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Georgia Institute of Technology

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Forecasting Technology Uncertainty in Preliminary Aircraft Design

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ABSTRACT

An evolved version of the Technology Identification, Evaluation, and Selection (TIES) method is presented that provides techniques for quantifying technological uncertainty associated with immature technologies. Uncertainty in this context implies forecasting. Forecasting the impact of immature technologies on a system is needed to provide increased knowledge to a decision-maker in the conceptual and preliminary phases of aircraft design. The increased knowledge allows for proper allocation of company resources and program management. The TIES method addresses the milestones encountered during a technology development program, the sources of uncertainty during that development, a potential method for bounding and forecasting the uncertainty, and a means to quantify the impact of any emerging technology. A proof of concept application was performed on a High Speed Civil Transport concept due to its technically challenging customer requirements.

INTRODUCTION

Aggressive performance and economic objectives of future aircraft concepts warrant the need for a change in the manner in which complex systems are designed. Future concepts must outperform current standards if they are to be viable alternatives meeting societal needs. These needs are encapsulated in projected commercial traffic growth, changing government regulations, increased throughput, and the desires of the traveling public for comfort, safety, and affordability. Specifically, commercial world air travel is expected to grow at a rate of 5.5% per year over the next decade [1], resulting in a 71% increase over current levels within a decade and increasing 192% in two decades. In addition, stringent regulations from government entities impose laws on emission and noise levels and increased safety while the traveling public desires lower ticket fares and more flight options. Further, the airlines want more opportunities for profit by lowering operating, support, and investment costs. All of these objectives are imposing more constraints on future aircraft concepts from the airframe and engine manufacturers. If a manufacturer were to design, test, and mass-produce a vehicle concept consisting of only present day technologies, it is doubtful that the aggressive and conflicting customer requirements could be met.

These shifting currents of commercial aviation have evoked a response from the current NASA administration in the form of the “Three Pillars for Success” program [2]. This program is a roadmap to guide U.S. aerospace endeavors for the next 20 years in accordance with the changing environment of future aviation. A recent National Research Council report urges that to achieve the goals set forth in the “Three Pillars for Success” program, breakthrough technological capabilities, both evolutionary and revolutionary, will be required [3]. NASA has launched the Scenario-Based Strategic Planning initiative to propel the identification and development of potential technology candidates to meet the future goals. Yet, the adaptation by manufacturers or operators of new technologies, which are not incremental or imposed by regulation, encounters strong opposition. Since manufacturers and operators are driven by economic incentives, conventional or existing technologies are usually preferred [3]. Yet, if a technology can be shown to the decision-maker to improve a system at a low risk and without significant negative impact to other subsystems or economics, the technology may buy its way onto the aircraft. To facilitate this objective in the conceptual and preliminary phases of design, a means to quantify and forecast the impact of emerging technologies, or mix of technologies, has been created. The method is an evolved version of the Technology Identification, Evaluation, and Selection (TIES) method developed in References [4,5]. In Reference [5], the focus was on a deterministic evaluation of the mix of technologies needed to meet some customer requirements with a brief discussion on the probabilistic nature associated with immature technologies. The new aspects contained herein address the probabilistic nature of immature technologies. In particular, a methodical logic is developed to create the ability to forecast the impact of any emerging technology, while accounting for technological uncertainty.

METHODOLOGY

The methodology developed to ascertain the impact of emerging technologies on aerospace systems is depicted in Figure 1. The nine step TIES method has been described in References [4,5] and fits into the modern aircraft design theory presented in References [6,7]. The current investigation addresses, in depth, the technological uncertainty and provides a robust means for assessment. These new aspects are entailed in Steps 6 through 9 and will be discussed in detail. A brief overview of the other steps is presented as a basic outline of the entire method.

OVERVIEW OF STEPS 1 THROUGH 5

The top portion of Figure 1 entails the first five steps of the TIES method. The process begins by defining the problem through a mapping of the customer requirements into quantitative evaluation criteria (also called system level metrics). Next, a potential class of vehicle concepts, e.g. a high capacity, long range, subsonic transport or a twin-engine fighter class, is identified that may fulfill the customer requirements. A functional decomposition of the class of vehicle is performed via a Morphological Matrix [8] to identify concept alternatives. From this matrix, a baseline vehicle is established which contains only present day technologies. A design space bounded by control variables such as wing aspect ratio, engine thrust, etc is then defined for the baseline. This space is investigated for technical feasibility and economic viability in a Modeling and

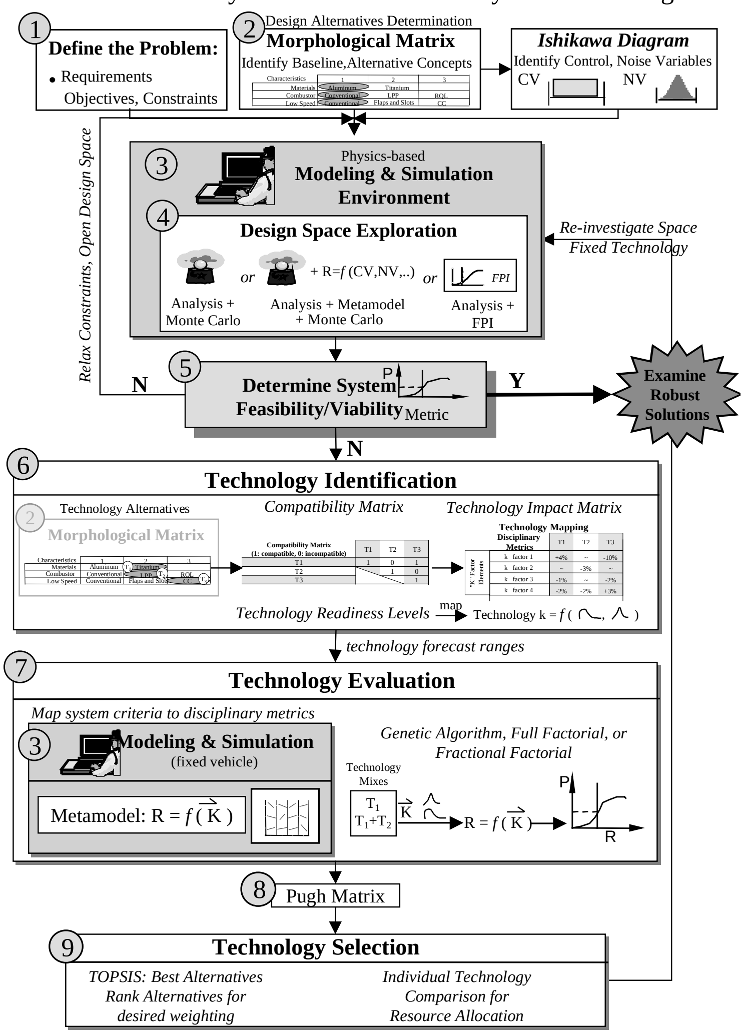

FIGURE 1: OVERALL METHODOLOGY

Simulation environment via the Response Surface Methodology (RSM) and/or Fast Probability Integration (FPI) technique. If the probability of success for feasibility and viability are unacceptable, the decision-maker has the option to expand the design space, relax the constraints, or infuse new or alternative technologies. The later option motivates the need for the TIES method. The current research focuses on the enhancing the quantification of the impact of technological uncertainty. The reader is referred to References [4,5,9,10] for more detailed information regarding steps 1 through 5.

