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ABSTRACT

In order to enable future space transportation systems, which in turn will enable new missions and markets in space, technology development is needed. But with limited financial resources, government and industry strategic decision makers need an inexpensive, timely, robust methodology for prioritization of advanced space transportation technological investment. The methodology described herein couples robust design simulation methods in a spreadsheet-based meta-model with technology ranking approaches to assess programmatic (i.e. cost and business case), safety, and performance uncertainties associated with future transportation systems. The simplicity of this technique offers the capability to perform Monte Carlo simulations to generate probability distributions rather than simple deterministic values for each output metric, which allows consideration of design risk. This methodology is described in detail through its application on a Two Stage to Orbit (TSTO) Reusable Launch Vehicle (RLV) based upon the Bimese concept (developed at NASA's Langley Research Center) using NASA's 2nd Generation space transportation technology assumptions.

INTRODUCTION

There is a modern emphasis on concurrent engineering with shortened times between research and development (R&D) and the engineering, manufacturing, and development (EMD) phase. With this focus, it becomes crucial to forecast the impact of new technologies, even before the maturation of those technologies. Due to limited technology development budgets, strategic space transportation decision makers in government and industry are forced to make tough decisions to direct scarce resources. A cornerstone of any engineering discipline is the belief that where physically sound calculations can be substituted for assumptions and objective evaluations substituted for subjective, accuracy and understanding improve. Therefore, finding ways to fold more parts of the technology investment process into an analytical methodology is appropriate and desirable. Typically, though, if analyses are conducted at all in technology investment decisions, they are single point solutions that necessarily ignore broad uncertainties across numerous programmatic and technical design parameters. Uncertainty, an ever-present character in the design process, can be embraced through a probabilistic design environment. The objective is to probabilistically quantify the impact of these technologies on the output metrics of interest from the design process. Therefore, decision makers need an inexpensive, timely, analytical, and robust methodology for prioritization of advanced space transportation technology investment.

The Technology Identification, Evaluation, and Selection (TIES) methodology is a systematic aggregation of decision-making techniques and probabilistic methods developed at the Aerospace Systems Design Lab (ASDL) in the School of Aerospace Engineering at the Georgia Institute of Technology. Previous versions of the TIES method have been applied by the ASDL to commercial transport aircraft, rotorcraft, and uninhabited combat aerial vehicles[1,2,3]. An abbreviated version of this method—called the ATIES process[4]—consists of six major parts: baseline concept determination, technology identification, technology compatibility, technology impact, technology evaluation, and technology selection. These steps will be discussed in detail below. (The ATIES method is also shown graphically in Figure 1.)

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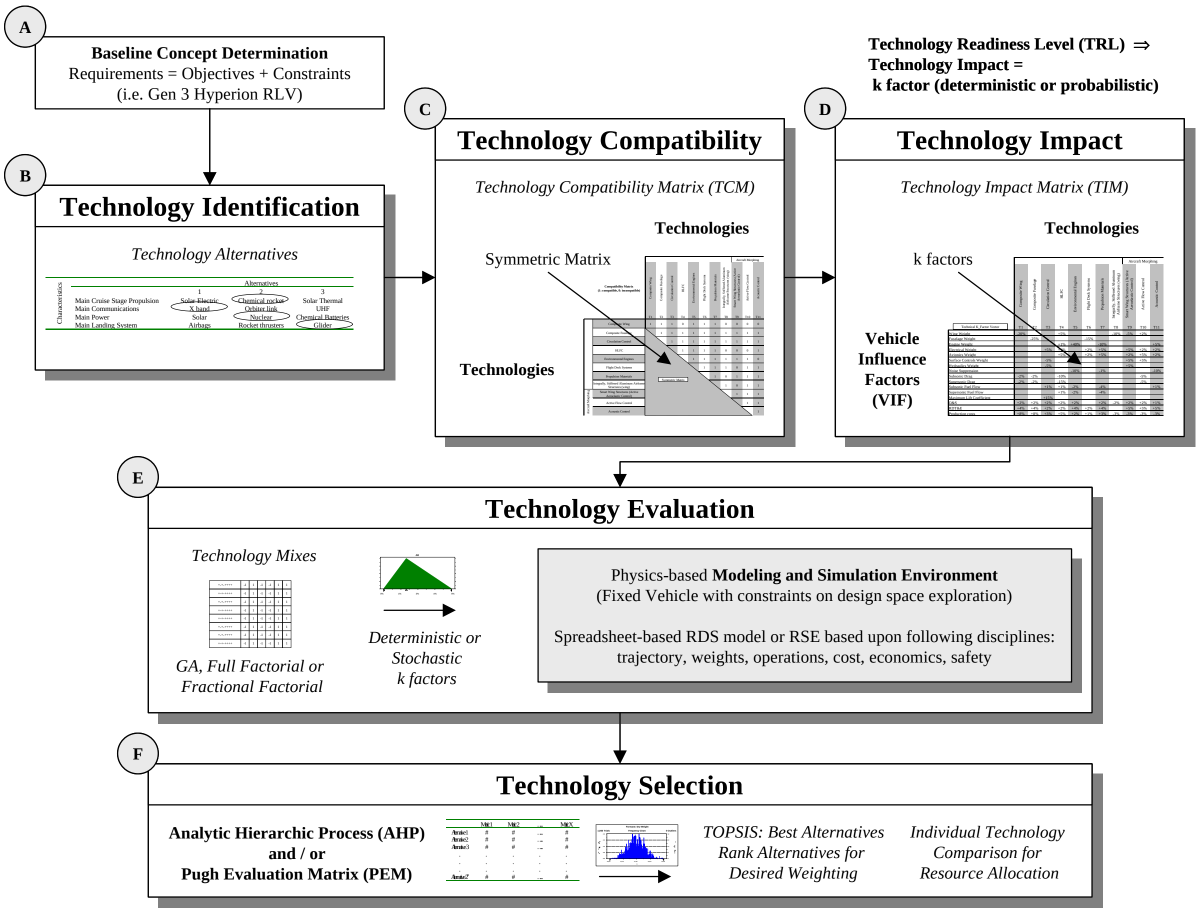


Figure 1 - Abbreviated Technology Identification, Evaluation, and Selection (ATIES) Method

ROSETTA MODELING PROCESS

In order to employ the ATIES method, an effective process is needed for concept simulation and technology evaluation. Therefore, the Reduced Order Simulation for Evaluation of Technologies and Transportation Architectures (ROSETTA) modeling process was created. A ROSETTA model is a spreadsheet-based meta-model which is a representation of the design process for a specific architecture (e.g., ETO, in-space LEO-GEO, HEDS). In a ROSETTA model, each traditional design discipline is represented as a contributing analysis in the Design Structure Matrix (DSM) that is based upon higher fidelity, legacy codes as shown in Table 1. In other words, ROSETTA models contain representations of the full technology evaluation step. Individual developers of each ROSETTA model determine the depth and breadth of the appropriate contributing analyses.

