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Launch Vehicle Propulsion Design with Multiple Selection Criteria

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An analytical optimization and evaluation approach is presented for sizing a liquid hydrogen/liquid oxygen, single-stage-to-orbit system. The approach uses a unique merging of historical data for weight relationships, Monte Carlo simulations for uncertainty analysis, technology factors, thermochemical analysis, and genetic algorithm solvers for concept optimization. The method models and optimizes engine chamber pressure, area ratio, and oxidizer/fuel ratio to determine the best vehicle design based on seven separate cost/weight figures of merit Model results show that a 53% increase in design, development, test, and evaluation cost results in a 67% reduction in gross liftoff weight. The uncertainty range for the design, development, test, and evaluation costs is shown to be from −45 to +76% of the mean value for the 95th percentile uncertainty case. The oxidizer/fuel ratio has a significant impact on the overall weight of the vehicle and vehicle components due to the large percentage of the gross liftoff weight that is dedicated to propellants. Other results show the effects of propulsion parameters, technology factors, and cost factors on weight and cost under different overall design constraints.

Nomenclature

A_c = regression coefficient
A^* = throat area
Æ = area ratio
B_c = regression coefficient
C_f = thrust coefficient
C_{star} = characteristic exhaust velocity
D = drag
D^* = engine throat diameter
g_0 = gravitational acceleration
I_{sp} = specific impulse
$I_{\mathrm{sp_{sl}}}$ = specific impulse at sea level
$I_{\mathrm{sp_{vac}}}$ = specific impulse at vacuum
M_{dot} = engine mass flow rate
P_c = chamber pressure
T = thrust
T_{sl} = thrust
T_{vac} = thrust at vacuum ambient conditions
T_{wi} = initial thrust/weight ratio
V = vehicle velocity
W = vehicle weight
W_{dot} = weight rate of change with time
Wg_{unc} = wing uncertainty
Wt_{unc} = weight uncertainty
Wt_{wing} = wing weight
γ = flight-path angle
Δ = change
ΔV = delta velocity
μ = mean
σ = standard deviation

I. Introduction

A MODEL is developed by fully integrating system design parameters into a closed-loop analysis of launch vehicle concepts. The parameters considered are specific impulse, engine mass, gross liftoff weight (GLOW), nozzle area ratio, chamber pressure, initial thrust/weight ratio, and oxidizer/fuel ratio. The primary goals are based on the weight reduction in the propulsion system and minimizing system cost. A major factor in minimizing overall systems development cost is accomplished by optimizing propulsion system components using historical engine data combined with a propulsion thermochemical code and optimization tools/techniques.

The model process flow defined in Fig. 1 is formed for a single-stage-to-orbit (SSTO) system using liquid oxygen (LOX) and liquid hydrogen (LH2). Seven key figures of merit (FOM) are defined for the evaluation. They are GLOW minimization; dry weight minimization; dry weight with margin minimization; design, development, test, and evaluation (DDTE) cost minimization; production cost minimization; and operations cost minimization. The approach uses a combination of historical data for weight relationships, Monte Carlo simulations for uncertainty analysis, technology factors, and cost influence factors for trading weight savings for cost savings, thermochemical analysis, and genetic algorithm solvers for concept optimization. Analysis for each design case results in optimized parameters for P_c, Æ, oxidizer/fuel ratio (OF), T_{wi}, mass ratio (MR), technology factors (TFs), and cost influence factors (CIFs). Monte Carlo simulation is used to determine the performance measures for cost and/or weight based on lognormal distribution input functions at a 95% uncertainty level. The results of the study reflect improvements in methodology and the practical use of the tool to measure propulsion parameter sensitivity when compared to the key performance measures.

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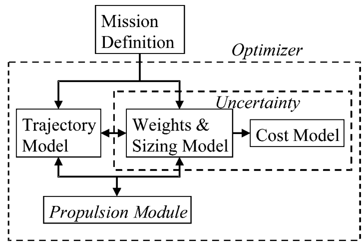

Fig. 1 Model process flow.

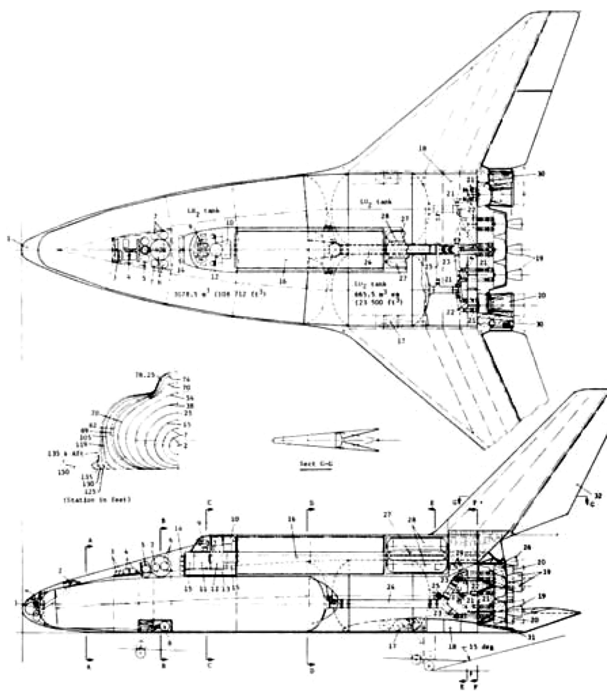

Fig. 2 SSTO concept vehicle.[1]

II. Approach

The optimization focused on several key areas. The first is the overall optimization of the vehicle T_{wi}, engine P_c, engine AR, engine OF, and TFs [for the thermal protection system (TPS), autonomous flight control, wing, tail, LH2 tank, LOX tank, basic structure, landing gear, engine accessories, engine, and flight autonomy). The TFs are used to vary the system weight by improved technology but also result in a DDTE cost increase/decrease due to the time and effort expended in developing an advanced technology. The combination of the propulsion variables and TFs is used to define the optimum system. A table of optimization results is calculated for each of the FOM. The vehicle MR, main engine throat diameter D^*, vacuum specific impulse $I_{\text{sp}_{\text{vac}}}$, seal level specific impulse $I_{\text{sp}_{\text{sl}}}$, per engine thrust T, and per engine weight estimation are defined for each FOM case. These levels will vary in each case because the optimization is focused on key FOM that drive the final optimized propulsion parameters and TFs toward different solutions or goals. In some cases, the solutions may be near identical because of the similarity of the parameter being optimized. A comparison is also made between the model output and the space shuttle main engine (SSME) design parameters. The information is defined to show how closely the solution proposed aligns with a current engine system design used by NASA.

