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Assessing the Self-Healing Technology Using Novel Technology Impact Forecasting

Ying Huang,¹ Danielle Soban², Dan Sun³

Queen's University of Belfast, Belfast, Northern Ireland, BT7 1NN, United Kingdom

Low technical readiness levels (TRL) technologies are attractive to the aerospace industry because their maturation cycles can happen simultaneously with the development lifecycle of the aircraft. However, due to the limited knowledge about a new technology in system evaluation, a low TRL technology's high potential is counterbalanced by its inherent high risk and high uncertainty. As a result, the assessment of the potential impact of low TRL technologies on a new system is exceedingly difficult. In this paper, a modified Technology Impact Forecasting (TIF) methodology has been proposed that incorporates the novel use of possibility distributions to more accurately quantify the potential of a low TRL technology on a baseline system. The proposed method has been demonstrated through a case study that considers composite self-healing technologies (i.e., microcapsule-based and 1D vascular based self-healing materials) as a representative low TRL technology, and quantifies the impact of infusing this set of technology onto a notional a commercial aircraft system. The results show that, compared to evaluation using a traditional TIF framework, the variability using possibility distributions is significantly reduced for the same system responses. This reduced variability decreases uncertainty, which implies further reduced risk.

I. Introduction and Motivation

In the aerospace industry, continuous adoption of innovation is required to make flight safer, more affordable, and more efficient. Yet adoption of disruptive technologies can be risky, given that the long development lifecycle of an aircraft can take a decade or more, and hence a new technology may become dated, less relevant, or even obsolete by the time the aircraft is in production. Further, new technology may or may not realize the potential benefits of its adoption, once placed and used on a system. It therefore becomes critical and advantageous to be able to assess the potential impact of new technologies on an aircraft system as soon as possible in its design cycle.

Low technology readiness level (TRL) [1] technologies are attractive to the aerospace industry because their maturation cycles can happen simultaneously with the development lifecycle of the aircraft, meaning that the technology can be implemented as soon as it matures. Identifying, and more importantly, assessing, the potential impact of these low TRL technologies is, however, exceedingly difficult. Observation, initial scientific confirmation, or even a working proof of concept does not guarantee a technically feasible or financially viable technology in production. A low TRL technology's high potential is counterbalanced by its inherent high risk and high uncertainty. This has created a growing need and interest in the development of effective technology impact analysis methods and

¹ Ph.D. Student, School of Mechanical and Aerospace Engineering, AIAA student Member

² Lecturer, School of Mechanical & Aerospace Engineering, Senior Member AIAA.

³ Lecturer, School of Mechanical & Aerospace Engineering

tools. Technology Impact Forecasting (TIF) is one of the formalized technology forecasting methods used for aerospace applications, including subsonic [2] and supersonic transports [3], rotorcraft [4] and military systems [5]. The purpose of TIF is to predict the effect a new or developing technology will have on system-level metrics. However, traditional TIF was developed and demonstrated primarily for mid-TRL technologies [6]; therefore the capability to accurately assess the system performance resulting from implementing low TRL technologies remains a significant challenge. Furthermore, past technology assessments for low TRL technologies have relied primarily on expert subjective opinions through the Delphi method due to the absence of experimental demonstrations [7]. However, care must be taken with a traditional application of the Delphi method, as biased estimates may occur. Additionally, the method is quite time-consuming and costly due to multiple rounds of questionnaires, interviews, and long temporal commitment.

Self-healing material is an example of a low TRL technology that can have a significant impact on the design, performance, and cost of aircraft. Nowadays, carbon fiber reinforced polymer (CFRP) composites are widely used in primary structures on both military and civilian aircraft. Unfortunately, damages such as cracks or microcracks may initiate and propagate within CFRP during the aircraft operation due to mechanical stress and environmental factors or a combination of both [8]. These defects, if not detected and repaired in time, may lead to catastrophic failure of the aircraft. Thus, self-healing technology offers great opportunities for material with the capability to sense and respond to damage, restoring the material's properties without costly detection and repair [9]. However, due to the lack of data, it is hard to cross-compare the performance of different self-healing materials and quantitatively assess their impacts on a complex aircraft system.

In this paper, a modified Technology Impact Forecasting (TIF) methodology has been proposed that incorporates the novel use of possibility distributions, based on possibility theory. The paper firstly provides a detailed review of the state of technology forecasting in aerospace engineering. Next, the concept of possibility theory and its application are given. In addition, a low TRL technology, self-healing material is selected as a relevant and illustrative example. Finally, the paper is concluded with a comparison of the novel TIF method against the traditional TIF method using this representative low TRL technology.