TECHNOLOGY IDENTIFICATION (STEP 6)

If the design space exploration yields an unacceptable system feasibility and viability, specific technologies must be identified for infusion. From the Morphological Matrix, applicable technologies or technology programs for the class of vehicle under consideration must be identified from the component alternatives. The designer or decision-maker must establish physical compatibility rules, quantitative impacts to the system, and the level of maturation of the technologies to facilitate the evaluation and selection steps.

Compatibility Matrix

A compatibility matrix is formalized through Integrated Product Teams to establish physical compatibility rules between technologies. An example matrix is shown in Figure 2 for three arbitrary technologies (T1,T2,T3) where a “1” implies compatibility and a “0” implies incompatibility. It should be noted that the limiting case of compatibility is a combination of two technologies. Hence, the matrix is two-dimensional and symmetric. In this matrix, T1 and T2 are not compatible. As an example, a composite wing structure could not have HLFC. Due to the nature of composite structures, the micro-holes needed for HLFC boundary layer suction would compromise the composite matrix, creating structural integrity problems. The purpose of this matrix is to eliminate combinations that are not physically realizable.

Compatibility Matrix (1: compatible, 0: incompatible)	T1	T2	T3
T1	1	0	1
T2		1	0
T3			1

FIGURE 2: EXAMPLE TECHNOLOGY COMPATIBILITY MATRIX

Technology Impact Matrix

Once the compatibility matrix is determined, the potential system and sub-system level impacts of each technology are established. The impact must include primary benefits and secondary degradations. In general, the impact of a technology is probabilistic in nature. The probabilistic nature arises from various contributing factors, especially if the technology has not fully matured, i.e. widespread commercial or military application. Hence, a brief discussion is presented on the unique aspects of an immature technology. In particular, an understanding is needed of the following:

- the milestones encountered during a generic technology development program,
- the sources of uncertainty during that development, and
- the potential methods for bounding and forecasting the uncertainty so that the impact may be quantified.

Technology Development

The innovative process by which a technology is developed can be qualitatively described through a monitoring of the major milestones achieved from concept formulation to widespread application. As defined by NASA for application in the aerospace community, the milestones have been characterized into a "metric known as the technology readiness level (TRL)" [3]. A description of the NASA defined TRLs is listed in Table I. The TRLs represent a checklist for monitoring the progress of a *successful* technology program and the expected impact. Consideration is not given to the influencing or constraining factors that may alter the progression such as schedule, budget, market demand, political or socioeconomic policy, physical limitations, etc. The TRLs simply describe the maturation and development process of a technology and provide a basis by which different technologies can be compared as they progress through the gates of maturation. For program monitoring, TRLs are appropriate, but should be mapped to a quantitative scale for the purpose of decision making. To do so, one must understand how a generic technology develops and matures.

"No single growth pattern describes the development and diffusion of all technologies. There are general concepts of how technologies develop, however, and these can be a useful guide" [11]. One of the prominent concepts is through the *method of analogy* to other "well-known physical or biological systems" [12] such as growth patterns of yeast cell populations. Historical data for various technology concepts, including aircraft speed, steam engines, and fluorescent lamps [13], has revealed an ordered pattern of development that resembles this biological growth curve, also known as a sigmoidal curve or an S-curve. The method of analogy assumes that a technology development program will follow this S-curve pattern *if a successful program is achieved*. A successful program is one that can achieve all goals within the allowed budget and schedule. An example S-curve growth pattern is shown in Figure 3 [11].

TABLE I: TYPICAL TECHNOLOGY READINESS LEVELS

Level	Readiness Description
1	Basic principles observed and reported
2	Technology concept and/or application formulated (candidate selected)
3	Analytical and experimental critical function or characteristic proof of concept or completed design
4	Component and/or application formulated
5	Component (or breadboard) verification in a relevant environment
6	System/subsystem (configuration) model or prototype demonstrated/validated in relevant environment
7	System prototype demonstrated in flight
8	Actual system completed and flight qualified through test and demonstration
9	Actual system flight proven on operational vehicle

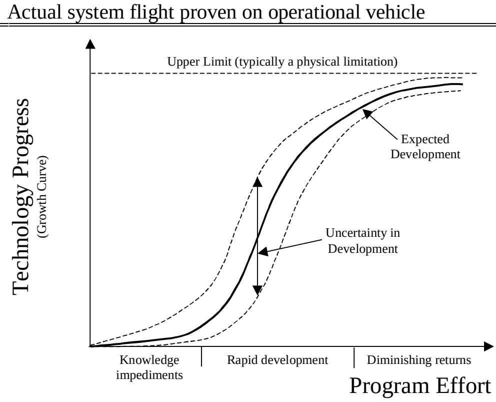

FIGURE 3: GENERIC TECHNOLOGY DEVELOPMENT

The solid S-curve is the expected or ideal progression of a technology as a function of program effort. The program advances "slowly as many impediments must be initially overcome, advances rapidly for a period and then slows as the easy improvements" [11] are achieved. The uncertainty bounds associated with the expected maturation curve are due to the influencing and constraining factors stated previously, i.e., resource allocation, political and socioeconomic policies, etc., in addition to assumptions made to assess the technology progress. As expected, the uncertainty diminishes as the program advances and knowledge and experience increases. The upper limit of this curve is typically viewed as a physical limitation of the functional capability of the technology and in most instances, a point of diminishing returns.

If one were to map this technology progress curve to the TRLs in Table I, the growth curve would be indicative of the component progression from TRL 1 to 5, *if the program is successful*. It should be noted that the uncertainty, which is reduced, is directly attributable to the specific disciplinary impact, e.g., drag reduction, for which the technology is being developed and not to other subsystems. As resources are invested and more knowledge is gained about the technology at the component level, the uncertainty reduces. Yet, when the component is integrated to the system in a relevant environment at a TRL of 6, the uncertainty of the system increases as shown in Figure 4. This increase results from integration difficulties, degradation to other systems, manufacturing uncertainties, etc. For example, Circulation Control (CC) is used to increase the lift capability of the wing at low speeds and its current TRL is 4, as applied to a high speed concept. This technology has been proven with various wind tunnel experiments [14,15] to achieve very high lift augmentation. Yet, with CC infusion into the full system, issues concerning integration arise, including power requirements for operation, redundant systems for certification, available wing volume for ducting, etc. Additionally, prior to the introduction of the technology, uncertainty already exists in the system due to ambiguous requirements, modeling and evaluation assumptions, to name a few, as shown on the left as the straight portion of the system uncertainty.

However, *if the technology development is not assumed successful*, the right hand side of Figure 4 may be obtained. If one were to track the actual technology impact at the component and system level as the TRL increases, the mode value of the confidence interval (distribution) *may deviate* significantly. This implies that the technology growth curve does not follow a regular or predictable pattern. Aside, the mode value is defined as the point of largest frequency [16]. For a symmetric distribution, the mode is equivalent to the mean. Although uncertainty reduces, the deviation in mode value is not evident with increasing TRL shown on the left. In fact, the desired impact may never be realized unless some physical limitation is overcome, or breakthrough technology advancements achieved. The movement of the mode value and the shape of the distribution are functions of several factors. Those factors include the resources allocated to the development of the technology, the methods and tools used to analyze and design the technology, the information available, the desired impact level, integration to the system, and disruptive progress. The next step is the identification of forecasting techniques to bound, quantify, and estimate the technological uncertainty.