A. Reference Vehicle

The first step was to define a reference vehicle for a rocket-propelled SSTO to build the optimization model. The reference vehicle, shown in Fig. 2, is based on a NASA report.[1] The vehicle uses LOX as the oxidizer, LH2 as the fuel, and fixed-area-ratio engines. The concept incorporates improved technologies for enhanced performance. It also established historical data to produce projections for future technology upgrades in the areas of material science for composite and metal matrix composites, rocket engine efficiency, and lighter and more thermally resistant protection systems for the vehicle exterior.

For the analysis of the launch vehicle and the launch vehicle propulsion system, a model of the entire system was developed using equations for rocket propulsion parameters, trajectory profiles, weights and sizing, cost and economics, and historical data regression curves. The important aspects of this computer modeling approach is to show how the model can be developed. The tool will also illustrate a method to design, analyze, and optimize the system at a conceptual level. The reference vehicle chosen requires the following specification: 1) vertical takeoff, 2) dual-engine mode, 3) 500-mission lifetime, 4) 65,000-lb (29,438.5-kg) payload, 5) 28.5-deg launch inclination from the NASA John F. Kennedy Space Center, 6) and 50-n mi orbit.[1]

B. Simulation Architecture

The trajectory model uses the rocket equation to formulate an MR for the vehicle system. This module also includes a pressure, temperature, and density parameter calculation based on altitude. The program uses input values for ΔV required, orbit inclination, orbit height, and drag reduction percentage. These values are set and determined based on the concepts for a specified mission and will not change during the optimization of the design process. The module also takes T_{wi}, AR, P_c, OF, ΔI_{sp}, engine throat area divided by the vacuum thrust (A^*/T_{vac}), and $I_{\text{sp}_{\text{vac}}}$ and uses these values to determine a value for MR of the vehicle for the given reference conditions. The T_{wi}, AR, P_c, OF, ΔI_{sp}, and A^*/T_{vac} are parameters input into the trajectory program by the user. The value(s) for $I_{\text{sp}_{\text{vac}}}$ are inputs from the propulsion module. The propulsion module defines a value for $I_{\text{sp}_{\text{vac}}}$ based upon the P_c, AR, and OF optimization outputs from the trajectory model. This relationship is described in more detail during the discussion of the Propulsion model in Sec. II C.

The rocket equation is based on the calculation of a ΔV by using the vehicles I_{sp}, MR, drag D, thrust T, weight W, and flight-path angle γ. When ΔV is solved for, the form of the equation is

$$\Delta V = g_0 \times I_{\text{sp}} \ln(\text{MR})(1 - D/T - W/T \sin\gamma) \tag{1}$$

The trajectory program solves for the vehicle MR as the primary output. The output also includes time-to-orbit, final velocity, and final altitude. The output values of final velocity and final altitude must match the inputs mentioned earlier. The rocket equation (1) is solved for MR and is

$$\text{MR} = \Delta V/(I_{\text{sp}} \times (1 - D/T - Wt/T \times \sin\gamma) \tag{2}$$

The input parameters for T_{wi}, AR, P_c, and OF are modified during the analysis of the system by using the genetic algorithm (GA) optimization Palisades Tool Evolver.[2] When the overall vehicle dry weight, for example, is chosen to be minimized, the program will define the best possible configuration for reduced weight by changing the input parameters. The weights and sizing model and the propulsion module use these parameters as inputs.

C. Propulsion

The propulsion module resides as a worksheet within the weights and sizing model. The propulsion module uses the Cequel™[3] thermochemistry module for EXCEL. Cequel uses the minimization of Gibbs free energy and provides combustion process outputs based on rocket inputs. After being optimized in the trajectory-model, the P_c, AR, and OF are input into Cequel. The code then calculates the $I_{\text{sp}_{\text{sl}}}$, $I_{\text{sp}_{\text{vac}}}$, thrust coefficient C_f, and characteristic exhaust velocity C_{star}, which are output to the weights and sizing and trajectory models to determine the overall vehicle weights and performance output. The P_c, AR, and OF change the engine performance based on the thermochemistry outputs from Cequel, and each parameter is interrelated as shown in Fig. 3. For example a higher P_c will result in a higher optimum AR (because of exit pressure and other considerations). However, a higher P_c will result in a higher engine mass, thus, reducing benefits of an increased performance due to the increased vehicle mass.

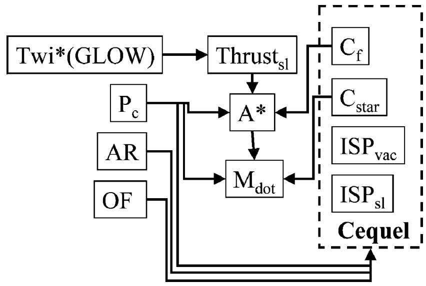

Fig. 3 System propulsion parameters.