Table 1 – Discipline-specific Legacy Design Codes

Discipline	Code
Aerodynamics	APAS (S/HABP)
CAD & Packaging	I-DEAS
Propulsion (rocket)	SCORES
Propulsion (RBCC)	SCCREAM
Trajectories	POST (3-DOF)
Aeroheating & TPS	T-CAT/Miniver/TPS-X
Mass Properties	Excel-based MERs
Operations & Facilities	AATe/RMAT/OCM
Safety & Reliability	GT Safety/Prism
Cost & Economics	CABAM/NAFCOM

Although the involvement of more disciplines obviously adds fidelity, ROSETTA models can be useful in various stages. As such, ROSETTA models have been grouped into three categories, which signify their level of development:

- Category I: Produces traditional physics-based outputs such as transportation system weight, size, payload, and/or the NASA metric in-space trip time
- Category II: In addition to items in Category I, adds operations, cost, and economic analysis outputs such as turnaround time, life cycle cost, cost per flight, return on investment, internal rate of return (IRR), and the NASA metric price per pound of payload
- Category III: In addition to items in Category II, adds parametric safety outputs such as catastrophic failure reliability, mission success reliability, and the NASA metric probability of loss of passengers and/or crew

A key feature of ROSETTA models is that they execute each architecture simulation in only a few seconds. This enables many deterministic (single point) simulation runs to be performed in the time it takes a typical high fidelity design code to be setup and run. But while deterministic simulations have their advantages—such as ease of use in large concept studies—they also fall short by tending to prefer more optimistic and less mature solutions that may ultimately have a higher payoff but also carry more programmatic and technical risk [e.g., low Technology Readiness Level (TRL) aerospike, composite tanks, etc.]. In a recent quote from Dan Goldin, the NASA administrator said

> "I am requiring the use of formal risk management processes, risk management technologies (e.g., failure modes and effects analysis, fault tree analysis, and probabilistic risk assessments), and design for safety on all NASA programs and projects…. Improved safety and mission success will result only from your complete, thorough, and across-the-board understanding and management of risk." --May 31, 2000

ROSETTA models can be used in robust design, which allows designers to quantitatively assess technology impacts while also treating risk. Because the models run rapidly, ROSETTA users may employ Monte Carlo simulation techniques to place uncertainty distributions on internal design parameters. The resultant outputs are cumulative and frequency probability distributions rather than simple deterministic values for each output metric. This way, a designer may be able to quickly determine, say, the delivered payload capability for a given vehicle with an analytically derived 80% confidence level that has accounted for rather objective risk factors. Figure 2 depicts the general strategy for using a ROSETTA model to generate probabilistic outputs.

A ROSETTA model for a given space vehicle concept contains several disciplinary worksheets and an Inputs/Outputs (I/O) worksheet. The disciplinary worksheets are developed by experts with certain technology assumptions in the vehicle concept. The architecture in the model is modified through Programmatic Influence Factors (i.e., government contribution, market growth, etc.) and Vehicle Influence Factors (I_{sp}, wing weight, Thrust-to-Weight, cost, etc.), which are contained in the I/O worksheet. Changes to a concept's technology assumptions require changing the PIFs and VIFs. When PIFs and VIFs are altered, however, the vehicle design assumptions may no longer match, so this requires the model to be reconverged both physically and financially—which will be described below.

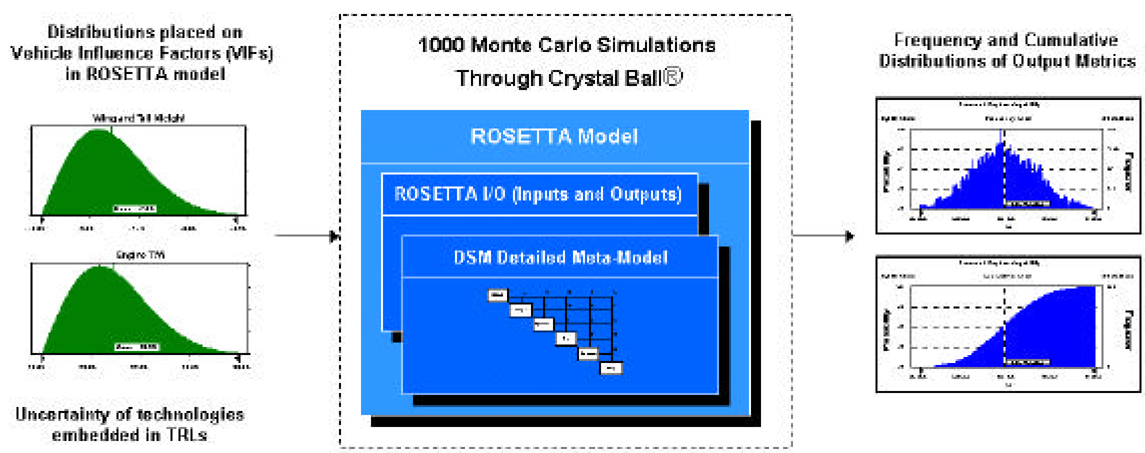


Figure 2 – Bimese TSTO ROSETTA Modeling Strategy

This modeling process, created at Georgia Tech and enhanced at SpaceWorks Engineering, Inc., was adopted and used by the Integrated Technology Assessment Center (ITAC) sponsored by NASA-Marshall Advanced Space Transportation Program[5]. Team members from across the industry were involved, most directly in steps two through four of the ATIES method described above, to model 3rd Generation Reusable Launch Vehicle (RLV) concepts such as an all-rocket Single Stage to Orbit (SSTO) vehicle with advanced engines and a concept with Rocket Based Combined Cycle (RBCC) propulsion. Other concepts, such as an in-space tug, a solar sail, and several 2nd Generation RLVs, have been simulated by the authors and others using the ROSETTA process.