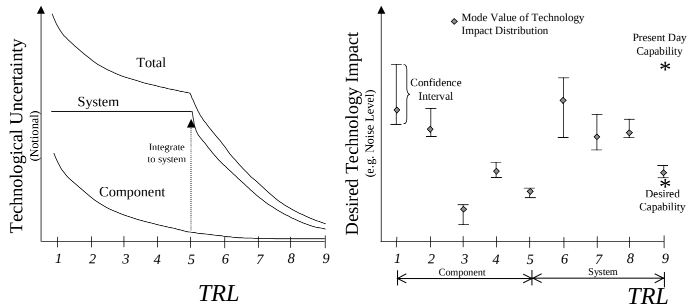

FIGURE 4: TECHNOLOGICAL UNCERTAINTY

Technology Forecasting

The primary purpose of forecasting, in any context, is to provide the decision-maker with adequate information on which future business decisions and company strategies may be based. Two broad categories of forecasting exist: exploratory and normative. Exploratory forecasting techniques consider historical trends and extrapolate into the future to see what may happen. "The feasibility of this process depends upon an assumption that progress is evolutionary and does follow a regular pattern" [8]. The normative method begins with future goals and works backward to identify the levels of performance needed to obtain the desired goals, if at all achievable with the resources available. Either perspective utilizes one, or combinations, of four traditional forecasting techniques: S-curves, trend extrapolation, the Delphi method, or scenario development [17]. The first two techniques assume a functional form of previous technological growth and extrapolate to a future time. Again, sufficient information must exist for the forecast to be accurate and of value to the decision-maker. The Delphi method is a structured means of incorporating expert opinions (usually subjective) through questionnaires and controlled feedback to estimate a technology impact and the confidence of achieving that impact. Finally, the scenario development assumes some future status of the world (economic, political, etc.) and its influence on the technology progress to shape the development curve [8,11] and usually disrupts the technology progress at a pre-specified time.

If sufficient program monitoring is performed in the early phases of a development, a technology impact trend may be established. This trend may then be forecasted to a future time (or a TRL) and the impact quantified. Yet, if a technology is in the infancy stages and little information is available as to the detailed progress, insufficient information exists for forecasting the mode value of the distribution. For example, if a technology were at a TRL of 3, as in Figure 4, one would assume that the trend continues to reduce. Thus, erroneous results are obtained and the forecasted impact would be more optimistic than what could actually be achieved. This is one major difficulty associated with forecasting methods. The irony exists that a good deal of data is required to sufficiently forecast, but the need for forecasting is more prominent when insufficient information exists, as in the conceptual phases of aircraft design. As will be shown in later sections, the specific technologies considered fall into this later category of insufficient information.

Bounding Technology Uncertainty

If a technology is in the infancy stage of development (low TRL), the shape of the development curve is not easy to predict, due to lack of substantial data to establish a trend. Hence, the forecast must rely on expert, subjective opinions through the Delphi method with an assumed growth pattern. Subsequently, the forecast should focus on the evaluation of "the potential commercial benefits (and penalties) that might be achieved IF the (program) is successful" [8] and can be matured to the point of full-scale application (i.e. TRL=9). As more information and data becomes available, the forecast is updated and re-evaluated.

Based on this rationale, the uncertainty, or confidence limits, may be bounded based on a logical reasoning of *what should* happen as a technology program progresses. For example, one may assume that a successful technology program develops along a linear trend as shown in Figure 5. Point "A" represents a technology in the infancy stage of development. The desired capability of the performance improvement is Point "D" and is assumed to be the expert defined impact. This point is not yet fully realized due to knowledge impediments, and may actually be higher or lower than the expert defined limit. Points "B" and "C" represent other levels of technology maturation. To bound the uncertainty of the technology, one must realize the two sources. One, the inherent uncertainty associated with the technology development as described previously. Second, there is uncertainty associated with forecasting the trend. Specifically, the confidence limits of achieving a desired value "broaden as the time frame of the forecast increases, reflecting the growing level of uncertainty" [18] in knowledge. A tangible analogy of this type of uncertainty is the forecasting of the price of fuel. One could forecast what the price of fuel would be for the next day with a very high confidence. However, the confidence of what the price will be in fifty years is very low. Now, if one applies this analogy to the forecasting of an immature technology impact to a future time (i.e. TRL), the limits of probability should spread. Consider Point "A", since the time frame of the forecast is large to the desired impact value, the distribution is very wide. Yet, for a higher TRL value, the confidence or probability of achieving the desired technology improvement increases since the forecast is for a shorter time frame and more information is available regarding the technology.

As shown in Figure 5 for the distributions ("a","b","c"), the uncertainty in achieving the desired improvement is not necessarily normally distributed and the mode value should deviate. In fact, the distribution should be skewed towards the desired level if the expert opinion is relatively accurate. Based on this rationale, shape distributions associated with different TRLs may be established and will be based on qualitative reasoning, since insufficient data is available for the technologies considered. However, the distribution definitions should be modified, as more information becomes available.

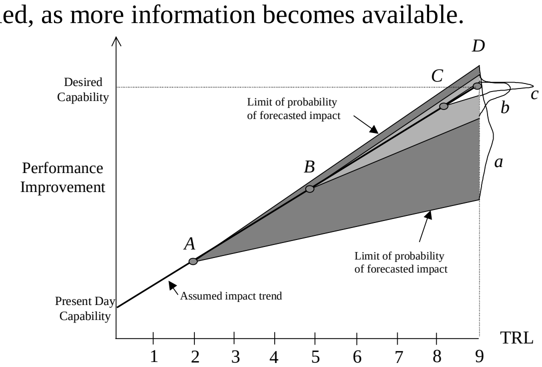

FIGURE 5: UNCERTAINTY IN FORECASTING A TECHNOLOGY

Based on the probabilistic nature described above, a Technology Impact Matrix (TIM) is formed for the technologies identified in the Morphological Matrix. Unfortunately, advanced technologies are difficult to assess within a conceptual modeling and simulation environment such as a sizing/synthesis tool. Sizing/synthesis tools are typically based on regressed historical data that limits or removes their applicability to exotic or revolutionary technologies. However, the impact of a technology can be qualitatively assessed by introducing technology "k" factors. These "k" factors modify disciplinary technical metrics, such as specific fuel consumption, cruise drag, and/or component weights that result from a sizing tool. The modification is essentially an incremental change in the technical metric, either enhancement or degradation. In effect, the "k" factors simulate the discontinuity in benefits and/or penalties associated with the addition of a new technology.

As a result, the impact of a technology can be defined by a technical "k" factor vector whose elements consist of the benefits and penalties associated with the technology. Each element of the vector has an estimated impact value and an associated distribution based on the technology's TRL. Not all technologies will affect each element of the vector, but the vector must capture all technologies. An example matrix for three technologies that influence four technical metrics is shown in Figure 6. In the deterministic example in Figure 6, T1 and T3 affect all "k" factors except for the second, while T2 does not affect the first or third. Each element of the vector is established via the Delphi method, literature reviews, or physics-based modeling [5]. The vector *must* include benefits *and* penalties to accurately assess the impact of technologies. The identification of the appropriate shape distribution for a given TRL of the "k" vector elements is discussed in later sections.

		Technologies Considered		
		T1	T2	T3
Disciplinary Metrics	k factor 1	+4%	~	-10%
	k factor 2	~	-3%	~
	k factor 3	-1%	~	-2%
	k factor 4	-2%	-2%	+3%

FIGURE 6: EXAMPLE TECHNOLOGY IMPACT MATRIX

TECHNOLOGY EVALUATION (STEP 7)

The technologies identified in Step 6 are applied to the vehicle concept and evaluated. The evaluation provides data and information to the decision-maker whereby selection of the proper mix of technologies is performed. Yet, the search for the mix that will satisfy the customer requirements is dominated by the "curse of dimensionality". Depending on the number of technologies (n) considered, the combinatorial problem can be enormous. If all combinations are physically compatible and assuming only an "on" or "off" condition, then 2^n combinations would exists. In addition, the technology "k" factor vector that influences a vehicle is probabilistic and a cumulative distribution function (CDF) must be generated for each combination, further complicating the evaluation. If the computational expense of the analysis is acceptable, a full-factorial probabilistic investigation could ensue. Yet, if the computational expense is too high (e.g., a finite element analysis), an alternate evaluation method is needed. One potential method is a genetic algorithm formulation. Reference [19] defines genetic algorithms (GA) as "a class of general-purpose search methods…which can make a remarkable balance between exploration and exploitation of the search (design) space" to find the best family of alternatives.