II. Technology Forecasting Techniques

Infusing off-the-shelf technologies into the design of a new aircraft system can be problematic, as a high TRL technology can be outdated and obsolete by the time the system is implemented, due to the typically long development cycle of a new aircraft program [10]. Since the aircraft design has shifted from a focus on design for performance to design for affordability, design decisions are more considered to result in the most economical criteria-satisfying design [11]. This change has implied that manufacturers and operators prefer to consider the economic ramifications as first order technology effects in decision process. The interaction with the vehicle configuration effects are secondary. This drives the need for a capability to assess the impact of low TRL technologies on a system at the earliest stages of aircraft design, not only to ensure the technology can enable the final aircraft system in meeting performance and economic goals, but also to influence resource allocation. In other words, this capability could help determine which candidate technologies deserve resource investment. However, it is extremely difficult to estimate the potential impacts of low TRL technologies because their capabilities may not be completely realized until product implementation and service exposure occur.

Technology assessment and forecasting techniques have begun to be used to quantify the impact a technology might have on system performance for the aerospace industry. The primary purpose of technology forecasting is to aid the decision-maker or designer in assessing the potential impact on business or company success as a result of incorporating an innovative technology [12]. Proper anticipation and evaluation of the potential direction, rate, characteristics, and effects of technology will give decision-makers a more complete understanding of the uncertainties they are facing, as well as defining alternatives, options, and consequences to consider in their decision-making process. One of the first examples of technology forecasting was conducted by the National Resource Commission (NRC) in 1935 when they were asked to predict the future of 13 major inventions in 9 different fields [13]. Since then, there have been a variety of forecasting methods and techniques developed, broadly categorized as either “exploratory” or “normative” [14]. The exploratory method looks at past and present information in order to extrapolate a future. Normative methods, on the other hand, start with an assessment of future goals and needs and work backward to determine how these futures might be achieved. Four general techniques are commonly used in exploratory and normative forecasting methodologies, namely: judgmental or intuitive methods, extrapolation and trend analysis, models, and scenarios and simulation, as summarized in Table 1.

Table 1 Technology Forecasting Techniques

Methods	Description	Reference
Judgmental or Intuitive	Rely on experts' opinions to generate a forecast. The most common of the judgemental methods is the Delphi Method, which uses a structured methodology that obtains expected technology impact from expert elicitation	[15]
Extrapolation and Trend Analysis	Use historical data to predict the technology impact in future by an assumption of the technology development will follow the existing trends	[16]
Models	Use a representation of reality to predict the effect of the change to the system in order to understand its impacts at a system level	[17]
Scenarios and Simulation	Explore the complex interaction of different future technology and how technologies will play out in the real world	[18]

In aerospace engineering, the research in technology forecasting is most broadly classified into two main approaches. One is to assess a technology-specific assessment of a sub-system. Another technology forecasting approach is to estimate the impacts of many different technologies at lower-levels and then propagate these results to the system level for various complex system applications. Table 2 summarizes the current state of the art of Technology Forecasting methods in the area of aircraft design. The majority of these studies concentrate heavily on assessing the impact of technology specifically with respect to environmental impact, especially with regard to fuel burn, emissions and noise levels. Technology forecasting methods and examples applied to predicting the impact of new materials for infusing and subsequent affordability assessment have been and remain scarce.

Table 2 Selected Applications of Technology Forecasting Technique in Aircraft Design

Technique	Key Function	Reference
Extrapolation and Trend analysis	Predict future launch vehicle capabilities and thereby support the R&D planning process	[19]
Extrapolation and Trend analysis	Predict the technology's performance, schedule, cost, and risk over the technology development time	[20]
Scenarios and Simulation	Assess the performance and societal cost of the new concepts and help in making informed decisions	[21]
Models	Assess the impact of new aircraft concepts and technologies on aviation's impact on environmental emissions and noise	[22]
Models	Assess the system level impact of multiple high-lift device active flow control architectures	[23]
Models	Provide meaningful insight regarding the selection of immature aircraft technologies for environmental goals and examine the effect of resource cost associated with each technology	[24]

Technology Identification, Evaluation, and Selection (TIES) [25] and Technology Impact Forecasting (TIF) [6] are two interrelated general methodologies for assessing the impact of infused technologies which are formalised for aerospace applications. Both TIES and TIF use probabilistic tools, such as RSEs (Response Surface Equations) and Monte Carlo Simulation and Fast Probability Integration (FPI). TIES, however, includes additional analysis tools, such as Morphological Matrices, Pugh Evaluation Matrices, and Multi-Attribute Decision-Making method, to generate a portfolio of candidate technologies for initial consideration [25] as illustrated in Fig. 1. The analysis techniques in TIF are then used to identify and select the most appropriate technology or set of technologies. The concepts and methods of TIES have been applied to NASA's short haul civil tiltrotor in order to provide a comprehensive, structured and robust methodology for decision making in the early phases of aircraft design [26]. The framework has also been applied to the analysis of aircraft gas turbine propulsion systems, which demonstrated the feasibility of TIES method in both subsystem design and system design [27].