ROSETTA CASE STUDY: BIMESE TSTO RLV

In terms of the ATIES method, the first step in technology prioritization is identification of a baseline concept. This paper details the development, operation, and application of a ROSETTA model on a Two Stage to Orbit (TSTO) 2nd Generation RLV based on the NASA-Langley Bimese concept[6,7]. Figure 3 contains a graphical depiction of this vehicle, along with some of the major vehicle and programmatic assumptions. The Category III ROSETTA model for this concept contains six disciplinary worksheets to allow complete assessment of the vehicle life cycle: Trajectory, Weights, Operations, Cost, Economics, and Safety.

The Trajectory worksheet for the Bimese case study was derived from a baseline ascent trajectory optimized using POST-3D. This trajectory assumes a launch from Cape Canaveral with two SSME Block II engines out (one per vehicle), which requires the 18 remaining engines to throttle from 104% to 109%—a “worst case” condition. The objective is a 50 x 248 nmi. x 51.6° Space Station transfer orbit. All engines use booster propellants up to staging (cross-feed), the orbiter is assumed full at staging near Mach 3.3, and the booster glides back to KSC unpowered. From this baseline, the reference ascent Mass Ratio (MR) and relative velocity losses were established, and the spreadsheet was set up with simple rocket equation relationships to model the effects of changing vacuum I_{sp} or changes in individual velocity losses. Vehicle mixture ratio was assumed to be constant.

Vehicle Assumptions:

- Mated “twin” approach (basic stages are identical and interchangeable)
- Wing-body stage configuration
- Forward LOX tank
- Vertical takeoff, unpowered horizontal landing
- Parallel burn with cross feed of propellants [10 SSME Block II engines per stage]
- External payload pod for cargo missions, external CTV for crew transfer missions
- Graphite/epoxy airframe/wing cold structure
- Aluminum-lithium propellant tanks
- AETB TUFI tiles and AFRSI blanket TPS
- Standard boiling point propellants

Programmatic Assumptions:

- Reference mission: 35,000 lbm payload to the International Space Station (ISS)
- Initial Operational Capability (IOC): 2010
- 20-year program life
- Commercial and government markets use the same price per pound
- Priced to achieve IRR of 10%
- Government contributions are: 100% facilities, 25% airframe
- Government-backed loans are provided

Figure 3 – Bimese TSTO Concept

The Weights worksheet included a full three-level sizing spreadsheet and WBS developed at Georgia Tech. Mass Estimating Relationships (MERs) were originally based on a mixture of NASA-Langley heritage for rocket-based RLVs and technology reduction factors approximated at by the authors for 2nd Generation vehicle assumptions. Vehicle elements were scaled photographically—by changing fuselage length—to match required orbiter MR. Subsystem weights were scaled to appropriate 2nd Generation assumptions, and a 15% overall dry weight margin was used. Block II SSME weights were not scaled as the vehicle was resized.

The necessity of using spreadsheet models in the ROSETTA process has been discussed above. For many design disciplines, it is possible to develop spreadsheet models with imbedded physics-based equations that represent higher-fidelity codes effectively. However, there are occasions that require simplification of those codes. In such circumstances, one may create sets of response surface equations (RSEs) to model output responses to given independent variables.

The Operations worksheet was built on a heritage from a NASA-Kennedy model, Architecture Assessment Tool-enhanced (AATe). This model requires both quantitative inputs and qualitative order of magnitude comparisons of the concept vehicle to the Space Shuttle. Inputs include: overall vehicle reliability, airframe life, payload weight, dry weight, vehicle length, and payload demand per year. Outputs include: ground turnaround time, facilities cost, labor cost per flight, line replaceable unit (LRU) cost per flight, and operating expenses per flight. RSEs were developed from AATe for the ROSETTA model for simplicity.

The Cost worksheet was a weight-based spreadsheet consisting of Cost Estimating Relationships (CERs) with complexity factors at subsystem level—based on the NASA Air Force Cost Model (NAFCOM) at NASA-Marshall. Programmatic costs included: system test hardware; integration, assembly, & checkout; system test operations; ground support equipment; systems engineering & integration; and program management. A 20% cost margin was applied to all design, development, test, and evaluation (DDT&E) costs and theoretical first unit (TFU) costs, but no DDT&E cost was included for the for Block II SSMEs.

The Economics worksheet was taken from CABAM, a cost and economics model originally developed at Georgia Tech. Two vehicle pricing schemes were available: assuming the same price for government and commercial missions or allowing different prices for government and commercial missions (where the commercial price is set at $1,000/lbm). Launch price was manipulated to obtain the desired IRR. The same price was assumed for cargo and crewed missions. Launch market elasticities (price versus payload demand) were available for three scenarios: low, most likely, and high demand. Elasticities included growth options for market demand and parameters to define competition through effects by new entrants. FCF, upon which both IRR and Net Present Value (NPV) depended, was based on income from operations (total operating expenses – gross profit), while the effect of financing (loan rate) was not included in the calculation of the FCF.

The Safety worksheet was based on GT-Safety, a tool developed at Georgia Tech which uses quantitative vehicle data coupled with linear base adjustments to Shuttle operating characteristics (a top down approach). Input vehicle data were: required crew and passengers per flight, passenger flights and total flights per year, ground personnel, vehicle configuration parameters, and single engine and airframe reliability. Outputs included: casualties per year (flight and ground), flights between ascent aborts, flights between loss of life, and flights between loss of crew. Safety calculations were made for three populations and weighted for public/collateral safety, ground personnel safety, and flight crew/passenger safety.

The DSM in Figure 4 shows how all of the inputs and outputs are connected in the Bimese TSTO ROSETTA model. Within the Excel workbook, there are links between disciplines—called either “feed forward” or “feedback” links—which model the interconnectedness of the design process. Vehicle weights, for example, are used to estimate hardware and other costs, so some values calculated in the Weights discipline worksheet must be fed forward to the Cost discipline worksheet, as shown by letter ‘B’ in the Figure. In addition to the linkages between the disciplinary worksheets, the I/O worksheet handles the inputs and outputs that the user most frequently follows. Assembling the I/O sheet and all disciplines into one Excel worksheet obviously allows data to be passed quickly and accurately.