The launch vehicle's required sea level thrust T_{sl} is determined by the GLOW and the initial thrust-to-weight ratio:

$$T_{sl} = \text{GLOW} \times T_{wi} \tag{3}$$

The propulsion module utilizes sea level thrust T_{sl} and the value for $I_{sp_{sl}}$, to calculate W_{dot}, which is defined as the rate of change in overall vehicle weight. The value is set by the gross liftoff weigh and sea level specific impulse:

$$W_{dot} = \text{GLOW} \big/ I_{sp_{sl}} \tag{4}$$

Any change to the vehicle model that impacts the value of these two parameters (GLOW and $I_{sp_{sl}}$) has an impact on the value of W_{dot}.

The value for T_{vac} is defined based on the W_{dot}, calculated in Eq. (4), being multiplied times the Cequel output for $I_{sp_{vac}}$. The relationship between T_{vac} and T_{sl} is established using W_{dot}, which is assumed constant during engine operation and a specific impulse ratio:

$$T_{vac} = \text{GLOW} \times \left(I_{sp_{vac}} \big/ I_{sp_{sl}} \right) \tag{5}$$

Combustion efficiency is assumed at 96% based on historical engine system and studies.[4] The I_{sp} value is an important component in the trajectory model's determination of the vehicle MR, as shown in Eq. (1). An important integration point is that the I_{sp} is a result of the design inputs being used to size the system and to define the propulsion system.

D. Weights and Sizing

The propulsion module also correlates engine parameters to the engine weight. The engine weight is determined using a combined Rocketdyne Power Balance, U.S. Air Force method, NASA Langley approach, and historical engine data. The four methods are averaged together to give an engine weight. The power balance and U.S. Air Force methods make use of a nozzle geometry model to determine nozzle weight. The engine mass relationship is important to the overall model because of the significance in the engine mass as a percentage of the overall GLOW. Equations (6) and (7) show which parameters are used to determine the nozzle mass and then overall engine mass. An important point is to note is that Cequel defines both C_f and C_{star} and provides a solution approach with the precision that only the thermochemical solution can provide:

$$\text{nozzle mass} = f(A^*, \text{AR}) \tag{6}$$

$$\text{engine mass} = f\left(m_{dot}, C_f, \text{AR}, P_c, \text{thrust}, \text{OF}, I_{sp_{sl}}\right) \tag{7}$$

An example for a vehicle component weight estimation is in Fig. 4, which shows how the vehicle sizing model and tail surface area are used to define the component weight for a tail section. Similar regression relationships were developed for all of the vehicle components using historical data and are used to calculate the overall vehicle weight.

E. Cost and Economics

The cost and economics model is derived based on the NASA cost projection methodology.[5] The model uses the component weights

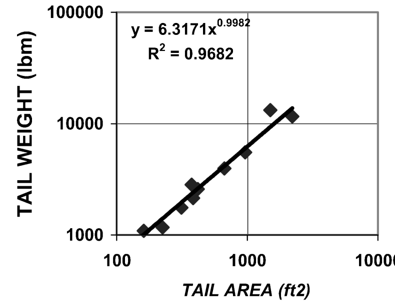

Fig. 4 Tail weight regression curve.

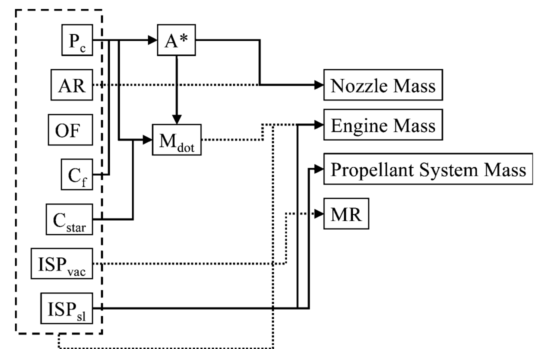

Fig. 5 Model process diagram.

of previous systems and plots the cost of the component vs the weight of the component. The resulting regression curves are used to project future cost for a particular system. The CIFs that result from using technology factors are used to calculate the DDTE cost of a component. Higher TFs will decrease the weight of component or increase the effectiveness of a component, but will almost always increase the cost of development. The factors, both TFs and CIFs, are model design and analysis parameters that will change as technology evolves and also as the ability to manufacture or develop a design efficiently is enhanced or minimized. A Boolean code is used to correlate 1, 2, or 3 with the desired TF and CIF. The uncertainty surrounding the DDTE cost is high due to the large number or data points used in the fitting the historical data to a regression curve. The approach uses a lognormal Monte Carlo uncertainty based on data standard errors (SEs). All of the subsystem components have SEs that are used in determining the overall DDTE cost uncertainty value.

F. Simulation Operation

The capability of the Evolver™ optimizer tool[2] enables the analyst to define a set or predetermined value for technology factors and key propulsion parameters. This feature allows the designer to define any of the FOM at a particular value or add a constraint to the optimization. An example would be to include DDTE cost as an independent variable and optimize the vehicle with this cost value as a design constraint. The model will allow any of the other FOM to have set values to meet various programmatic constraints. The same ability to set predefined levels for FOM or other variables also applies to the propulsion system if, for example, the use of existing engines was mandated.

The second capability of the model is to show how each of the key engine parameters, P_c, OF, and AR are optimized against the FOM and measure the changes to the system when the optimized value is not met. The sensitivity of these key propulsion parameters is extremely important to the system designer. The model provides results that show how changes in each propulsion parameter affect the FOM. Understanding the impacts that a parameter has on the overall system is crucial to vehicle system design.