Figure 1 Process flowchart for Technology Assessment Process [5]

III. Self-Healing Fiber-reinforced Polymer Composites

With the overriding duty of safety, airlines have to regularly perform inspection and maintenance to ensure the continuing airworthiness of an aircraft or aircraft part to avoid catastrophic failure. Traditional structural composites inspection and repair are normally labor intensive. The process normally involves detecting internal cracks using non-destructive testing (NDT), infrared thermography, or X-ray tomography, etc. [28], followed by manual repair where the cracks are sealed by the resin, and the broken fibers are replaced by new fibers or a fabric patch [29].

Inspired by the human biological healing system, the concept of self-healing composites has been proposed in the 1990s [30], and has since attracted increasing interest worldwide as a technology to autonomously address the effects of damage in composite materials. Transport-assisted self-healing composite systems such as microvascular and microcapsule-based system are receiving the most research interest. These systems rely on embedded microvascular or microcapsules within the fiber-reinforced composites for the delivery of healing agents into the damaged region to seal the cracks [31]. Specifically, the microvascular self-healing material provides multiple healing events through the

embedded interconnected one-dimensional (1D) [32][33], two-dimensional (2D) [34][35], or three-dimensional (3D) [36][37] channels. The latter two present additional challenges due to their disruption to the fiber architectures and hence, a compromised host material mechanical performance [38][39]. While the microvascular based systems can achieve a healing efficiency of 70% (for 3D channels [36]) to 96% (for 1D channels [40]), its associated manufacturing complexity is much higher [41] and the encapsulated healing agent introduces a significant mass penalty. The requirement for an on-board autonomous delivery system to refill the channels from an external source or from an undamaged vasculature remains the bottleneck for microvascular systems [42].

In microcapsule-based self-healing composites, on the other hand, the healing agent is encapsulated in discrete microcapsules within the matrix resin. Damage ruptures the microcapsules and triggers the release of the agent, which subsequently polymerized upon contacting the pre-embedded catalyst [43][44]. Literature suggests that the microcapsule-based structure can achieve a healing efficiency of 80% -100% [45] [46] [47][48] without causing any weight penalty. However, the deployment of such self-healing material is limited by the depletion of the local healing agent (refill is not possible) after a certain number of healing cycles and the high price of the catalyst.

Although the aerospace industry is still facing complex technical challenges on the path to designing structures with self-healing polymer composites material, the implementation of self-healing on aircraft components has been studied. Table 3 summarizes some of the recent studies dealing with self-healing materials in the aerospace industry.

Table 3 Recent Studies on Self-healing Material Composites for Aerospace Applications

Host Material	Fillers	Key Material Functionality	Targeted Applications	Reference
Carbon Fibre Reinforced Polymer (CFRP)	Poly (ethylene- co-methacrylic acid) (EMAA) thermoplastic	Synergistic combination of toughness and multiple healing repair of delamination and matrix cracks	T-joint in turbine vanes, stringers, and wing spars, etc.	[49]
Ceramic Matrix Composites (CMCs)	Silicon Carbide (SiC) Particles	Effective self-healing under high temperature and low oxygen partial pressure	Gas turbine components,i.e., turbine blades and stator vanes	[50]
E-glass Fibre Reinforced Polymer (FRP)	Double Layer Unidirectional Hollow Glass Capillary Tubes	Significant restoration of mechanical strength	Aerostructures	[51]
E-glass Fibre Reinforced Polymer (FRP)	Lewis acid-catalysed epoxy self-healing agent	Full recovery of mechanical properties	Aerostructures	[52]
AA2024 Alloy	Vanadia based chemical conversion coating	Effective surface corrosion resistance	Fuselage and structural Parts	[53]

Self-healing composites, being one of the low technological readiness level (TRL) technologies, is attracting significant scientific interest and has been the subject of intensive research. However, due to a lack of experimental data, it is hard to cross-compare the performance of different self-healing materials and quantitatively assess their impacts in a complex aircraft system.

IV. Possibility Theory

A. Definition of Possibility Theory

In previous research, the impact of a technology was modelled as changes to a baseline system's disciplinary metrics, represented by technology "k_factors" [2]. The range of values for a k_factor are estimated based on expert opinions and modelled through the use of probability distributions (i.e. shape functions) to represent the likelihood of achieving a particular value [54]. Noting that these expert opinions are subjective and highly dependent on human perception and knowledge, the accuracy of these ranges is inherently uncertain. The most common method used to solicit the opinions of experts is the Delphi method. The Delphi method is a forecasting process based on expert

opinions obtained through a series of questionnaires and controlled feedback. Its goal is to reach a consensus from a group of experts and to use this estimate to inform the values of the k -factors through the identification of the likelihood of achieving a particular technological impact [55]. However, the Delphi method is quite time-consuming due to multiple rounds of questionnaires, interviews, and long temporal commitment. Additionally, biased estimates may occur because the facilitator's view may dominate or influence the results. Finally, knowledge of the experts and their geographic, cultural background, and location are all factors that may lead to poor technology forecasts.