When some performance parameter (a VIF) was changed by the inclusion of a new technology, the new performance may have affected the vehicle mass ratio as calculated from the weights and sizing worksheet, creating a discrepancy between this mass ratio and the one required for trajectory. In this case,

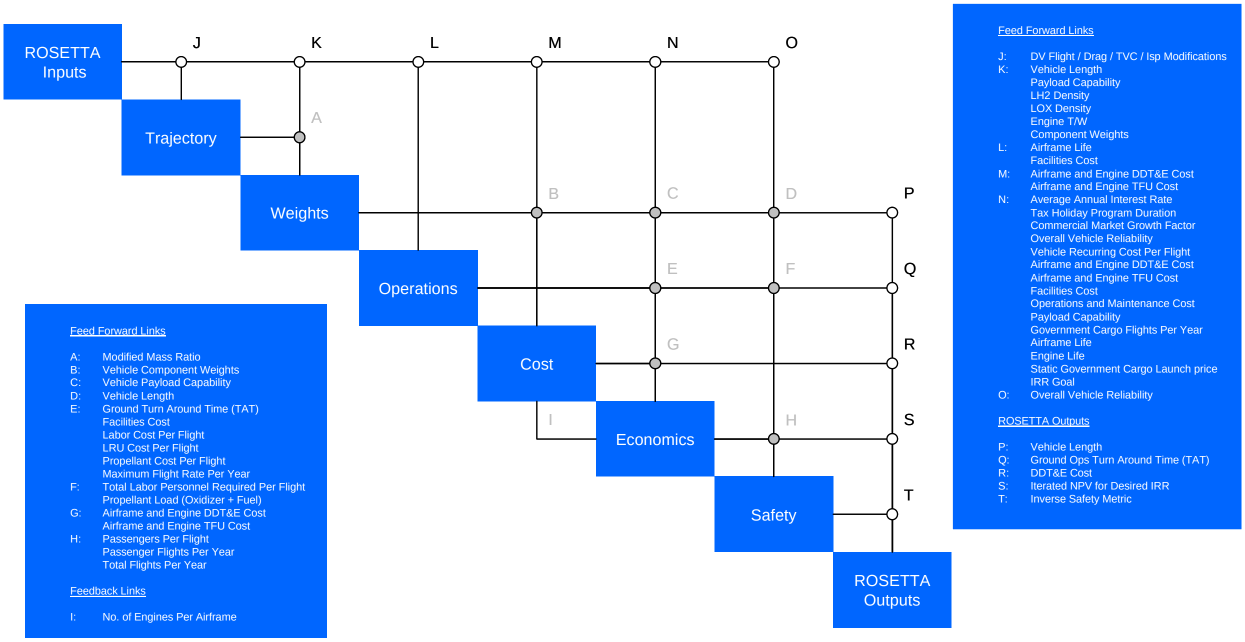


Figure 4 – Bimese TSTO ROSETTA Design Structure Matrix

the vehicle length had to be manipulated in order to make both mass ratios equivalent. This manipulation was done through MS Excel® Solver (in a VBA macro). At the same time, technologies may have changed the vehicle's cost and economic picture, and any change that resulted in a change to Free Cash Flow (FCF) resulted in a change of the price required to converge the economic model to the desired IRR, which was based on costs and the price per pound charged for delivery of payload. Thus, the vehicle sizing optimization was completed first through an MS Excel® Solver, then the required economic case was converged in a separate tasking of MS Excel® Solver. These two steps could be accomplished within seconds due to the nature of the ROSETTA model.

After concept identification, the next step in technology prioritization is technology identification. The infusion of new technologies requires the identification of those technologies that are applicable to the concept of interest and are to be available in the desired timeframe. For the present case study, five typical 2GRLV technologies were chosen to be evaluated on the Bimese TSTO vehicle: a long-life, high thrust-to-weight rocket engine; a Ti/Al-SiC metal matrix composite (MMC) airframe; self-healing, robust thermal protection system (TPS) materials; densified fuel (slush hydrogen); and graphite/epoxy, linerless tanks. Since the focus of this paper is not the technologies themselves, detailed descriptions of the five chosen for evaluation will not be included.

Once technologies are chosen for evaluation, the physical compatibility of all possible technology portfolios (combinations of technologies) must be determined. In the case of the five technologies chosen for this study, all are compatible. That is, using any of the selected five technologies will not preclude use of any or all of the others.

Before the various technology portfolios can be evaluated, the impact of each individual technology on the vehicle model's independent variables must be determined. Their impact is assessed through qualitative impact factors known as "k-factors". These k-factors mimic the discontinuities in benefits and/or penalties associated with the infusion of new technologies. The process of determining k-factors is notoriously subjective; even experts frequently vary in their estimates. However, in order to evaluate technologies in any analytical methodology, technology impacts must somehow be provided. Therefore, the user must either account for this subjectivity or arrive at consensus; typically, it is more practical to chose the former.

Tables 2 through 6 show the k-factors for each of the five technologies chosen. The values are in percentages because they are the impacts on each of the factors *relative* to the baseline vehicle assumptions. For example, the baseline rocket

Table 2 - Long-Life, High T/W Engine k-Factors

Factor	min	nom	max
Booster Vac. I_{SP}	99.5%	100.5%	101.5%
Orbiter Vac. I_{SP}	99.5%	100.5%	101.5%
Engine T/W	115.0%	125.0%	150.0%
Engine DDTE	90.0%	110.0%	150.0%
Engine Proc Cost	80.0%	110.0%	150.0%
Ground TaT	95.0%	100.0%	105.0%
Engine Life	100.0%	150.0%	200.0%
Engine Reliab	100.0%	150.0%	200.0%

Table 3 - Airframe Ti/Al-SiC MMC k-Factors

Factor	min	nom	max
Wing, Tail Wt	95.0%	97.0%	100.0%
Fuselage Weight	95.0%	97.0%	100.0%
TPS Weight	85.0%	90.0%	100.0%
Airframe DDTE	98.0%	100.0%	103.0%
Airfr Proc Cost	98.0%	100.0%	105.0%
Rec Cost / Flight	95.0%	98.0%	102.0%
Ground TaT	90.0%	95.0%	100.0%
Airframe Life	100.0%	150.0%	200.0%

Table 4 - Self-Healing TPS Materials k-Factors

Factor	min	nom	max
TPS Weight	95.0%	100.0%	105.0%
Airframe DDTE	100.0%	105.0%	110.0%
Rec Cost / Flight	85.0%	90.0%	95.0%
Ground TaT	85.0%	90.0%	95.0%