Figures 3 and 5 show how the given propulsion parameters are used as inputs to determine nozzle mass, engine mass, propellant system mass, and vehicle MR. An overall system flow diagram is shown in Fig. 6. Each section of the model has input and outputs

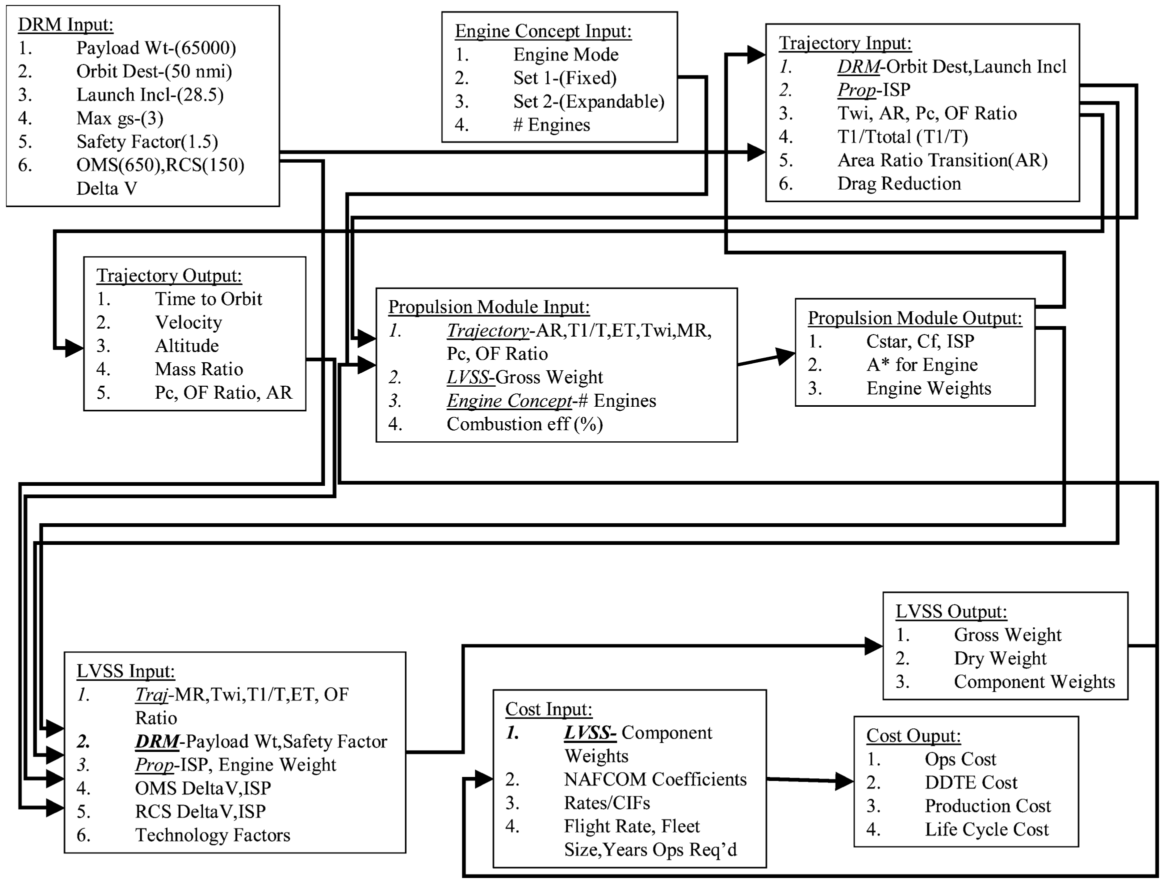

Fig. 6 Model flow process.

that feed the system and form the closed-loop optimization (CLO) methodology so desired. The overall schematic shows how mission requirements are fed to the system and how each model component [launch vehicle sizer and synthesizer (LVSS) propulsion module, trajectory, cost, and economics] interacts and what key variables are passed between the models.

The approach uses uncertainty principles to bind the final outputs with a measure of goodness or certainty. In the case of the LVSS and the DDTE cost, the historical data curves were used to develop estimates for the component vehicle weights and regression curves defined the ± regression range for each of the curves.

III. Results and Discussion

A. Cost and Weight

For each of the optimization cases, the propulsion parameters are determined using the Palisades Evolver optimization tool. Secondary engine design parameters were determined as well so that the engine system specification could be written from the model output. The range of TFs and corresponding CIFs are based on the Boolean code for technology 1, 2, or 3. Tables 1 and 2 show the results of the GA Evolver Tools for the optimal vehicle design. The three cases of weight minimization are shown in Table 1. They are minimum GLOW, minimum dry weight, and minimum dry weight with margin. Table 2 shows three cost minimization cases. They are minimum DDTE cost, minimum production cost, and minimum operations cost.

The relationship between the weight components shows an absolute correspondence between the dry weight and the dry weight with margin. The cost numbers were slightly different between the GLOW and dry weight, with the upfront cost (DDTE/production) of the GLOW optimized solution being higher. The downstream cost of the GLOW optimized system was slightly lower that the dry weight optimized solution. The P_c and AR were nominally unchanged but the OF and T_{wi} were significantly different between the dry weight and GLOW cases. The OF for dry weight optimization is focused on tank weight, whereas the GLOW optimized solution is focused on lower fuel weight. Flight autonomy is the only TF that differed between the multiple runs of the two weight optimization cases. The Boolean code for the flight autonomy relates 1) shuttlelike, 2) semiairplanelike, and 3) airplanelike. The remaining TFs can be understood by referencing Table 3. Table 3 explains the Boolean code link to the material property for each, either 1, 2, or 3.

The optimization parameters for the cost cases are shown in Table 2. The propulsion parameters are closely tied together for each of the cost optimization cases. The only exception is the T_{wi} value. The T_{wi} for the minimum DDTE and production cost is lower than the T_{wi} for the minimum Operations cost. The significant difference for the cost cases is in the Boolean codes (1, 2, or 3) for each of the cost cases. This is logical because the TFs and, more importantly, the CIFs have a significant impact on cost because the CIFs are multiplying factors in the cost of each component.