In the area of aircraft design, the impact of a technology might have on system performance is represented with the use of statistical and probabilistic methods since the mid-1990s [56]. By considering the variability due to inherent uncontrollable technological and economic uncertainties, capturing and quantifying design uncertainty can be accomplished in a more mathematical fashion. Using probabilistic methods became challenging, however, when faced with analyzing systems dominated by uncertainty in the form of lack of knowledge or little data. This is because probability theory requires the greatest amount of information to construct the distribution, but in many practical situations, the decision-maker has less information than required to use probability theory. Using probability distribution with incomplete or partial information will distort the result of analysis in an unknown way, making any decisions based on the analysis highly suspect [57]. But for a new system where little is known or where physical testing is too costly to perform, prior knowledge and information is often unavailable. This lack of data and incomplete knowledge of the real world make useful and accurate assumptions and estimations extremely difficult. Moreover, since assumptions that are made under these circumstances are subjective and highly dependent on the experience and knowledge of the expert, the reliability of the model is ultimately uncertain. In response to these challenges, in 1978, Zadeh introduced the concept of possibility theory to provide a complementary relationship to mathematically represent uncertainty and vagueness for the inherent variability of the evidential support based on human cognition [58]. Possibility theory is different from but related to probability theory: probability theory predicts the degree of likelihood of things occurring, while possibility theory focuses on whether the occurrence of an event can happen or not. Possibility theory “deals with the possible rather than probable values of a variable with the possibility of being a matter of degree”[59]. Although possibility theory has not been used extensively for engineering application to date, its wide application can be found in fields of operation research [60], data analysis [61], structural learning [62], database querying [63], belief revision [64], and argumentation [65].

The foundational element of possibility theory is the possibility distribution, denoted π [58]. The possibility distribution $\pi_x(u) \in [0,1]$ represents a state of knowledge (i.e. degree of possibility) about the assignment $x = u$, where $\pi_x(u)$ can be any one number between 0 and 1, and where 0 means $x = u$ is considered an impossible (false) situation and 1 means that it is a fully possible (true) situation. If U is the complete range of x (i.e. $x \in U$), then at least one of the elements of U should be fully possible as a value of x . For example, Fig. 2 shows a possibility distribution of the variable x , in which the possibility value of $x_1 = u_1$ is $\pi_{x_1}(u_1) = \alpha_1$, the possibility value of $x_2 = u_2$ is $\pi_{x_2}(u_2) = \alpha_2$, etc., where α is called α -cut of the possibility distribution π . The α_1 -cut of the possibility distribution shown in Fig. 2 is given by the interval $[a, u_1]$ and the α_2 -cut is given by the interval $[b, u_2]$. The α -cut represents the confidence interval of presumption by an expert, where the value of variable x should lie within this interval. The possibility distribution contains all the possible values which are predicted by all experts with confidence about the occurrence of related events. The construction of a possibility distribution of a variable, therefore, necessitates the collection of a series of possible confidence intervals specified by experts. To do so, first one needs to decide how many linguistic terms from experts are needed to determine the domain of possible interest values, and secondly one needs to determine the shape of the possibility distribution to represent expert opinions about the value of that variable. Clearly, the possibility distribution of a certain variable is improved as more α -cuts are considered. However, increasing the number of α -cuts will also increase the computational expense.

Figure 2 Example of a trapezoidal possibility distribution.

B. Possibility-Probability Transformation

In general, probability theory offers a quantitative model in handling uncertainty where evidence is based on outcomes of independent random experiments, while possibility theory offers a qualitative model for formalizing uncertainty that results from information that is imprecise or partially informed [66]. These theories are not competitive, but rather are complementary of each other, with each representing different types of information and uncertainty. There are some states of information that probability can describe while possibility cannot (e.g. randomness), and conversely, a probability distribution cannot express ignorance [67]. It is therefore recognized that uncertainty is a multidimensional concept and can be expressed in several diverse forms. The transformation between probability and possibility is meaningful when used to capture the full scope of uncertainty when uncertainty is conceived solely within one theory, which manifests only one of its dimensions [68]. The transformation from one theory to the other is dependent on the problem domain and type of evidential information processed. Transforming a probability distribution to a possibility distribution leads to loss of information because the value is transformed from a point value into an interval value while transforming a possibility distribution to a probability distribution leads to the addition of some incomplete knowledge information to the content of the considered representation [69]. The former transformation is used when weak sources of information make probabilistic data unrealistic or to reduce computational complexity, the latter is useful in the case of decision-making. In many practical situations, the decision-maker has less information than required to use probability theory. When a decision must be made, the decision-maker's beliefs and cognitions must be included in order to guarantee that no information is unwittingly obscured. Zadeh [70] claimed that an event must be possible before being probable. Therefore, a decision should be derived from a probability function which is transformed from a possibility function to represent all available information and account for all types of uncertainties.