Table 5 - Densified Hydrogen Propellant k-Factors

Factor	min	nom	max
Prop Tank Wt	95.0%	100.0%	115.0%
Engine T/W	100.0%	103.5%	107.0%
Fuel Density	114.9%	115.0%	115.1%
Facilities Cost	200.0%	250.0%	300.0%
Airframe DDTE	102.0%	105.0%	110.0%
Airfr Proc Cost	102.0%	105.0%	110.0%
Rec Cost / Flight	105.0%	112.0%	118.0%
LH2 Prop Cost	200.0%	250.0%	300.0%

Table 6 - Graphite-Epoxy Linerless Tank k-Factors

Factor	min	nom	max
Prop Tank Wt	95.0%	100.0%	115.0%
Airframe DDTE	90.0%	100.0%	110.0%
Airfr Proc Cost	90.0%	100.0%	110.0%
Airframe Life	90.0%	100.0%	110.0%

engine for the Bimese concept is the SSME Block II, so rocket engine improvements due to the first technology are relative to SSME performance and cost. Not only nominal values are given for k-factors, but minimum and maximum k-factors are also provided. These triangular distributions model the risk/uncertainty involved in technology development, as previously discussed. The first two rows in Table 2 show that the first technology—a new rocket engine—is assumed to offer vacuum specific impulse at least 99.5% of that provided by the SSME, nominally 0.5% higher than the SSME, and possibly up to 1.5% higher. On the other hand, the new engine's procurement cost—shown in row five of the same table—is expected to be between 90% and 150% of the SSME's procurement cost, with a nominal expected cost at 10% higher than the baseline. In similar fashion, the other technologies are compared to baseline assumptions, and k-factors are determined relative to the baseline. Please note that the k-factors provided are simply the authors' choices for the purposes of this paper and are not expected to reflect industry-wide consensus.

In addition to k-factors, which reflect the impact of potential technologies, the designer must also be concerned with the inherent uncertainty in vehicle performance and programmatic variables—that is, the uncertainty associated with the design and development process. This uncertainty, or noise, in the driving design parameters is captured in ROSETTA models through "n-factors". As uncertainty exists independent of design, n-factors are distributions placed on VIFs and PIFs regardless of technologies used. Table 7 shows the n-factors used for this case study.

With technology impacts established, it is possible to evaluate the potential technologies on selected space transportation concepts. For the decision maker, however, it is necessary to evaluate more than just the individual technologies. One must evaluate all

Table 7 – Noise Assumptions ("n-Factors") for Bimese Case Study

Vehicle Influence Factor (VIF)	minimum	most likely	maximum
ISP_vac: Booster & Orbiter	99.0%	100.00%	101.0%
Drag Losses and TVC Losses: Booster & Orbiter	90.0%	100.0%	115.0%
Wing and Tail Weight & Fuselage Weight & TPS Weight	95.0%	100.0%	105.0%
Propellant Tank Weight	95.0%	100.0%	115.0%
Engine T/W	80.0%	100.0%	110.0%
Subsystem Weight & Undercarriage Weight	80.0%	100.0%	125.0%
Facilities Cost	50.0%	100.0%	200.0%
Airframe DDT&E Cost	65.0%	100.0%	135.0%
Engine DDT&E Cost	75.0%	100.0%	200.0%
Airframe Procurement Cost (TFU)	65.0%	100.0%	135.0%
Engine Procurement Cost (TFU)	75.0%	100.0%	150.0%
Vehicle Recurring Cost / Flight	90.0%	100.0%	110.0%
DDT&E Commonality b/w Stages: Airframe & Engines	90.0%	100.0%	100.0%
Booster / Orbiter Ground Turnaround Time	90.0%	100.0%	110.0%
Booster / Orbiter Airframe Life (MTBR)	80.0%	100.0%	120.0%
Booster / Orbiter Engine life (MTBR)	50.0%	100.0%	125.0%
LH2 Propellant Cost & LH2 Propellant Cost	50.0%	100.0%	200.0%
Overall Vehicle Reliab. (MTBF) & Single Engine Reliab. (MFBF)	50.0%	100.0%	150.0%

possible technology combinations, because although various technologies may be physically compatible, their respective impacts may overlap or cancel each other out when used in concert. It may seem intuitive that simply employing all potential technologies will offer the greatest benefit. However, managers usually have limited budgets and therefore may not be able to fund all technology development projects. Both cost *and* benefit are important.

Some decision makers have advocated using cost-to-benefit ratios to make funding selections. This method, however, often adds complexity to already difficult evaluation processes. Recognizing that advanced technology budgets usually have fixed ceilings rather than depending on the available technologies, it may make more sense to narrow the list of possible portfolios based on fixed annual and/or multi-year budgets *before* evaluating those portfolios. This is the method used for the Bimese case study.

First, all possible technology portfolios were set up using a full-factorial Design of Experiments (DOE) method for the five technologies selected—a total of 32 possible runs. Then, annual funding requirements for each technology project were derived. Using the nominal funding assumptions and assuming budgetary limits of $75 million per year and $300 million over five years, technology portfolios were eliminated from consideration. Table 8 shows the assumed funding requirements and the DOE used to narrow the list of portfolios (note that the highlighted rows in violated either the annual or 5-year funding constraints, or both). Eighteen portfolios were left for consideration.