The most significant differences between the weight parameters and cost parameters in Tables 1 and 2 are the TFs and corresponding CIFs. For the weight minimization cases, the TFs are driven to a Boolean value of two and the DDTE cost minimization case in generally equal to one. These results are expected because the weight savings for the Boolean value of two represents a weight savings over current baseline technologies but represent a cost increase by a multiple of 2.1 times the cost for current technology for a Boolean value of one. The GLOW, dry weight, and dry weight with margin reflect near identical TFs based on the fact that the technologies defined in the database by Boolean two represent a multiple for component weights that is less than one. The production and operations and cost reflect a wider range of TF and CIF possibilities. This is true because the most significant cost impact for new technologies is absorbed by the DDTE cost and will in some cases result in cost savings during the other cost phases of the program. In essence, increased cost incurred during the DDTE phase results in cost savings for the vehicle.

Table 1 Weight optimization results

Parameter	GLOW minimization parameters	Dry weight minimization parameters	Dry weight with margin minimization parameters
GLOW, lbm	4,629,778	4,848,013	4,848,013
Dry weight, lbm	439,754	428,123	428,123
GLOW plus dry weight, lbm	5,069,533	5,276,136	5,276,136
Dry weight with margin, lbm	475,590	463,011	463,011
DDTE, billion	\$43.023	\$42.508	\$42.508
Production costs, billion	\$127.297	\$125.177	\$125.177
Operations costs, billion	\$194.879	\$195.913	\$195.913
Life cycle cost (LCC), billion	\$365.198	\$363.598	\$363.598
Thrust to weight ratio	1.67	1.40	1.40
Engine			
Chamber pressure, psi	2712.8	2464.9	2464.9
OF	6.87	7.43	7.43
Area ratio	93.3	87.5	87.5
MR	7.5	8.0	8.0
Throat diameter, in.	13.7	13.4	13.4
Vacuum I_{sp}, s	446	441	441
Per engine vacuum thrust, lbf	803,616	707,829	707,829
Per engine weight, lbm	9,954	8,851	8,851
Number of engines	10	10	10
Technology			
Wing TF	2	2	2
Tail TF	2	2	2
LH2 tank TF	2	2	2
LOX Tank TF	2	2	2
Basic structure TF	2	2	2
Thrust structure TF	2	2	2
TPS TF	2	2	2
Gear TF	2	2	2
Engine accessories	2	2	2
Main propulsion system (MPS) TF	2	2	2
Engine TF	2	2	2
Flight autonomy	3	3	3

Table 2 Cost optimization results

Parameter	DDTE cost minimization parameters	Production cost minimization parameters	Operations cost minimization parameters	LLC minimization parameters
GLOW, lbm	7,732,600	7,796,955	5,719,590	6,436,192
Dry weight, lbm	733,872	735,936	542,143	608,671
GLOW plus dry weight, lbm	8,466,471	8,532,891	6,261,733	7,044,862
Dry weight with margin, lbm	793,675	795,907	586,323	658,271
DDTE, billion	\$26.079	\$30.972	\$45.715	\$39.900
Production costs, billion	\$93.186	\$56.713	\$83.369	\$70.855
Operations costs, billion	\$287.301	\$237.704	\$171.223	\$183.601
LCC, billion	\$406.566	\$325.388	\$300.307	\$294.357
Thrust to weight ratio	1.43	1.41	1.67	1.53
Engine				
Chamber pressure, psi	3162.4	3167.3	3033.6	3044.6
OF	7.45	7.54	7.69	7.57
Area ratio	101.5	103.8	99.7	98.4
MR	7.9	7.9	7.7	7.8
Throat diameter, in.	15.0	15.0	14.3	14.5
Vacuum I_{sp}, s	444	443	441	442
Per engine vacuum thrust, lbf	1,147,237	1,143,811	993,328	1,028,207
Per engine weight, lbm	13,814	13,887	12,244	12,517
Number of engines	10	10	10	10
Technology				
Wing TF	1	2	2	2
Tail TF	1	1	2	1
LH2 tank TF	1	1	2	2
LOX tank TF	1	2	2	2
Basic structure TF	1	1	2	2
Thrust structure TF	1	1	2	2
TPS TF	2	3	3	3
Gear TF	1	2	2	2
Engine accessories	2	2	2	2
MPS TF	2	2	2	2
Engine TF	1	1	2	1
Flight autonomy	1	1	3	3

Table 3 Boolean code logic

Parameter	Boolean code	Factor	Material
Wing TF	3	0.869	MMC
Tail TF	3	0.970	MMC
LH2 tank TF	3	0.900	MMC
LOX tank TF	2	0.700	Composite
Basic structure TF	2	0.700	Composite
Thrust Structure TF	2	0.740	Composite
Gear TF	1	1.000	Aluminum
Engine accessories TF	1	1.000	Aluminum
Wing CIF	3	10.000	MMC
Tail CIF	3	10.000	MMC
LH2 tank CIF	3	10.000	MMC
LOX tank CIF	2	2.100	Composite
Body CIF	2	2.100	Composite
Basic structure CIF	2	2.100	Composite
Thrust structure CIF	2	2.100	Composite
Landing gear CIF	1	1.000	Aluminum

B. Propulsion Design

The propulsion design parameters shown in Tables 1 and 2 vary based on the specific minimization case. The chamber pressure influence follows the same trend for the GLOW, dry weight with margin, and dry weight minimization cases. The chamber pressure is slightly higher for the GLOW minimization case. This is because the I_{sp} level is higher at increased chamber pressure, and thus, the vehicle requires less fuel. The dry weight minimization chamber pressure is lower due in great part to the sole focus on reducing engine mass. The lower the chamber pressure results in smaller engine mass. At high chamber pressures, the chamber size and weight, lines and valves, and support structure must be more robust, and this drives the engine mass up. The cost optimization cases define the chamber pressure level at approximately 3100 psi.