Identifying and assessing low TRL technologies as applied to complex aircraft system designs introduces uncertainties about the technology's impact for decision-makers. Moreover, due to little or no available experimental data, future orientated forecasts are inevitably based upon expert cognition, which is mainly possibilistic rather than probabilistic in nature. Therefore, in this study, a possibility distribution is constructed using available information to estimate the plausible value of technology k_factor and subsequently transformed into a probability distribution to

predict the frequency of which that value may occur. By applying the Laplace Insufficient Reason principle and procedure proposed by Dubois [69], the probability density resulting from a transformation of possibility distribution is given by:

$$P(x)=\sum_{i=1}^n \frac{\pi_i-\pi_{(i+1)}}{i} \text{ (in discrete case)} \quad (1)$$

or

$$P(x)=\int_0^{\pi(x)} d\alpha / |A_\alpha| \text{ (in continuous case)} \quad (2)$$

where $|A_\alpha|$ is the length of the α -cut of π .

V. Methodology

In the latest research by the authors, a modified TIF method has been proposed for assessing a novel low TRL technology (i.e., advanced materials for lightning strike prevention), where statistically significant simulations were created through the construction of a multi-scale modelling framework with appropriate uncertainty bands [71]. However, due to the lack of knowledge and experimental data, a series of assumptions and estimation of the design variables (i.e. value of technology k_factors) were represented by assigning a uniform or triangular probability distribution based on expert opinions. The range of these distributions had been set broadly to capture all the possible k_factor values, meaning that the variability is higher, and therefore the result more dissimilar and extreme values become more likely. To address this limitation, possibility theory is deployed in this work to represent the value of design variables (i.e. technology k_factors). The modified TIF methodology will be used to assess a new low TRL technology, namely, self-healing materials for carbon fiber reinforced polymer (CFRP) composite repair. This is the first implementation of the possibilistic technique in TIF for assessing the impact of a low TRL technology. Two typical self-healing systems, namely, microcapsule-based and 1D microvascular self-healing materials will be investigated, and their level of impact on selected aircraft system responses will be compared and presented in the case studies.

This section firstly provides a brief overview of the TIF method for implementation and then provides results from TIF when incorporating the possibility distribution concept. A comparison results both with and without using possibility theory is given and discussed to show the proposed method's capability and precision. For more details on the traditional TIF methodology, the reader is referred to Reference[6].

A. Model Environment

The selected microcapsule-based self-healing material was based on studies by Jones et al. [72] and Kim et al. [73]. These studies utilized thermoplastic/epoxy resin blends and microencapsulated solvent healing agents, which eliminated the use of large volumes of costly catalysts as reported in other studies [44][45][46]. For comparison, a 1D microvascular self-healing material [74] [75] will also be investigated, where low melting temperature alloy solder wire was used as the embedded inter-channel within the synthetic CFRP laminates and subsequently removed via a lost wax process. The associated material information deployed for the present study has been summarized in Table 4.

Table 4 Materials information for the selected self-healing materials

Self-Healing material	Material Constituents	Content	Price (\$/lb)
Microcapsule-Based[72][73]	Ethyl Phenylacetate (EPA)	3.1 (vol.%)	9.1
	Poly (bisphenol a- co-epichlorohydrin (PBAE)	20 (wt.%)	11.3
1D microvascular [74][75]	Alloy Solder wire (0.5 mm diameter)	~0.97 (vol.%)	22.7
	RT151 epoxy resin		4.5

A multi-scale modelling environment consisting of a material model, a wing model and an aircraft model, was constructed following the previously established methods as shown in Fig. 3 [71].

Figure 3 Multiscale Modelling Framework of Technology Impact Forecasting [71].

Specifically, for this study, the inputs for the material model are the features of each constituent material within the selected self-healing materials, as listed in Table 4. The outputs of the material model include weight and cost of

the finished multi-functional composites, which were subsequently propagated upward and ultimately fed into the aircraft level to determine system performance. The wing model was extracted and modified from the aircraft sizing and synthesis analysis code FLOPS/ALCCA [76][77], which is well established within the industry and academia in conceptual and preliminary aircraft design. A user-created shell script was used to link each model, which facilitates automatic multiple runs and allows quick changes to input variables. With the completion of the multi-scale framework, a continuous mapping between the material model and the system level aircraft model has been established. Any changes at the material model level can thus be propagated all the way up to the aircraft (system) level. Optimization and assessment of the impact of material selection can occur not only at the aircraft level, but also at the wing model level, as integrated with the material model.