Finally, the ROSETTA models were run to evaluate the five technologies in the Bimese TSTO vehicle. To run deterministically, nominal k-factor values corresponding to the technology portfolio were used—no triangular distributions were required. For portfolios with multiple technologies that had more than one k-factor for a given VIF or PIF, the k-factors were multiplied together to arrive at a single k-factor value. For example, if both airframe MMCs and slush hydrogen were used, there were two k-factors for vehicle recurring cost per flight, 98% and 112%, respectively. The value used for recurring cost was, then, 109.76%. For deterministic runs, no n-factors were used, because inherent uncertainty cannot be modeled in single point designs. Following are most

Table 8 – Design of Experiments for Bimese Case Study
(highlighted rows over budget limit)

Technology	Symbol
Long-Life, High T/W Rocket Engine	A
Ti/Al-SiC MMC Airframe	B
Self-Healing/Robust TPS Materials	C
Densified Fuel (Slush H_2)	D
Graphite/Epoxy Linerless Tanks	E

	Design of Experiments (DOE)					Annual Technology Portfolio Cost					5-Year Total Portfolio Cost
Run	Tech A	Tech B	Tech C	Tech D	Tech E						
1						0	0	0	0	0	0
2	1					40	40	50	60	60	250
3		1				30	30	40	40	40	180
4			1			10	10	10	10	10	50
5				1		10	10	15	15	20	70
6					1	10	10	10	10	10	50
7	1	1				70	70	90	100	100	430
8	1		1			50	50	60	70	70	300
9	1			1		50	50	65	75	80	320
10	1				1	50	50	60	70	70	300
11		1	1			40	40	50	50	50	230
12		1		1		40	40	55	55	60	250
13		1			1	40	40	50	50	50	230
14			1	1		20	20	25	25	30	120
15			1		1	20	20	20	20	20	100
16				1	1	20	20	25	25	30	120
17	1	1	1			80	80	100	110	110	480
18	1	1		1		80	80	105	115	120	500
19	1	1			1	80	80	100	110	110	480
20	1		1	1		60	60	75	85	90	370
21	1		1		1	60	60	70	80	80	350
22	1			1	1	60	60	75	85	90	370
23		1	1	1		50	50	65	65	70	300
24		1	1		1	50	50	60	60	60	280
25		1		1	1	50	50	65	65	70	300
26			1	1	1	30	30	35	35	40	170
27	1	1	1	1		90	90	115	125	130	550
28	1	1	1		1	90	90	110	120	120	530
29	1	1		1	1	90	90	115	125	130	550
30	1		1	1	1	70	70	85	95	100	420
31		1	1	1	1	60	60	75	75	80	350
32	1	1	1	1	1	100	100	125	135	140	600

of the outputs provided: vehicle data on the booster and orbiter, including gross and dry weights, fuselage lengths, and DDT&E costs; recurring cost per flight; vehicle turnaround time; price per pound and per flight; program NPV; various life cycle cost statistics; total program revenue and equity financing; flights per year and total flights in program; annual casualty rate; incomplete mission rate; and total loss of life rate.

As discussed above, what makes the ROSETTA process especially useful is that rapid evaluations allow concepts to be run probabilistically to model risk. In the case study, triangular distributions were placed on both k- and n-factors, as shown in Tables 2 through 6 and 7. Decisioneering's Crystal Ball® software was used to run 1000 Monte Carlo simulations for each technology portfolio. All 1000 simulations for a given portfolio could be easily run on a laptop PC overnight. The resultant outputs from were probability distributions of the output metrics described above.

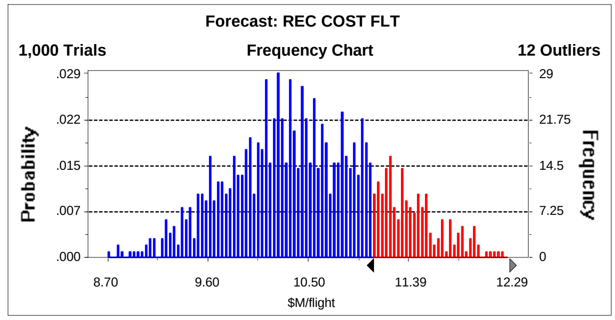
The importance of the ATIES process is that the user obtains analytical data with which to guide technology investment decisions. Although the purpose of this paper is to demonstrate the ROSETTA method rather than compare technology portfolios, some results will be discussed to demonstrate how technologies are selected using output data. When run deterministically, ROSETTA models provide quick information on fixed point designs. Table 9 shows abbreviated results from the technology portfolios selected in the case study. Note that the selection of an optimal portfolio depends heavily on the output of interest. For example, a manager may opt to fund both the new rocket engine and self-healing TPS materials (technologies A and C) if he is interested in high safety and low recurring cost. But he may choose differently if operations (turnaround time) is his focus area. Obviously, managers must decide how to value each output (more discussion is given on this topic below). One should also note that technology portfolios may give similar output responses—for example, there are three portfolios that share the lowest gross weight and turnaround time. Since the risk of each individual technology is not built into these analyses, it is more difficult to differentiate between sets of outputs.

Table 9 – Example Bimese TSTO ROSETTA Deterministic Results
(highlighted items are best values for given output)

Portfolio	Gross Weight	Recurring Cost	Turnaround Time	Price per Pound	Casualty Rate Year
notech	5,988,898	11.84	76.65	9,570.1	3.484E-02
TechA	5,429,470	11.14	74.68	8,670.1	2.187E-02
TechB	5,726,038	11.25	75.63	8,949.4	3.305E-02
TechC	5,988,898	10.70	76.65	9,654.5	3.484E-02
TechD	5,526,130	13.21	73.21	9,484.6	3.482E-02
TechE	5,988,898	11.84	76.65	9,570.1	3.484E-02
TechA_C	5,429,470	10.07	74.68	8,865.8	2.155E-02
TechA_E	5,429,470	11.14	74.68	8,670.1	2.187E-02
TechB_C	5,726,038	10.17	75.63	9,163.2	3.254E-02
TechB_D	5,302,274	13.12	72.41	9,298.0	3.220E-02
TechB_E	5,726,038	11.25	75.63	8,949.4	3.305E-02
TechC_D	5,526,130	12.44	73.21	9,760.9	3.482E-02
TechC_E	5,988,898	10.70	76.65	9,654.5	3.484E-02
TechD_E	5,526,130	13.21	73.21	9,484.6	3.482E-02
TechB_C_D	5,302,274	11.85	72.41	9,455.5	3.190E-02
TechB_C_E	5,726,038	10.17	75.63	9,163.2	3.254E-02
TechB_D_E	5,302,274	13.12	72.41	9,298.0	3.220E-02
TechC_D_E	5,526,130	12.44	73.21	9,760.9	3.482E-02

Recurring Cost per Flight
$M / Flight

Mean	10.50
Median	10.45
Standard Deviation	0.69
Variance	0.48
Range Minimum	8.64
Range Maximum	12.63
80% Confidence <	11.07