The area ratio for the cases follows a similar pattern to the chamber pressure described earlier. The area ratio is lowest for the dry weight minimization case because smaller area ratios result in a lighter engine nozzle. However, the ratio must be high enough to enable the appropriate I_{sp}. The GLOW case defines a slightly higher area ratio that is due in part to the increased specific impulse for the higher area ratio and the higher chamber pressure as described earlier. The area ratio for the cost minimization cases is slightly higher than the weight cases. The higher area ratio for the cost cases is driven by the increased specific impulse but is not impacted as severely by the magnitude of increased weight due to increasing the area ratio. Recall that the area ratio relationship to chamber pressure and OF is directly linked in the Cequel thermochemical calculation for C_{star} and I_{sp} as shown in Fig. 3.

The optimized OF is defined for each of the seven minimization cases. The value for OF is driven to an optimized solution for the GLOW case based on decreased engine propellant mass. The OF for the dry weight minimization case is higher because this ratio impacts the propellant tank volume only. Therefore, in essence, the optimized value for the OF is most impacted by the propellant density and propellant volume. The OF for the cost minimization cases is in the range similar to the GLOW minimization case. The ratio value for the DDTE cost minimization and the dry weight minimization cases are identical due to the correlation between the component weight relationships within the DDTE cost estimates. OF has a significant impact on the overall weight of the vehicle and vehicle components due to the large percentage of the GLOW dedicated to fuel and oxidizer. The results from varying the P_c and Æ prove that these parameters have a much lower impact on the GLOW and dry weight than the OF. The results in subsequent sections reflect how each of the propulsion parameters will affect the vehicle and how the vehicle will be impacted when a propulsion parameter is changed to a value that is different than the optimum value.

The OF effects on vehicle dry weight, GLOW, and $I_{sp_{vac}}$ are shown in Figs. 7–9. The incremental values for the OF are run against overall vehicle optimization case for dry weight minimization. The data for the OF that corresponds to the minimum dry weight, minimum

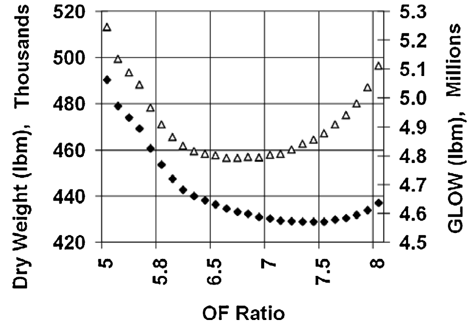

Fig. 7 Effect of OF on dry weight: ♦, dry weight and △, GLOW.

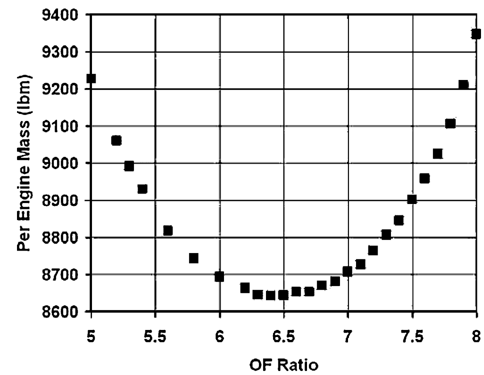

Fig. 8 Effect of OF on engine mass.

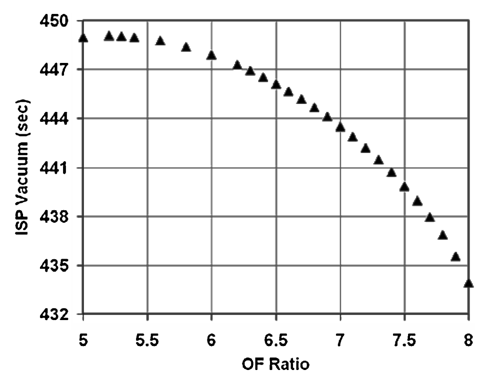

Fig. 9 Effect of OF on specific impulse.

GLOW, maximum $I_{sp_{vac}}$, minimum propellant volume, minimum propellant weight, and minimum engine mass are found using a search that returns the value for the OF that results in the minimum or maximum of the case being analyzed.

When Fig. 7 is examined, the OF value for minimum GLOW has a range from approximately 6.2 to 7.1, where there is little impact on the GLOW. The results show that for optimum GLOW, the best takeoff OF is in the range of 6.2–7.2, if the system is a LOX/H2 fixed bell nozzle engine configuration. The results for minimum engine mass in Fig. 8 are also consistent with this range of values. An OF in the range of 6.2–7.2 is best for the initial phase of the trajectory when the vehicle propellant mass is most important.

The maximum $I_{sp_{vac}}$ is found at the OF of 5.2. These results are shown in Fig. 9. An OF from 5.0 ($I_{sp_{vac}} = 449.0$) to 5.6 ($I_{sp_{vac}} = 448.8$) would be best for the later phase of the trajectory profile, when higher I_{sp} is important. The I_{sp} value changes only slightly over this range of values for OF. These OF results are consistent with the early plans for the SSME that called for an adjustable OF. The preliminary plans for the SSME included a value for OF equal to 6.5 for the initial takeoff, with the ratio being modified to 5.5 later in flight when the higher I_{sp} was more important.