For the purposes of the current investigation, the computational expense is manageable due to the means by which the technology "k" vectors are modeled. Consider the TIM in Figure 6 and a metamodel representation of a system metric [20]. If one were to bind each "k" factor element of the technical vector, a metamodel in the form of a second-order Response Surface Equation (RSE), Equation 1, could be generated for each of the system level metrics [5].

$$R = b_o + \sum_{i=1}^{k} b_i k_i + \sum_{i=1}^{k} b_{ii} k_i^2 + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} b_{ij} k_i k_j \qquad (1)$$

For example, "k" factor 1, k_1, is bounded between –10% and +4%, while "k" factor 4, k_4, is bounded between –4% and +3%. Hence, the system metrics could be defined as a function of the "k" factors for a fixed geometry using Equation 1, through a Design of Experiments [21]. An RSE of this form is thus defined for each system metric and is valid for the "k" factor ranges specified. The impact of a technology on a system metric can be evaluated via a simple calculation of Equation 1 with the appropriate technology "k" vector values. Since the impact of a technology is probabilistic, the "k" factor elements are distributions rather than the deterministic values in Figure 6. Hence, to quantify the impact on a system metric, a Monte Carlo Simulation is performed with user defined frequency distributions *for each "k" factor element*. Thus, a CDF is obtained for each system metric. If one assumes that the technologies are additive, then a combination of two or more technologies remains a simple Monte Carlo Simulation 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 "k" vectors*. Then, a random number generator would select 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 then inserted into Equation 1 and the system metrics value calculated. This is done for each element and each time a new combination of technologies is desired. This process is automatically performed with the software package Crystal Ball [22] and the CDF values extracted.

POPULATION OF THE PUGH MATRIX (STEP 8)

The Pugh Evaluation Matrix [23] is a method where concept formulation and evaluation is performed in an organized manner. The concepts identified in Step 6 form the rows and the system metrics from the problem definition form the columns as shown in Figure 7. The deterministic elements of the matrix are populated from the results obtained in step 7 for each alternative and metric. Since the metrics are in the form of CDFs, the decision maker has the ability to select a confidence level associated with a given metric. The confidence level is also related to the risk or uncertainty associated with a particular technology, and the selection of these levels is purely subjective. The corresponding value of the metric at a fixed confidence level is then inserted into the appropriate cell of the matrix. This process is repeated for each metric and each compatible technology concept.

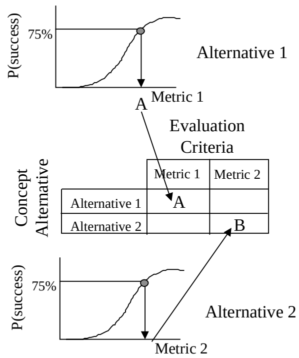

FIGURE 7: POPULATING THE PUGH MATRIX

STEP 9: TECHNOLOGY SELECTION

A Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [24] is utilized to down select the proper mix of technologies satisfying the system level metrics. TOPSIS provides a preference order of the deterministic values obtained in the Pugh Matrix, at a given confidence level, resulting in a ranking of the best alternative concepts. The method by which TOPSIS ranks the alternatives is described below.

From the Pugh matrix, each element of a metric vector (i.e., a given column) is non-dimensionalized by the Euclidean norm of that metric vector. If so desired, subjective weights may be placed on each metric to establish a relative importance. Next, each metric vector must be classified as a "benefit" or a "cost" whereby a maximum of a benefit and a minimum of a cost are desired. Positive and negative ideal solution vectors are then established. The positive vector elements consist of the maximum value of the "benefit" metrics and the minimum value of the "cost" metrics. The negative vector is the compliment of the positive vector. Next, the distance of each alternative from the positive and negative ideal solution is measured by the n-dimensional Euclidean distance, where "n" is the number of alternatives. Finally, each alternative is ranked from "best" to "worst" based on the closeness to the positive solution and distance from the negative ideal solution. These rankings can change depending upon the level of confidence and metric weightings assumed.

Once the top alternatives have been identified, the decision-maker has an abundance of information on which business decisions and strategies can be based. One can explore the robustness of each alternative with the Robust Design Simulation method, which has been implemented for various vehicle concepts [6,25,26]. Additionally, the "best alternative(s)" design space may be re-investigated to determine if geometric optimization may further improve on the customer requirements [4]. Finally, the individual technologies may be compared on a one-to-one basis to identify which technology programs have the more significant impact on the systems so that resource allocation may be optimized.

IMPLEMENTATION

The TIES method described herein was applied to a High Speed Civil Transport (HSCT). This vehicle was a perfect test-bed for the TIES method due to the technically challenging customer requirements and the need for revolutionary advances over present day technological capabilities. For brevity, the new aspects of the method are emphasized in the current investigation, in particular Steps 6 through 9, while only the pertinent information needed for context from Reference [4] is presented. For more information regarding the details of the beginning steps of the TIES method as applied to an HSCT refer to References [4,25].

OVERVIEW OF STEPS 1 THROUGH 5

In the recent NASA High Speed Research program effort, an HSCT was defined as a Mach 2.4, 300 passenger aircraft with a 5,000 nm range [27] and four mixed-flow turbofan engines [28]. The system level metrics that must be met for a successful HSCT concept are summarized in Table II. Although the TOGW is constrained to less than 10^6 lbs, previous work has indicated that a nominal value of 750,000 lbs is desirable for economic purposes. Baseline and alternative concepts were established via the Morphological Matrix in Reference [4]. The optimal geometric baseline concept that was established at the end of that investigation served as the baseline for the current investigation. The only exceptions included the use of a fuselage nose droop in lieu of synthetic vision and a conventional nozzle without a mixer-ejector nozzle and an acoustic liner.

The configurations analyzed in this study were sized for a 5,000 nm mission with the primary cruise altitude of 67,000 ft at Mach 2.4. A subsonic cruise portion preceded the primary cruise segment at an altitude of 35,000 ft at Mach 0.9. The payload of the aircraft was assumed 300 passengers with baggage and a flight crew of two, nine flight attendants, and a fuselage length of 310 ft with a maximum diameter of 16 ft. The primary geometric and propulsive characteristics of the baseline configuration were described in Reference [4] and a three-view is shown in Figure 8. All aircraft sizing and analysis tasks for this study utilized an enhanced [4] version of the Flight Optimization System, FLOPS [29], code. FLOPS was linked to the Aircraft Life Cycle Cost Analysis, ALCCA [30], code.

The HSCT design space exploration performed in Reference [4] revealed that more than 50% of the design space considered could meet the LdgFl and TOGW requirements. Yet, the TOFL, Vapp, and FON could only be satisfied by 19.5%, 3.5%, and 2.5%, respectively. The concept "show-stopper" was the SLN, which could not satisfy the 103 EPNLdB requirement with any combination of design parameters. Since no feasible design space exists, the economic viability did not need to be investigated and technologies were infused. It should be noted that emissions were not considered in the current investigation.