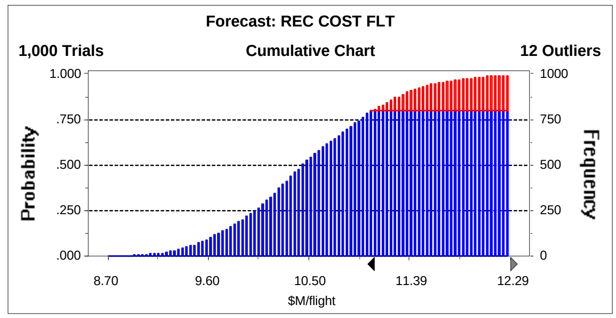


Figure 5 – Example Bimese TSTO ROSETTA Probabilistic Results
(Portfolio: Long-Life, High T/W Rocket Engine and Self-Healing/Robust TPS Materials)

While deterministic runs provide fixed design point data, running the same models probabilistically offers much more telling results. Not only are all output data available for each run, but the designer can also compile and sort these data to assess the risk involved in a given design. In the case study, the Crystal Ball software provided statistics (mean, median, mode, standard deviation, variance, range minimum, range maximum, etc.), sensitivities of outputs to inputs, and distributions in terms of frequencies, percentiles, and cumulative counts. Figure 5 provides a look at just a fraction of the data available through this method for a single technology portfolio. One can determine, say, the recurring cost per flight for the Bimese concept at an 80% confidence level—which accounts for rather objective risk factors. This accounting for risk offers a manager much more detailed and useful information than simple fixed design points.

To graphically depict the difference between deterministics and probabilistics, see the graph of a single design point versus an 80% confidence level for gross liftoff weight of all technology portfolios (Figure 6). Assuming that 80% confidence is a reasonable level, this demonstrates that using one design point without accounting for risk may grossly underpredict key vehicle and programmatic output parameters. In addition to the likelihood of misrepresenting the risk inherent in a design, deterministic results may lead decision makers to choose different technology portfolios than would be selected if risk were considered.

Managers often attempt to select the optimal technology portfolio based on greatest benefit within a given budget. Although the budget may be known, determining the meaning of "greatest benefit" can still be tricky. Often, decision makers try to weight various metrics based on their notion of relative importance. For example, a DoD user may put much greater emphasis on performance and operations than on cost or safety, while a NASA user may value safety first with cost a close second. Obviously, optimum technological solutions depend on the chosen weighting scenarios. Various methods may be used for applying weightings. For the case study, the Technique For Order Preference By Similarity To Ideal Solution (TOPSIS) was used, and many weighting scenarios were evaluated.

In TOPSIS, weights are allocated to each output metric or output category (performance, operations, etc.). Those weights, then, are multiplied by the outputs (typically normalized by their root sums of the squares) of each converged solution in order to arrive at an Overall Evaluation Criterion (OEC) value, as is shown in the equation