B. Aircraft Baseline

A notional short-medium range commercial transport aircraft, modelled after the Airbus A320, was used as the baseline for this study. The baseline aircraft configuration was established for a 1600 nautical mile mission with a maximum cruising altitude of 35,000 ft at Mach 0.78. The payload of aircraft was assumed to be 150 passengers plus baggage, two flight crew, four flight attendants, two wing-mounted engines, and a fuselage length and diameter of 132.39 ft and 13.6 ft, respectively. The mission has been divided into a taxi out, climb to maximum altitude and cruise at Mach 0.78, and descent and landing at the destination airport. The basic aircraft parameters are listed in Table 5. Since composites constitute 28 % of the weight of the A320 airframe [78], the percentage of composite materials used in a wing structure is estimated to be 28% in this study.

Table 5 Baseline aircraft parameters

Parameter	Baseline	Unit
Take-off Gross Weight	154,939.9	lb
Thrust-to-weight ratio	0.3	-
Wing area	1,330	ft ²
Wing aspect ratio	9.39	-
Wing sweep	25	degree
Wingspan	117.5	ft
Wing taper ratio	0.24	-
Utilization	3,800	Block hour/year
Number of climbs	1	-
Climb minimum Mach number	0.3	-

C. Design Variables and System Responses

Variable Selection

In this work, six economic k _factors have been identified, which will be examined against the implementation of the selected self-healing technologies, as shown in Table 6. The baseline value of each k _factor was set as the default value within FLOPS/ALCCA. The range of feasible (i.e. minimum and maximum values in Table 6) and shape (i.e. shape function) of k _factors were obtained through the construction of individual possibility distributions. Assumptions for the possibility distribution were made independently or in conjunction with the data in references [79][54]. The possibility distribution was then transformed into a probability distribution for later analysis. Fig. 4 (A) shows an example of the possibility distribution for the complexity factor represented by design variable k _CFWCO. Based on the procedure described in the last section, a normal probability density function was obtained for k _CFWCO, as shown in Fig. 4 (B), which was subsequently used as the input shape function to the TIF environment.

Table 6 k _factors and their range of variability in this study

Design Variables	Variable	Baseline	Minimum	Maximum
Complexity factor for composites wing structure basic design engineering	k _CFWCO	1	-10%	+25%
Complexity factor for composites wing tooling and factory test equipment	k _CFWCOTF	1	-10%	+25%
Wing structure composites complexity factor	k _CFWINGCO	0.502	-10%	+25%
Airframe Learning Curve Factor	k _LEARN	82	87	90
Assembly Learning Curve Factor	k _LEARNAS	82	87	90
Maintenance man-hours per block hour reduced by using self-healing material	k _MMC	0	-7%	+7%

Figure 4 (A) A representative possibility distribution and (B) The transformed probability density function used for k_{CFWCO} .

Responses of Interest

Once the range and shape of all $k_{factors}$ (i.e. design variables) are established, the appropriate system responses (i.e. system metrics) that vary with respect to the change in each of design variables need to be identified and selected in order to judge the impact of the system associated with the infusion of this technology. Ideally, these metrics should be relevant and representative of the customer (user) interests with respect to their objectives. The impact of a new technology is assessed by comparing system metrics (system responses) of the baseline system both with and without the infused technology. The selected system responses used in this study were grouped by aircraft size and cost, as shown in Table 7.

Table 7 Selected responses of interests for the aircraft system and their baselines

Responses			Unit	Baseline
Aircraft Size	TOGW	Take-off Gross Weight	lb	158,317.9
	OEW	Operating Empty Weight	lb	77,985.6
	FUEL WT	Fuel Weight	lb	48,982.3
	W/S	Wing Loading	lb/ft ²	119.04
	THRUST	Engine Thrust	lb	23,747.7
Aircraft Cost	RDT&E	Research, Development, Testing and Evaluation Cost	\$M	8,070.86
	OSC	Operation and Support Cost	\$M	48.78
	FUC	First Unit Cost	\$M	224.54
	AUAC	Average unit airplane cost (including spares)	\$M	79.47

D. Creating Surrogate Models

A modern aircraft system is extremely complex, and most system responses of interest are a function of hundreds of design variables. Through the use of surrogate models, the relative contributions of each design variable to the selected system response can be clearly identified through a simple polynomial equation. Various methods can be used for creating surrogate models, such as regression techniques [80], kriging [81], and neural networks [82]. The TIF methodology was originally developed using RSEs methodology facilitated by DoE (Design of Experiment) process to create surrogate models. Once RSE has been created for each system response, it can be used to rapidly evaluate the impact of technologies based on a particular k_factor setting in lieu of executing FLOPS/ALCCA directly. While the TIF framework does not preclude the use of other methods instead of surrogate modelling, their use remains the preferred method of implementation. A Monte Carlo simulation is then performed by randomly choosing variable values from pre-transformed probability distributions (i.e. shape function) to calculate the system responses through the use of the surrogate models. The result is a cumulative distribution function (CDF) that indicates the likeliness of achieving a certain value of a system response. Figure 5 shows the shape functions used for both self-healing materials, which were developed through the transformation of the possibility distribution. Six normal distributions have been applied to each k_factor to enable the subsequent Monte Carlo Simulation and ultimately generate CDFs for each of the system responses.