TABLE II: HSCT SYSTEM LEVEL METRICS

Parameter	Target/ Constraint	Units
Performance		
Approach Speed (Vapp)	≤ 155	kts
FAR 36 Stage III Flyover Noise (FON)	≤ 106	EPNLdB
Landing Field Length (LdgFL)	$\leq 11{,}000$	ft
FAR 36 Stage III Sideline Noise (SLN)	≤ 103	EPNLdB
Takeoff Field Length (TOFL)	$\leq 11{,}000$	ft
Takeoff Gross Weight (TOGW)	$\leq 10^6$	lbs
Economics		
Acquisition Price (Acq $)	*minimize*	FY96 $M
Research, Development, Testing, and Evaluation Costs (RDT&E)	*minimize*	FY96 $M
Average Required Yield per Revenue Passenger Mile ($/RPM)	$\leq$ $ 0.10	FY96 $
Total Airplane Related Operating Costs (TAROC)	*minimize*	FY96 $
Direct Operating Cost plus Interest (DOC+I)	*minimize*	FY96 $

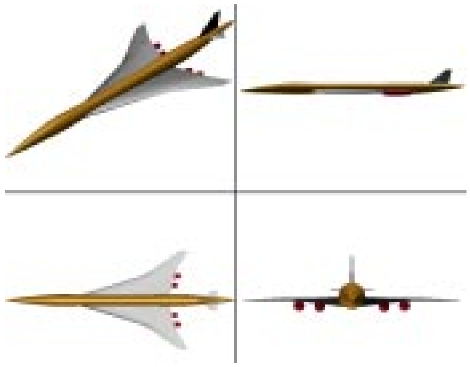

FIGURE 8: BASELINE HSCT CONCEPT

TABLE III: CONVENTIONAL BASELINE HSCT DATUM POINTS

Metric	Baseline Value	Target/ Constraint	Needed % Reduction
TOGW	855353	10^6	ok
TOFL	10707	11000	ok
LDGFL	9231	11000	ok
Vapp	156.3	155	-0.89
FON	107.4	106	-1.34
SLN	110.5	103	-7.28
Acq $*	185.7	reduce	nominal
RDT&E*	15205.4	reduce	nominal
$/RPM*	0.1085	0.10	-8.5
TAROC*	5.318	reduce	nominal
DOC+I*	4.496	reduce	nominal

* Economic results are optimistic due to assumed 800 production units

TABLE IV: ALTERNATIVE TECHNOLOGIES

Technology	TRL	Purpose
Composite Wing [31]	3	Wing weight reduction
Composite Fuselage [31]	3	Fuselage weight reduction
Circulation Control [32,33]	4	Increased low speed performance
Hybrid Laminar Flow Control [34]	3	Cruise drag reduction
Environmental Engines [28, 35, 36]	3	Noise suppression, lower fuel burn and emissions
Advanced Flight Deck Systems [27]	4	Pilot visualization without fuselage nose droop weight penalty
Advanced Propulsion Materials [37]	3	High temp. materials, reduced engine weight, lower fuel burn
Integrally Stiffened Aluminum Wing Structure [38]	4	Wing weight and part complexity reduction
Smart Wing Structures [39]	3	Reduced flutter and wing weight
Active Flow Control [39]	3	Cruise drag reduction
Acoustic Control [39]	3	Noise suppression

											Aircraft Morphing		
Compatibility Matrix (1: compatible, 0: incompatible)		Composite Wing T1	Composite Fuselage T2	Circulation Control T3	HLFC T4	Environmental Engines T5	Flight Deck Systems T6	Propulsion Materials T7	Integrally, Stiffened Aluminum Airframe Structures (wing) T8	Smart Wing Structures (Active Aeroelastic Control) T9	Active Flow Control T10	Acoustic Control T11
	Composite Wing	1	1	1	0	1	1	1	0	0	0	0
	Composite Fuselage		1	1	1	1	1	1	1	1	1	1
	Circulation Control			1	1	1	1	1	1	1	1	1
	HLFC				1	1	1	1	0	0	0	1
	Environmental Engines					1	1	1	1	1	1	0
	Flight Deck Systems						1	1	1	0	1	1
	Propulsion Materials							1	0	1	1	1
	Integrally, Stiffened Aluminum Airframe Structures (wing)								1	0	1	1
Aircraft Morphing	Smart Wing Structures (Active Aeroelastic Control)									1	1	1
	Active Flow Control										1	1
	Acoustic Control											1

Symmetric Matrix

FIGURE 9: HSCT TECHNOLOGY COMPATIBILITY MATRIX

TECHNOLOGY IDENTIFICATION (STEP 6)

Since the probability of success for feasibility was non-existent for the SLN, eleven technologies and technology programs were considered for infusion. The technologies, listed in Table IV, were identified through a literature search of potential sub-component alternatives. The primary purposes of the technologies are also listed. The TRLs were established by comparing the information available in the literature to the definitions in Table I.

Compatibility Matrix

A full factorial combination of the eleven technologies resulted in 2,048 combinations. However, some combinations are not physically realizable. In order to screen non-realistic combinations from biasing the results, a compatibility matrix is created. The compatibility rules for these technologies were determined from brainstorming activities and literature reviews and are shown in Figure 9. As a result, this process reduced the number of alternatives to 273 combinations, which was computationally manageable.

Technology Impact Matrix

The Technology Impact Matrix (TIM) was constructed for the eleven technologies based on a literature review of applied research and expert opinions. The TIM shown in Figure 10 contains the expert predicted impact values if each technology were matured to the point of full-scale application. In the context of the technology development milestones described previously, the impact values were those associated with a TRL of 9. The elements of the technical metric "k" vector are listed on the left. The elements encompass all technology impacts, although not all technologies contribute to every element. The technical "k" vector consisted of 16 elements and was unique for a given technology. The values shown are conservative impacts from the cited references in Table IV. The "k" vector included primary benefits and secondary penalties to both performance and economic metrics. For example, the infusion of a composite wing could reduce the sized vehicle wing weight by 20% and the cruise drag (due to a smoother wing surface) by 2%. Yet, the costs associated with manufacturing and maintaining this type of wing are more than a conventional aluminum wing structure. This secondary penalty was simulated by increased Research, Development, Testing, and Evaluation (RDT&E), production, and Operation and Support (O&S) costs.

									Aircraft Morphing		
Technical K_Factor Vector	Composite Wing T1	Composite Fuselage T2	Circulation Control T3	HLFC T4	Environmental Engines T5	Flight Deck Systems T6	Propulsion Materials T7	Integrally, Stiffened Aluminum Airframe Structures (wing) T8	Smart Wing Structures (Active Aeroelastic Control) T9	Active Flow Control T10	Acoustic Control T11
Wing Weight	-20%			+5%				-10%	-5%	+2%	
Fuselage Weight		-25%				-15%					
Engine Weight				+1%	+40%		-10%				+5%
Electrical Weight			+5%	+1%		+2%	+5%		+5%	+2%	+2%
Avionics Weight				+5%		+2%	+5%		+2%	+5%	+2%
Surface Controls Weight			-5%						+5%	+5%	
Hydraulics Weight			-5%						+5%		
Noise Suppression					-10%		-1%				-10%
Subsonic Drag	-2%	-2%		-10%						-5%	
Supersonic Drag	-2%	-2%		-15%						-5%	
Subsonic Fuel Flow			+1%	+1%	-2%		-4%				+1%
Supersonic Fuel Flow				+1%	-2%		-4%				
Maximum Lift Coefficient			+15%								
O&S	+2%	+2%	+2%	+2%	+2%		+2%	-2%	+2%	+2%	+1%
RDT&E	+4%	+4%	+2%	+2%	+4%	+2%	+4%		+5%	+5%	+5%
Production costs	+8%	+8%	+3%	+5%	+2%	+1%	+3%	-3%	-3%	-3%	-3%

