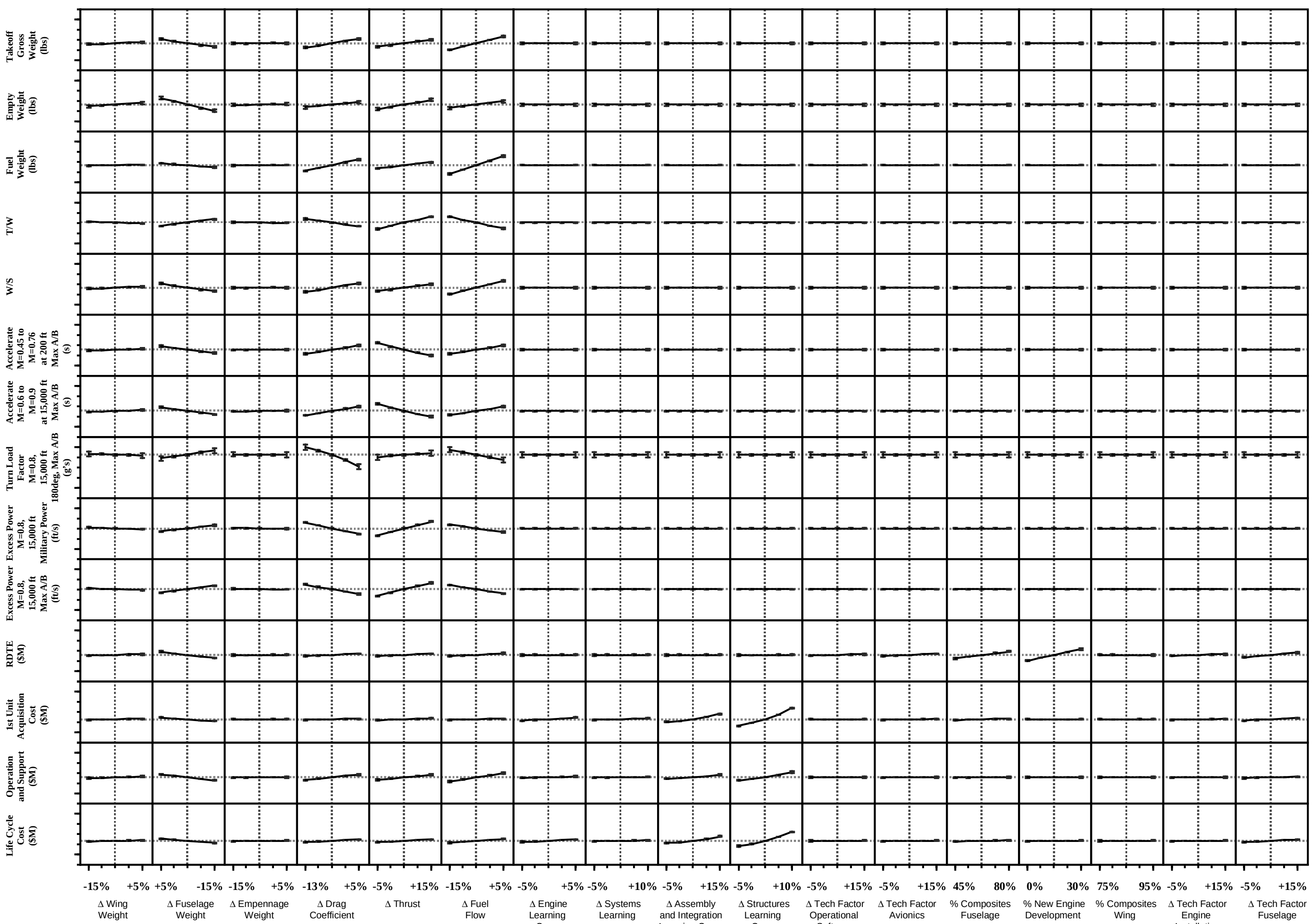


Figure 12- Technology Impact Environment (Deterministic) for LMTAS UCAV

The RSEs, created with the K_factors as the variables, were then imported into Crystal Ball and the Technology Impact Forecast (probabilistic) Environment created. For each technology concept scenario, shape functions were selected (based on input from LMTAS and previous information) and defined in the environment. It is again emphasized that in the TIF process, specific technologies are not identified and modeled. Rather, general (or generic) technology concepts are considered, with the goal being the identification of the technology area that would most benefit the baseline concept, aiding in resource allocation for further study. An advanced technology scenario is created by selecting and grouping together several K_factors that could represent the benefits and risks associated with that concept.