Figure 5 The shape functions for (A)Microcapsule (B) 1D Vascular self-healing materials

The modified TIF methodology process flow used in the present study is illustrated in Fig. 6.

Figure 6 Modified TIF methodology process flow for low TRL technology (Blue boxes represent the original TIF process flow)

E. Results

Table 8 summarizes the system responses for aircraft size as a result of infusing the respective self-healing technologies. This represents a complete replacement of all relevant composite materials with corresponding self-healing technologies. The benefit or penalty caused by these technologies was identified by evaluating their deviations from the baseline, shown as percentage deviations. It can be seen that, compared to 1D vascular self-healing material, the introduction of microcapsule-based self-healing material provides an autonomous self-healing functionality without incurring a mass penalty. Although 1D vascular self-healing material offers multi-cycle healing and large area healing abilities, it may require further development before being implemented, due to its small, but existing mass penalty.

Table 8 Aircraft size responses with self-healing technology infusion

System Responses for Aircraft Size		Baseline (without any self-healing materials)	Microcapsule- Based Self- Healing		1D Vascular Self- Healing	
Response	Units	Value	Value	% diff	Value	% diff
Take-off Gross Weight	lb	158,317.9	158,317.9	0.00	158,358.3	0.03
Operating Empty Weight	lb	77,985.6	77,985.6	0.00	78,015.6	0.04
Fuel Weight	lb	48,982.3	48,982.3	0.00	48,991.7	0.02
Wing Loading	lb/ft ²	119.04	119.04	0.00	119.07	0.03
Thrust	lb	23,747.7	23,747.7	0.00	23,753.6	0.03

The system responses pertaining to cost as a result of the new technology infusion are shown as cumulative distribution functions (CDFs) in Fig. 7. The economic viability of both self-healing materials on the baseline aircraft system have been examined by assessing the following costs: research, development, testing, and evaluation cost (RDT&E); operation support cost (OSC); first unit cost (FUC) and average unit airplane cost (AUAC).

Fig. 7 Resulting CDFs for self-healing material for aircraft on A) research, development, testing, and evaluation cost; B) operation support cost; C) first unit cost; and D) average unit airplane cost in \$M US

Table 9 and Table 10 list the representative data obtained from the CDF in Fig. 7 upon the infusion of the two self-healing technologies. An 80% confidence level was selected as a reasonable confidence level [71] and confidence levels 50% and 20% are additionally presented for comparison. The confidence level is related to the uncertainty associated with the new technology and represents the risk level the decision-maker is willing to take. Therefore, an 80% confidence level can be interpreted as a high certainty, low risk level whereas a 20% confidence level would indicate a high risk (and potentially high benefit) but low level of certainty in the outcome. These confidence intervals are subjectively provided by the decision-maker [83]. In the tables, each column gives the probability of achieving at least the value given, which is stated as a percentage of change from the baseline. A low confidence level implies that the application of this new technology would be risky since the desired impact has a high probability of not being achieved.

Table 9 Aircraft cost responses with microcapsule-based self-healing material infusion

System Responses for Aircraft Cost	Baseline	Microcapsule-Based Self-Healing					
		80% Prob.	% diff	50% Prob.	% diff	20% Prob.	% diff
RDT&E (M\$)	8070.86	8,080.67	0.12%	8,077.78	0.09%	8,074.77	0.05%
OSC (M\$)	48.78	52.65	7.93%	52.42	7.46%	52.21	7.03%
FUC (M\$)	224.54	227.52	1.33%	226.49	0.87%	225.43	0.40%
AUAC Cost (M\$)	79.47	115.32	45.11%	113.19	42.43%	111.24	39.98%

Table 10 Aircraft cost response with 1D vascular self-healing material infusion

System Responses for Aircraft Cost	Baseline	1D Vascular Self-Healing					
		80% Prob.	% diff	50% Prob.	% diff	20% Prob.	% diff
RDT&E (M\$)	8070.86	8,085.27	0.18%	8,082.67	0.15%	8,080.02	0.11%
OSC (M\$)	48.78	52.67	7.97%	52.43	7.48%	52.22	7.05%
FUC (M\$)	224.54	227.67	1.39%	226.64	0.94%	225.55	0.45%
AUAC (M\$)	79.47	115.41	45.22%	113.24	42.49%	111.32	40.08%