FIGURE 10: HSCT TIM (EXPERT PREDICTED IDEAL VALUES)

TRL Distribution Shapes

As shown in Table IV, the technologies considered for application were at a TRL of 3 or 4 and insufficient data existed in the literature to establish a well-defined growth curve. Hence, the uncertainty of achieving the expert predicted technology impact was estimated based on qualitative reasoning and mapped to a quantitative growth pattern. The estimation was performed via a sensitivity investigation of the system metrics to a Weibull distribution. The Weibull distribution was chosen since it "is a family of distributions that can assume the properties of other distributions" [22] such as an exponential, normal, or Rayleigh. The formula that describes a Weibull distribution for a "k" vector element is shown in Equation 2, where L represents the apex location of the distribution, α is a scale parameter, β is the shape parameter, and x is the random variable. An illustration of the variation in the different Weibull parameters and the influence on the frequency distribution is provided in Figure 11. As the shape (β) increases the distribution narrows although the mode value slightly shifts from the location of –0.2 and the distribution shifts from an exponential to more of a typical Weibull. As the scale (α) increases, the distribution spreads and the mode value shifts even further.

$$k_i(\mathrm{x})\big|_{T_i} = \begin{cases} \left(\dfrac{\beta}{\alpha}\right)\left(\dfrac{\mathrm{x}-L}{\alpha}\right)^{\beta-1} \exp\left(-\left(\dfrac{\mathrm{x}-L}{\alpha}\right)^{\beta}\right) & \mathrm{x} \geq L \\ 0 & \mathrm{x} \leq L \end{cases} \qquad (2)$$

To establish the appropriate "k" factor shape distribution for a given TRL, a DoE combined with a Monte Carlo Simulation was utilized, such that a metric was defined in terms of the Weibull distribution parameters. For each technology "k" vector element, $k_i|_{Ti}$, in the TIM, the impact value was assumed to take the shape distribution of Equation 2. For each element, a range of applicable values for L, α, and β were defined based on the predicted impact, k_i, as listed in Table V. Based on these ranges, a DoE was executed for the metrics in Table II for a given technology. For each DoE case, the "k" factors were assigned the appropriate distribution parameters and a Monte Carlo Simulation executed. For a given confidence level, the metric values were extracted and supplied as data to the JMP statistical package [40]. Eleven DoEs were executed so that the sensitivity of a metric to a given technology distribution could be investigated.

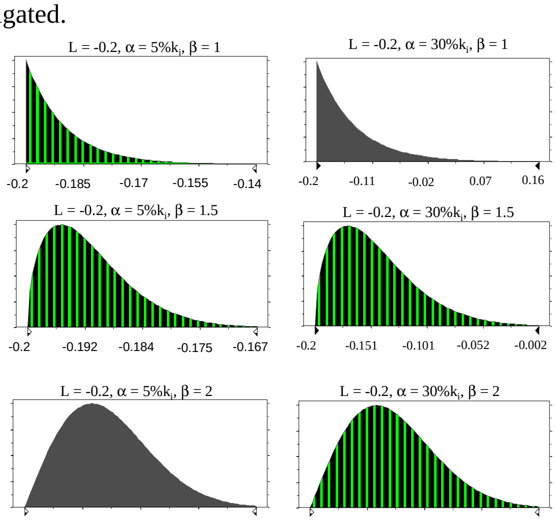

FIGURE 11: VISUALIZATION OF A WEIBULL DISTRIBUTION

TABLE V: RANGE OF WEIBULL DISTRIBUTION PARAMETERS

Weibull Parameter	Minimum	Maximum
L	± 5% k_i	k_i
α	5% k_i	50% k_i
β	1	2

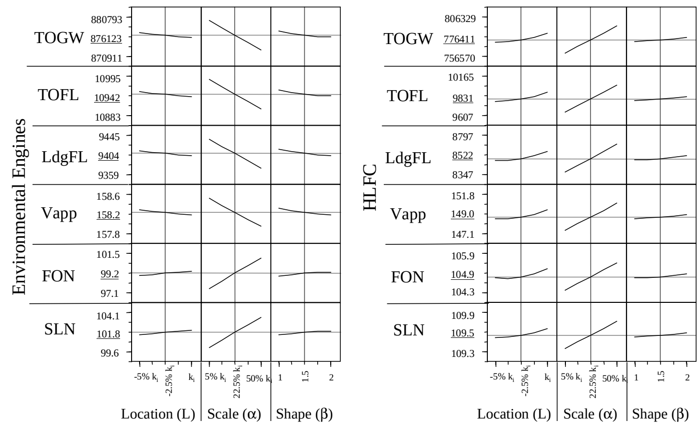

FIGURE 12: METRICS SENSITIVITY TO A WEIBULL DISTRIBUTION VARIATION OF TWO PROPOSED TECHNOLOGIES

As an example, the metric sensitivities due to the addition of environmental engines are shown in Figure 12. The disciplinary metrics that the environmental engines influence are: increased engine weight and noise suppression from a mixer-ejector nozzle and acoustic lining, reduced fuel flow from improved combustion efficiency, and increased RDT&E, production costs, and O&S costs. The results shown below were for a 50% confidence level and were consistent for all other levels for this technology. The metrics were highly sensitive to the scale parameter which stretches out the distribution over a larger range. Furthermore, some of the metrics (TOGW, TOFL, and Vapp) were insensitive to the variation in the "k" vector distributions, and varied less than 1% in magnitude as seen on the left. This result provided valuable insight to the significance of secondary impacts on the system. Specifically, the primary purpose of the application of the environmental engines was to reduce FON and SLN. This indeed was the impact, and there was minimal influence to other performance metrics. This result was consistent for the remaining technologies and HLFC is shown for comparison.

Based on the above sensitivity investigation, a more detailed look at the individual "k" factor element distributions ensued. The focus was to identify the Weibull distribution parameter values that could mimic the total uncertainty of the technology impact as the TRL varied. In essence, bound the uncertainty of the technology impact, as was shown in Figure 4 and Figure 5, so that a quantitative assessment could be performed. For brevity, the investigation resulted in the location defined as the "k_i" value from the TIM and a shape value, β, of 2 for all technologies. The only parameter that varied was the scale (α) and was defined based on the TRL as shown in Equation 3.

$$\alpha\big|_{k_i, T_i, L=k_i, \beta=2} = 30\% k_i - (TRL-1)\frac{(30\% k_i - 5\% k_i)}{8} \qquad (3)$$

As a visual aid, the variation in wing weight reduction due to a composite wing is shown in Figure 13. For a composite wing, the expert predicted the impact on the wing weight was to be a 20% reduction. This value was achieved when the TRL reached 9 since all technology developments were assumed successful. The impact was assumed deterministic at this point. Yet, at lower TRL, the uncertainty in knowledge about the technology was represented by the more spread out distributions shown. As the TRL increases, the variability reduces and the mode value approaches the expert defined value. This logic was used for all technology "k" vectors and the distribution scale parameter used corresponded to Equation 3. The shape of these distributions followed the rationale of the technology uncertainty described in earlier sections.