Figure 13 gives an example of the shape functions used for the advanced structures scenario (for proprietary reasons, the actual values have been removed). A Monte Carlo simulation was then conducted, based on the shape functions given. An example of the resulting cumulative probability distributions for aircraft performance in the structures scenario is found in Figure 14.

Table 5 shows the results for the advanced structures scenario. Each column gives the probability of achieving at least the value given, stated as percentages of change from the baseline. For example, the table shows that there is a 50% chance of achieving a reduction of takeoff gross weight of 5.3% or higher. The designer can thus use this information to decide what level of risk is associated with a specific goal or payoff. Normally, an 80% confidence level is assumed to be a reasonable expectation level. For this confidence level, and given the assumptions made, the UCAV shows a decrease in key weights, both performance benefits and drawbacks, and an increase in economic responses. While this at first may seem counterintuitive, the trend is attributed to the high use of composites and the associated modeled cost of their use. Clearly, at least in the model, this cost dominates any benefit gained from increased composite use. Realize, however, that this conclusion can only come from a user that is intimately familiar with both the modeling code used and the assumptions made.

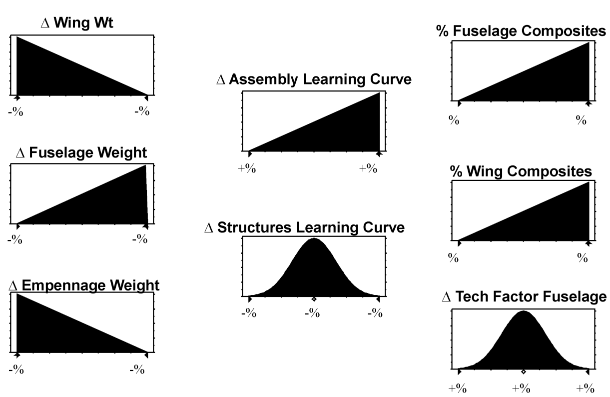


Figure 13- Assumed Shape Functions for the Advanced Structures Scenario

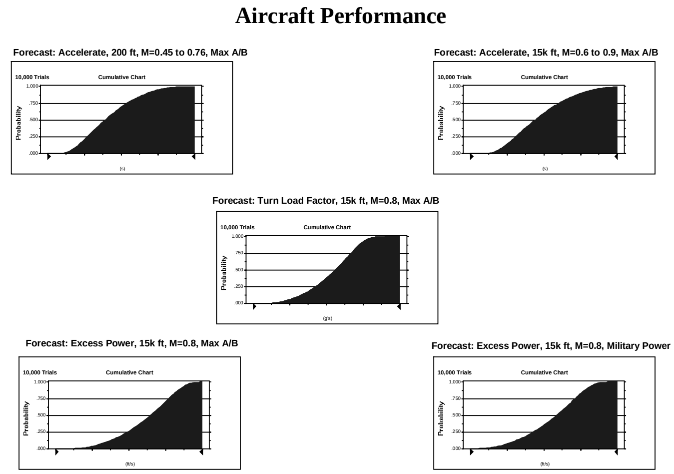


Figure 14- Performance Cumulative Distribution Functions for Advanced Structures Scenario

Table 5- Results for Advanced Structures Scenario

Advanced Structures Scenario	20% Probability	50% Probability	80% Probability	100% Probability
Takeoff Gross Weight	-5.62%	-5.30%	-4.89%	-4.00%
Empty Weight	-8.02%	-7.58%	-7.00%	-5.78%
Fuel Weight	-4.28%	-4.02%	-5.30%	-2.93%
Thrust to Weight	6.67%	8.00%	8.00%	8.00%
Wing Loading	-5.62%	-5.29%	-4.88%	-3.99%
Acceleration: 200 ft, M=0.45 to 0.76, Max A/B	-6.73%	-6.35%	-5.90%	-4.69%
Acceleration: 15k ft, M=0.6 to 0.90, Max A/B	-6.86%	-6.47%	-5.98%	-4.77%
Turn Load Factor, 15k, M=0.8, Max A/B	1.79%	2.24%	2.54%	2.99%
Excess Power, 15k ft, M=0.8, Mil Power	9.67%	9.86%	10.35%	10.98%
Excess Power, 15k ft, M=0.8, Max A/B	8.42%	9.02%	9.48%	10.05%
RDTE Cost	5.11%	6.23%	7.30%	10.30%
First Unit Acquisition Cost	20.72%	23.62%	26.27%	34.76%
Operation and Support Cost	-0.67%	-0.52%	-0.33%	0.20%
Life Cycle Cost	2.71%	3.27%	3.80%	5.50%