As can be seen from Table 9, all aircraft system costs have increased upon infusion of microcapsule-based self-healing material. This recognizes the importance of material technology and material selection in aircraft design and manufacture. Introducing microcapsule-based self-healing in the aircraft system slightly increases research, development, testing and evaluation cost (RDT&E) by 0.12% from the baseline with an 80% confidence. This is due to the increased engineering hours spent on new airframe design and efforts required to analyse (includes stress, aerodynamic performance), test (includes laboratory, ground and flying) and build wind-tunnel models and mock-ups. Because each airline has their own methods for estimating operation support cost related to their particular type of operation and due to the high variability of maintenance tasks, it is difficult to quantify the actual aircraft operation cost. Therefore, the results here are only used firstly to show that there will be an increase in OSC, and also to try and show the relative variation of operation costs between the two different self-healing materials, given a generic estimation of operation costs. Due to the increased labour hours required for the complex repair process and new maintenance facilities requirement, a more significant increase in operation support cost (OSC) of 7.93% with 80% probability is evident with the infusion of the microcapsule-based self-healing material. Due to the increased cost of the material itself as well as the inherent increased complexity of the manufacturing process, the microcapsule-based self-healing material has a significant influence on the first unit cost (FUC) and average unit airplane cost (AUAC). Given an 80% confidence, the FUC is likely to be increased by 1.33% for microcapsule-based self-healing, and a dramatic rise of 45.11% in AUAC can be shown. As the percentage of probability decreases to 50% and 20%, all system responses show slight decreases accordingly, however, the lower percentage of probability implies this value is less likely to be achieved.

The data in Table 10 for the 1D vascular self-healing material shows slightly greater variability in system responses for categories as compared to Table 9. For instance, with 80% probability, FUC shows a deviation of 1.39% from the baseline, and system response for AUAC shows a deviation of 45.22%. Although the system response values decreased slightly at a lower percentage of probability of 50% and 20%, the values are still much higher than those found for the microcapsule-based system. The results suggest that although both self-healing materials involve greater design and development cost, the microcapsule-based self-healing material would be a more financially viable option.

F. Comparison of Use of Possibility Transformations to Traditional TIF method

In order to demonstrate the benefit of using possibility distributions compared to the traditional TIF method, the analysis was repeated using a standard triangular probability distribution as a shape function (see Fig. 8). Results are compared in Figures 9 and 10.

Figure 8 Triangular probability distribution shape functions for (A) Microcapsule (B) 1D Vascular self-healing materials

Figure 9 Aircraft cost responses for microcapsule-based self-healing material upon using a triangular probability distribution

Figure 10 The aircraft cost response for 1D vascular self-healing material upon using a triangular probability distribution.

It is clear from Figures 9 and 10 that the new TIF method and the traditional TIF method provide results that are roughly of the same magnitude but are still clearly different. Even small differences in percentages can represent a large impact, particularly in cost. It is therefore important to assess which method gives a truer representation of potential qualitative impact. Since these CDFs model the uncertainties and risks associated with the infusion of a new technology in the form of variability, many methodologies strive to reduce the potential range of variability. This is because the wider a probability distribution is, the higher the variability of the design space, and therefore the more imprecise the result [83]. Thus, a probability distribution with smaller variation is more desirable in order to yield a higher probability of achieving a certain value. Figures 11 and 12 show the CDFs generated for aircraft economics, using both possibility distributions (new TIF method) and traditional probability distributions (traditional TIF) as their

respective input k_factors. It is clear in the figures that the variability using possibility distributions is significantly reduced as compared to the triangular distribution inputs for the same system responses. This reduced variability decreases uncertainty (i.e. smaller variability over a wider range of confidence intervals), which implies further reduced risk.

Figure 11 Resulting CDFs generated for aircraft cost for microcapsule-based self-healing material upon using both possibility distributions and traditional probability distributions.

Figure 12 Resulting CDFs generated for aircraft cost for 1D vascular self-healing material upon using both possibility distributions and traditional probability distributions.

VI. Conclusion

This paper presents a novel Technology Impact Forecasting (TIF) methodology with the ability to quantify the impact of infusing a low Technology Readiness Level (TRL) self-healing composite technology in the context of a commercial aircraft system. Possibility distribution was deployed for the first time to replace probability distribution in making assumptions/estimations based on expert opinions. Two representative self-healing technologies, microcapsule-based and 1D vascular based self-healing materials, have been investigated in the case study using both traditional and modified TIF. Results show that the microcapsule-based self-healing material has less impact on the aircraft size and cost as compared to the 1D vascular based self-healing material under both methods. However, with the modified TIF, the variability using possibility distributions is significantly reduced for the same system responses. This reduced variability decreases uncertainty, which implies further reduced risk.

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