TECHNOLOGY EVALUATION (STEP 7)

The technology evaluation was performed by creating a metamodel of each system metric in Table II as a function of the "k" vector elements. The metamodels were second-order RSEs as in Equation 1. The RSEs were created with a DoE by bounding the "k" vector elements of the TIM. The ranges used to generate the RSEs are summarized in Table VI. The "0" implies no change in the technical metric, while a negative denotes a reduction and a positive an increase. Once Equation 1 was determined for each metric via the statistical package, JMP [40], the 11 metric RSEs were used to rapidly evaluate technology combinations as described previously. As a visual aid to the decision-maker, a full factorial deterministic investigation was performed and shown as a prediction profile in Figure 14. One can immediately determine which technology had the most influence on a given metric when turned "on". Recall that the SLN was the concept "show-stopper" for technical feasibility. As can be seen, T5 and T11 both significantly reduced the SLN when turned "on", as indicated by the negative slope of the sensitivity. Hence, both technologies show promise for achieving a feasible design, but, the compatibility rules were not inherent in the sensitivities shown, and care should be taken before arbitrarily turning "on" a mix of technologies. If T5 and T11 were both turned "on", the SLN results would be meaningless, since both technologies were engine concepts and only one can be applied.

The next step of the evaluation process was to assess the impact of the compatible technology combinations in a probabilistic space. This was performed by assigning the appropriate Weibull distributions, as defined by Equation 3, to all the technology "k" vector elements. As described previously, a Monte Carlo Simulation was executed on the metric RSEs for each of the 273 combinations of technologies with the Crystal Ball software package [22]. As an example of the evaluation step, the impact of three technology combinations on the TOGW is shown in Figure 15. The variability of the CDFs is a function of the number of uncertain parameters. The combination including four technologies has the largest variability. These results were similar for all metrics and technology combinations consisting of 273 CDFs per metric.

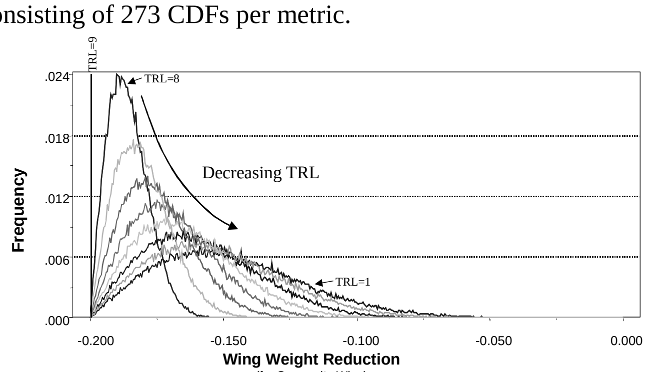

FIGURE 13: EXAMPLE TRL "K" FACTOR DISTRIBUTION

TABLE VI: BOUNDED NONDIMENSIONAL "K" FACTORS

Technical Metric "k" Factors Elements	Minimum (%)	Maximum (%)
Wing Weight	-35	7
Fuselage Weight	-40	0
Engine Weight	-10	46
Electrical Weight	0	22
Avionics Weight	0	21
Surface Controls Weight	-5	10
Hydraulics Weight	-5	5
Noise Suppression	-21	0
Subsonic Drag	-19	0
Supersonic Drag	-24	0
Subsonic Fuel Flow	-6	3
Supersonic Fuel Flow	-6	1
Maximum Lift Coefficient	0	15
O&S	-2	17
RDT&E	0	39
Production costs	-12	30

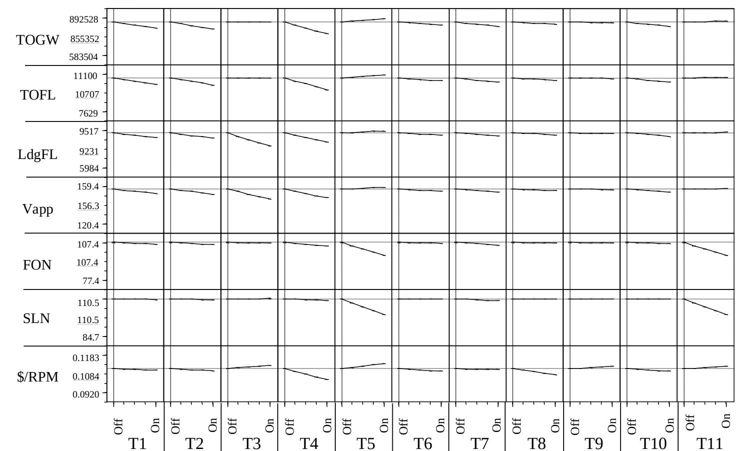

FIGURE 14: FULL FACTORIAL DETERMINISTIC TECHNOLOGY INVESTIGATION

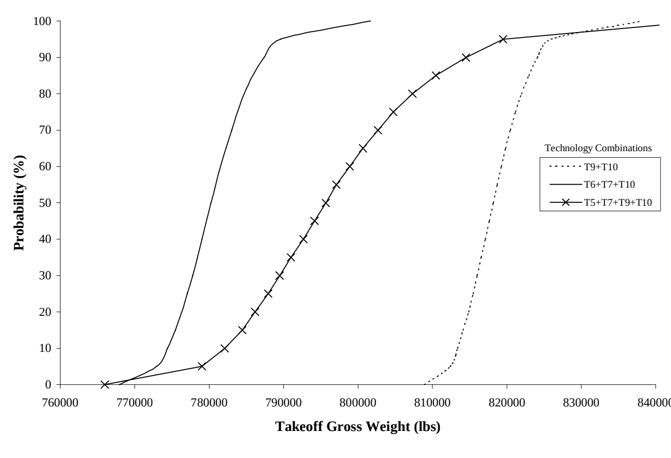

FIGURE 15: EXAMPLE TECHNOLOGY COMBINATION CDFS

POPULATION OF THE PUGH MATRIX (STEP 8)

Four Pugh matrices were used in the current investigation. One consisted of the deterministic values, and the remaining three were populated by extracting the 10%, 50%, and 90% confidence levels from each CDF. Each matrix was 273 by 11, where 273 represented the number of alternatives and 11 the number of system metrics. Each of the matrices were used in Step 9 to determine the best mix of technologies to meet the system metrics.

TECHNOLOGY SELECTION (STEP 9)

The TOPSIS method was used on all four Pugh matrices to identify the best mix of technologies. Each metric was classified as a "cost" since minimization was desired. Furthermore, various weighting factor scenarios were considered in the ranking process, and ranged from heavy performance to relatively evenly distributed, as listed in Table VII. TOPSIS was executed for each Pugh matrix and each weighting scenario. The top 15 technology combinations were compared for each matrix and weighting scenario and an interesting result obtained. The same 10 combinations ranked in the top 15 regardless of the weighting or confidence level considered. Although the absolute ranking order varied, the same technology mixes appeared. These 10 dominant technology mixes are listed in Table VIII. At first, this result would suggest that a probabilistic assessment might not be needed when evaluating the impact of immature technologies. Upon further consideration, this is an erroneous conclusion. The ranking of the best technology mixes was relatively consistent since all technologies were approximately at the *same* TRL. Hence, the frequency distributions assigned to the "k" vector elements were also similar. If the TRLs were at different levels for the 11 technologies, the metric CDFs obtained in Step 7 would have different variability. For example, consider the three mixes of technologies in Figure 15. If T5 were at a TRL of 9, the CDF for the 'T5+T7+T9+T10" combination would have less variability and the TOPSIS ranking would be different. Additional insight was gained from the different weighting scenarios in the form of the recurring technologies. In particular, T2, T4, and T6 occurred in eight of the alternatives. This result would suggest that a composite fuselage, HLFC, and the flight deck systems provided significant benefit with minimal penalty to the performance and economics of the system.

Resource Allocation

Although each of the dominant alternatives satisfied every system level metric, it is unlikely that a company has the R&D budget and resources to successfully develop more than one or two technologies. As stated previously, all technologies were assumed to have a successful development program. This assumption implied that any amount of funds and resources may be used at a given time to develop the technology. This will not happen in a real development program. Hence, as a decision-maker, guidance is desired as to which technology is the most influential for R&D resource allocation for overcoming constraints or meeting objectives.