The values for dry weight and GLOW vs P_c are shown in Fig. 10. The dry weight and GLOW, for the range of P_c from 2000 to 3700 psi, increased only slightly above the minimum weights for the

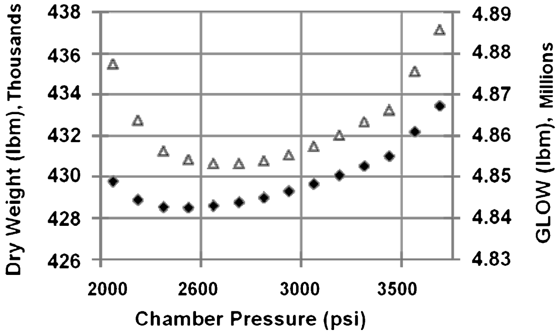

Fig. 10 Effect of chamber pressure on dry weight: ♦, dry weight and △, GLOW.

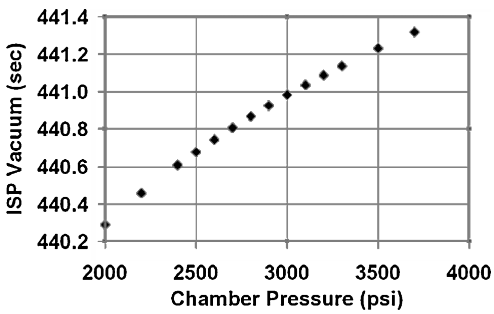

Fig. 11 Effect of chamber pressure on I_{sp}.

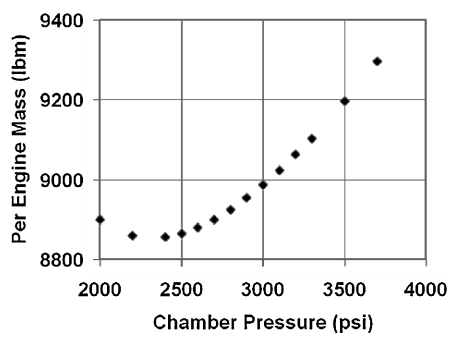

Fig. 12 Effect of chamber pressure per engine mass.

optimized P_c. The optimum value for lowest dry weight and engine mass correlated to a P_c value near 2400 psi. The value for the lowest GLOW is near 2700 psi. Figure 11 shows that the $I_{sp_{vac}}$ increases as P_c increases. Figure 12 shows a significant increase in the per engine mass as the P_c approaches 3700 psi or as the P_c value increases. The increased engine mass is due to the thickness and design of the thrust chamber and increased robust design for valves, ducts, and lines needed at the higher pressures. The overall engine mass increase, due to higher pressures, is at such a rate that the improved weight of the nozzle mass does not offset the core engine mass increase.

The effects of area ratio on the vehicle system are shown in Figures 13–15. The dry weight and GLOW change very little over the range of AR from 50 to 120. The incremental changes in vehicle dry weight and GLOW are shown in Fig. 13. The optimum value for lowest dry weight correlated to an AR value is in the range of 70–105 for a SSTO vehicle. Historically, the AR range for engines of multistage vehicles is from 45 to 60. The AR range, for engines used to complete the entire trajectory from launch to orbit, is 69–85.

Figure 14 shows that the lower is the AR the lower is the engine mass. This is understandable due to the nozzle mass required for an AR = 50 vs an AR = 120. An AR = 50 corresponds to a much smaller exit area than the exit area for and engine with AR equal to higher values. Figure 15 shows that $I_{sp_{vac}}$ increases with the larger values for AR. This does not take into account the possibility of shocks in the nozzle due to overexpansion at the fixed chamber pressure defined for the weight optimization case.

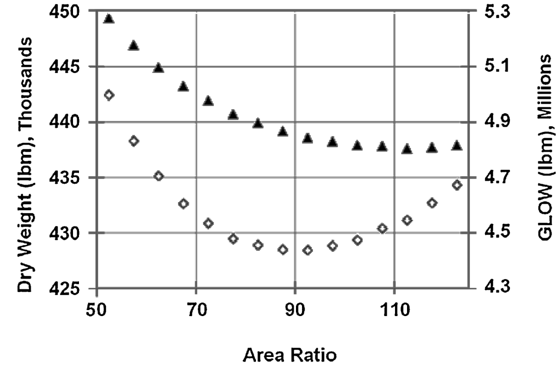

Fig. 13 Effect of area ratio on dry weight: ◇, dry weight and ▲, GLOW.

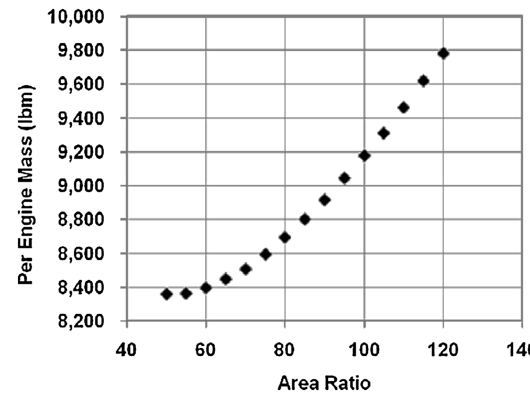

Fig. 14 Effect of area ratio on per engine mass.

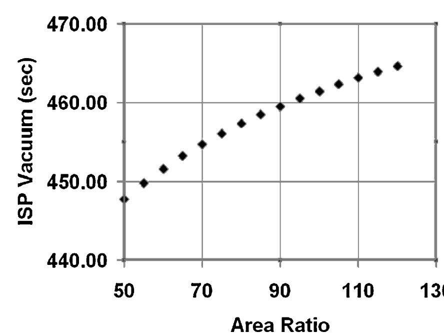

Fig. 15 Effect of area ratio on I_{sp}.

C. SSME Comparison Case

An SSME comparison case involves optimization where the total thrust level is in the SSME range of T_{vac} equal to 500,000 lbf. The optimized cases are shown in Table 4. Table 4 relates the OF, AR, and P_c that corresponds the SSTO case where the SSME thrust level is used. The error percentages are given for the GLOW minimization using an engine T_{vac} of 500,000 lbf as compared to the SSME design case.