After all of the technology scenarios were run and analyzed, the results were tabulated into Table 6. This table shows not only the examination of a single technology, but allows the technologies to be compared in a side-by-side manner. It is clear from the table that the structures scenario has the lowest takeoff gross weight, yet has the highest life cycle cost. This is due to the extensive use of composites and the associated high cost, as discussed earlier. The aerodynamics scenario has the lowest life cycle cost, with corresponding decreases in weight. The economics program is heavily weight-driven, but contains few variables that allow for modeling of the increased complexity of an advanced aerodynamics technology. In other words, it is possible in this case that the benefits have been captured by the model, but not necessarily the penalties. A similar effect was seen in the stability and control scenario. Economic variables existed that allowed the scenario to be penalized for extensive complexity, including software and avionics modeling. Traditional synthesis and sizing codes, however, do not often contain modeling routines for aircraft agility. In this particular case, it was difficult to model the agility and maneuverability benefits of an advanced stability and control scenario with the given synthesis environment. The results, therefore, showed that there was very little benefit and to an advanced stability and control scenario. Overall, it is seen that the propulsion scenario gives the best performance results for roughly the baseline acquisition cost. This is due to the higher thrust and lower takeoff gross weight. Operations and support cost were also low.

Table 6- Comparison of all Technology Scenarios

Scenario	Advanced Aerodynamics 80% Probability	Advanced Structures 80% Probability	Advanced Propulsion 80% Probability	Advanced Stability/Control 80% Probability
Takeoff Gross Weight	-4.11%	**-4.89%**	-1.72%	-0.75%
Empty Weight	-1.93%	**-7.00%**	1.37%	-0.88%
Fuel Weight	**-9.05%**	-5.30%	-7.02%	-0.84%
Thrust to Weight	6.67%	8.00%	14.67%	0.00%
Wing Loading	-4.10%	-4.88%	-1.71%	-0.73%
Acceleration: 200 ft, M=0.45 to 0.76, Max A/B	-5.37%	-5.90%	-10.51%	3.10%
Acceleration: 15k ft, M=0.6 to 0.90, Max A/B	-5.92%	-5.98%	-10.92%	3.24%
Turn Load Factor, 15k, M=0.8, Max A/B	7.77%	2.54%	4.04%	-0.75%
Excess Power, 15k ft, M=0.8, Mil Power	12.95%	10.35%	19.27%	-1.96%
Excess Power, 15k ft, M=0.8, Max A/B	8.55%	9.48%	15.92%	-1.49%
RDTE Cost	**-1.63%**	7.30%	18.34%	1.20%
First Unit Acquisition Cost	**-9.65%**	26.27%	0.53%	1.62%
Operation and Support Cost	**-1.73%**	-0.33%	-0.55%	-0.16%
Life Cycle Cost	**-2.94%**	3.80%	-0.10%	0.10%

CONCLUSION

A comprehensive and structured process for determining the impact of generic technologies on a given baseline aircraft has been presented. This process, called Technology Impact Forecasting, is a part of a more robust methodology that allows for complete technology identification, evaluation, and selection. The TIF process is a probabilistic method that allows the designer to quantify the effects of technologies represented by multiplicative factors of design variables. Results are compared by selecting a desired confidence interval and assessing the changes to the baseline aircraft. Advantages of the method include the ability to model both generic and specific technologies, as well as make decisions concerning resource allocations for promising technologies. The designer is cautioned against using the shape factors in order to manipulate specific results, as well as to be cognizant of the limitations of the synthesis environment.

In collaboration with Lockheed Martin Tactical Air Systems, the TIF methodology was applied to an Uninhabited Combat Aerial Vehicle concept. The results yielded valuable insights, which could have the effect of reducing cycle-time for decision-making for this or other concepts to which the methodology is applied. Once the TIF environment is created, it further allows the analysis of “what if” scenarios without having to recreate the problem or run further synthesis cases.

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CONTACT

For more information on this study and other methodologies being developed by the Aerospace Systems Design Laboratory, please visit our website at http://www.asdl.gatech.edu.

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