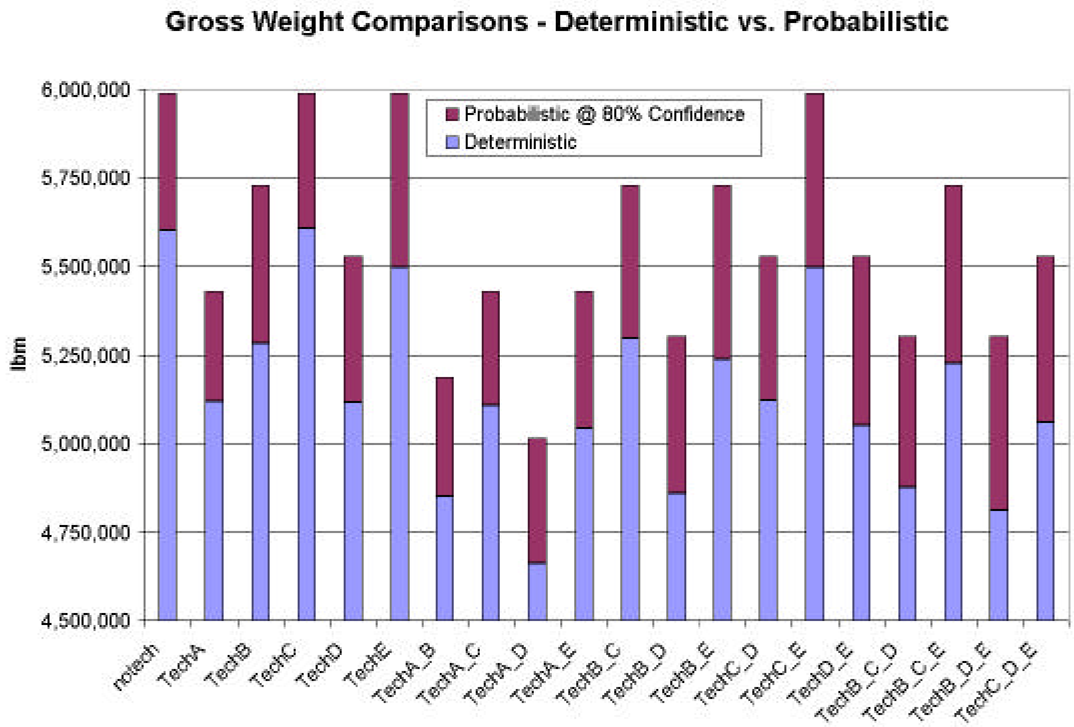


Figure 6 – Comparison of Deterministic and Probabilistic Results

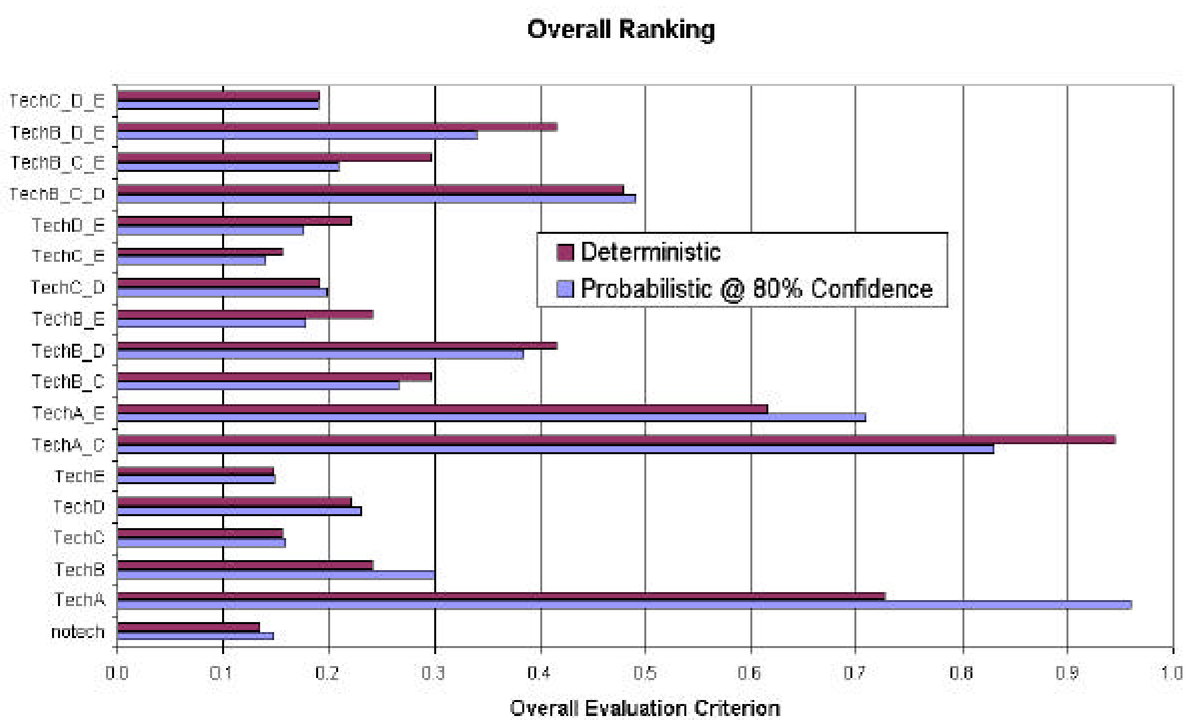


Figure 7 – Comparison of Deterministic and Probabilistic Ranking

$$OEC = W_{perf} \times N_{perf} + W_{\cos t} \times N_{\cos t} + W_{ops} \times N_{ops} + W_{safe} \times N_{safe}$$

where W represents the weighting (a percentage) and N represents a normalized output value for the categories performance, cost/economics, operations, and safety/reliability, respectively. Table 10 shows the resultant rankings from the probabilistic runs based on various weighting scenarios. Obviously, the choice of technology portfolio depends on the weighting scenario favored. Even if a user favors one metric over others, he must consider the weights; ignoring all but one metric may not produce the same result as overweighting that same metric, as can be seen in the performance-based columns.

Rather than settle on a single weighting scenario in this paper, all resultant OECs from all scenarios considered (more than fifty) were averaged to arrive at a single OEC for each technology portfolio. Figure 7 shows how the rankings based on these "average OECs" differ between deterministic and probabilistic approaches. Note that a different portfolio achieves the highest OEC for deterministic analyses than for probabilistic. Whereas deterministic runs would suggest that both the new rocket engine and self-healing TPS materials (technologies A and C) should be funded, probabilistic results suggest that funding only the rocket engine could offer the highest payoff when risk is included. This fact would be crucial to a manager with a limited technology budget. If the manager wishes to fully account for risk in his technology investment planning, these differences between deterministic and probabilistic results should be considered.

Although more discussion will not be provided here, a future paper is planned to illuminate more post-processing options for probability data and offer comparisons of the methods described above to other industry methods.

Table 10 –Bimese TSTO ROSETTA Probabilistic TOPSIS Rankings

	Even Weights	Performance-Based Weights		Cost/Economics-Based Weights		Operations-Based Weights		Safety/Reliability-Based Weights	
Performance	0.25	0.4	1	0.2	0	0.2	0	0.2	0
Cost/Economics	0.25	0.2	0	0.4	1	0.2	0	0.2	0
Operations	0.25	0.2	0	0.2	0	0.4	1	0.2	0
Safety/Reliability	0.25	0.2	0	0.2	0	0.2	0	0.4	1
	Ranking	**Ranking**	**Ranking**	**Ranking**	**Ranking**	**Ranking**	**Ranking**	**Ranking**	**Ranking**
Notech	16	16	16	16	11	16	16	16	16
TechA	2	1	3	2	2	2	9	2	2
TechB	7	9	12	7	6	9	12	7	4
TechC	15	15	15	15	9	15	15	15	15
TechD	9	7	8	10	16	7	5	9	12
TechE	17	17	17	18	14	17	17	17	10
TechA_C	1	2	4	1	1	1	8	3	3
TechA_E	3	3	6	3	3	3	10	1	1
TechB_C	8	10	11	8	4	11	11	8	7
TechB_D	5	5	2	5	10	5	2	6	8
TechB_E	14	14	13	12	7	14	14	14	17
TechC_D	10	8	7	11	15	8	4	12	18
TechC_E	18	18	18	17	13	18	18	18	11
TechD_E	13	12	10	14	18	12	6	13	14
TechB_C_D	4	4	1	4	8	4	1	4	5
TechB_C_E	12	13	14	9	5	13	13	10	9
TechB_D_E	6	6	5	6	12	6	3	5	6
TechC_D_E	11	11	9	13	17	10	7	11	13

CONCLUSIONS

Typically, space system designers have used single point designs to analyze concepts. But typical deterministic simulations require long run times and fall short by selecting overly optimistic solutions and carrying more programmatic and technical risk. Immature technologies and incomplete knowledge of the conceptual design are sources of uncertainty that are not often modeled and lead to program risk.
The ROSETTA modeling process was created at Georgia Tech and enhanced at SpaceWorks Engineering, Inc. This process, which can be coupled with systematic decision-making techniques and probabilistic methodologies, has been shown to be an inexpensive, timely, robust technique for prioritization of advanced space transportation technological investment. It harnesses the knowledge inherent in legacy, high fidelity codes to address a lack of knowledge about the future (and specifically the impact of technologies) in a spreadsheet-based meta-model to assess programmatic, safety, and performance risk associated with future transportation systems. ROSETTA models therefore enable rapid and robust technology investment decisions.

ROSETTA models have been created for 2nd and 3rd Generation RLV concepts as well as in-space vehicles. For the case study described in this paper, a 2nd Generation Bimese TSTO RLV was evaluated. Both deterministic and probabilistic results were produced, and examples were provided to demonstrate the usefulness of detailed probabilistic data.

The ROSETTA modeling process is an effective approach to providing quantitative input to technology investment decision-making. Using this process may lead to more successful investment choices, thereby enabling future space transportation systems.

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