TABLE VII: TOPSIS WEIGHTING SCENARIOS

	Weighting Scenario									
	Heavy Performance → Evenly Distributed									
Factor	1	2	3	4	5	6	7	8	9	10
TOGW	0.1	0.15	0.2	0.15	0.2	0.2	0.05	0.05	0.05	0.1
TOFL	0.1	0.1	0.1	0.15	0.1	0.1	0.05	0.1	0.1	0.1
LdgFL	0.05	0	0.05	0	0.05	0.05	0.05	0.05	0.05	0.05
Vapp	0.15	0.15	0.05	0.15	0.05	0.05	0.05	0.05	0.05	0.1
FON	0.2	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.1
SLN	0.3	0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1
Acq $	0.1	0.05	0.1	0.05	0.1	0.1	0.1	0.1	0.1	0.1
RDT&E	0	0	0.1	0	0.1	0.1	0.1	0.1	0.1	0.1
$/RPM	0	0	0	0	0	0	0.1	0	0.1	0.05
TAROC	0	0.05	0	0.1	0.1	0	0.1	0.1	0	0.1
DOC+I	0	0	0	0	0	0	0	0.05	0.05	0.1

TABLE VIII: DOMINANT TECHNOLOGY MIXES

Concept	Technology Mix	Concept	Technology Mix
1	T4+T6+T7+T11	6	T2+T4+T5+T7
2	T3+T4+T6+T7+T11	7	T2+T3+T4+T6+T7+T11
3	T2+T4+T7+T11	8	T2+T3+T4+T6+T11
4	T2+T3+T4+T5+T6	9	T2+T3+T4+T5+T6
5	T2+T3+T6+T8+T10+T11	10	T2+T3+T4+T5+T6+T7

A resource allocation investigation was performed by a comparison of the infusion of the individual technologies to the conventional configuration, and evaluation of the deviations in metric values. The SLN and the $/RPM are shown in Figure 16 and Figure 17, respectively, as examples. For the SLN, the target percent reduction needed from the conventional configuration to obtain a feasible concept was 7.28%, as shown by the vertical line. Both engine concepts (T5 and T11) provide the needed reduction with a confidence level of approximately 60%. Hence, either one of the engine technologies would be prime targets for increased R&D resources. Yet, one must also consider the impact of the technology on the affordability and other performance metrics of the system. As shown in Figure 17, T5 and T11 increase the $/RPM relative to the conventional configuration, and could potentially hinder the success of the program. In fact, T5 increased the Vapp for all confidence levels to a point where the constraint of 155 kts was violated by as much as 4.5 kts at the 100% confidence level. T5 negatively impacted all metrics except for the FON and SLN. To the decision-maker, the further development of the environmental engines should be in question, unless another technology was infused countering the negative impact. One example would be the flight deck systems (T6). This technology counters the negative impact of T5 by reducing all metrics. If a company could invest the resources needed for both technologies, the system metrics could be achieved. A similar result was obtained for T11, and the same trade-off rationale could be applied to this technology.

As mentioned previously in the TOPSIS analysis, T2, T4, and T6 were dominant technologies. In the resource allocation investigation, each of these three technologies reduced all metrics as compared to the conventional configuration, with the exception of increased acquisition price for T2 and T4 at all confidence levels. Although neither of the technologies could provide the needed SLN reductions, both provide sufficient benefits to other metrics to meet the imposed targets from Table II.

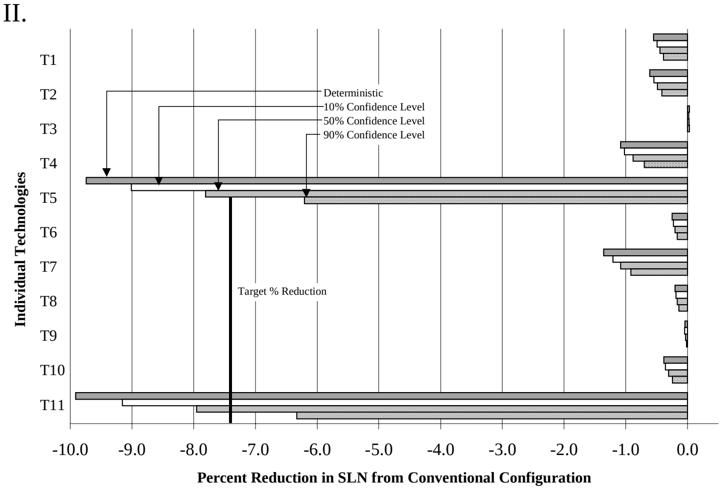

FIGURE 16: PROBABILISTIC IMPACT OF TECHNOLOGIES ON SLN

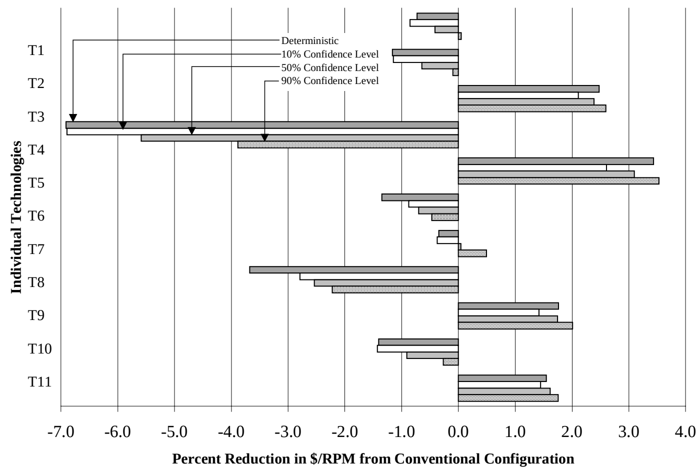

FIGURE 17: PROBABILISTIC IMPACT OF TECHNOLOGIES ON $/RPM

CONCLUSIONS

This paper described research in the area of probabilistic technology assessments and techniques to forecast the impact of any emerging technology in the conceptual and preliminary phases of aircraft design. The thrusts of the techniques developed were focused on the description of technology development programs, and the various milestones encountered during a successful program. The identification of sources of uncertainty associated with an immature technology were described and applied to the determination of frequency distributions of a technology's impact on an aerospace system. Furthermore, the sensitivity of customer requirements to technology shape distributions was investigated and provided valuable insight for mapping technological uncertainty to technology readiness. These aspects are enhancements to the Technology Identification, Evaluation, and Selection (TIES) method. The incorporation of technological uncertainty into the TIES method provides increased knowledge to the decision-maker.

A proof of concept investigation was performed on a High Speed Civil Transport. This vehicle was used as a test bed due to the technically challenging customer requirements. Eleven technologies and technology programs were infused into a conventional configuration. The technology readiness level of each technology was established through a literature search of applied research. From the search, the readiness levels were mapped to a probabilistic space, and subsequently infused to the vehicle. Physically compatible technology combinations were evaluated and ranked based on the improvements to the customer requirements. Three technologies were identified as significant for further investigation and include: composite fuselage structures, Hybrid Laminar Flow Control, and advanced flight deck systems, such as synthetic vision.

Future effort in the development of the TIES method will include a decomposition of the elements that contribute to technological uncertainty, which were not considered in the current investigation. In particular, resource allocation for the development of an immature technology in the form of budgets available and schedules and how those issues vary with time. Furthermore, a more rigorous quantitative development of the technology readiness distributions is needed.

ACKNOWLEDGMENTS

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