The key comparison focuses on how the models optimum values for P_c, AR and OF differ from the actual design values for the SSME. The optimizer defined P_c is 2250 psi, where the SSME is designed to 3141 psi. This also manifest itself in a higher throat area due to the direct correlation between P_c and A^* in calculating the engine thrust level. The OF and AR are approximately 10% higher than the SSME design case suggesting that the OF could be higher to achieve optimum GLOW minimization. A more detailed trajectory model would aid in proving this finding. The models optimum engine OF is equal to 6.63. This value is consistent with the historical desire to have the shuttle system initial OF set to 6.5, instead of the 6.0 to which it is currently designed.

D. Uncertainty

There are two areas that uncertainty values apply in the model. The first is the DDTE cost uncertainty and the second is the uncertainty in the vehicle weight. The DDTE cost uncertainty is

Table 4 SSME comparison case

Parameter	GLOW with SSME thrust level minimization	GLOW minimization SSME thrust, P_c, OF, $\mathcal{A}\!R$	GLOW case, % difference
GLOW, lbm	4,798,118	4,933,651	2.7
Dry weight, lbm	450,979	473,894	4.8
GLOW plus dry weight, lbm	5,249,097	5,407,545	2.9
Dry weight with margin, lbm	487729.6	512511.3	4.8
DDTE, billion	\$41.475	\$41.355	−0.3
Production costs, billion	\$128.648	\$131.461	2.1
Operations costs, billion	\$230.634	\$250.427	7.9
LCC, billion	\$400.757	\$423.242	5.3
Thrust to weight ratio	1.57	1.63	4.1
	Engine		
Chamber pressure, psi	2243.0	2871.0	21.9
OF	6.63	6.00	−10.4
Area ratio	86.7	77.0	−12.6
MR	7.6	7.5	−1.5
Throat diameter, in.	12.2	10.1	−20.5
Vacuum I_{sp}, s	445	446	0.2
Per engine vacuum thrust, lbf	520,340	491,460	−5.9
Per engine weight, lbm	10,238	10,929	6.3
Number of engines	15	17	11.8
	TF		
Wing	2	1	
Tail	2	2	
LH2 tank	2	2	
LOX tank	2	2	
Basic structure	2	2	
Thrust structure	2	2	
TPS	2	2	
Gear	2	2	
Engine accessories	2	2	
MPS	2	2	
Engine	2	2	
Flight autonomy	2	1	

approached in two parts. The first part is the weight of the components that directly feed the cost regression curves and the other is the cost regression curves themselves. The component weight distributions will be used for both the uncertainty in weight and uncertainty in the DDTE cost because weight is the basis for the cost curves.

The historical weight data in the form of regression curves were used to define the SE, μ, and σ for the vehicle components. The high and low values for the power series regression curve fits are defined along with the corresponding lognormal parameters necessary to formulate the distributions. The weight-only portion of the overall DDTE cost uncertainty represents the first part of the total uncertainty in cost. This portion is dedicated to the uncertainty in the weight of the vehicle components. The second component of the uncertainty due to the regression errors is defined using the NASA/Air Force cost model (NAFCOM) historical data/curve fits. The SEs for the NAFCOM regression fits are not shown herein but are combined with the data from the weight distribution curves to define a total uncertainty distribution for the projected cost of the vehicle.

The uncertainty in the DDTE cost is computed by taking each of the component cost equations and multiplying the weight by the uncertainty in weight and the overall cost equation by the uncertainty in the NAFCOM regression curve. Equations (8–10) are an explanation of the DDTE cost uncertainty and show how the lognormal distributions for weight uncertainty Wt_{unc} and NAFCOM uncertainty $\mathrm{NAFCOM_{unc}}$ will be exercised as a multiplier of the terms to determine the total uncertainty in the cost number for a specified component (wings, tail, tanks, etc.) including the complexity factor (CompFactor),

$$\mathrm{wing_{unc}} = \mathrm{CIF} \times \mathrm{CompFactor} \times A_c \times Wt_{\mathrm{wing}}^{B_c} \tag{8}$$

$$Wt_{\mathrm{wing}} = Wt \times Wt_{\mathrm{unc}} \tag{9}$$

$$A_c \times Wt_{\mathrm{wing}}^{B_c} = A_c \times Wt^{B_c} \times \mathrm{NAFCOM_{unc}} \tag{10}$$

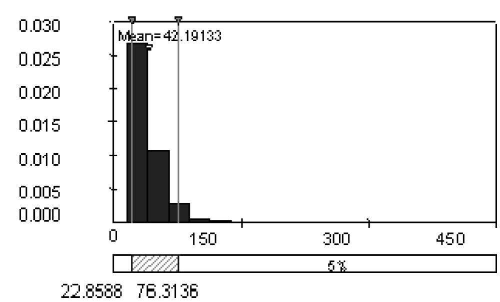

Fig. 16 Distribution of DDTE.

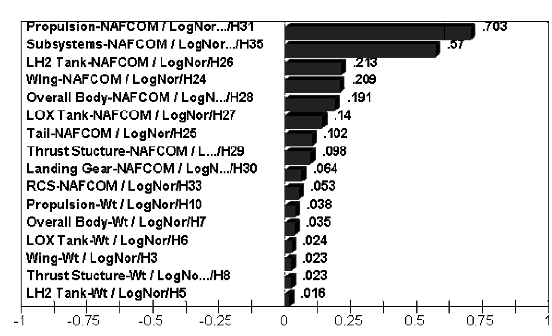

Fig. 17 Regression sensitivity for DDTE cost.

The total DDTE cost uncertainty was defined by operating 10,000 Monte Carlo runs in @RISK™ using NAFCOM lognormal distributions that result from the SEs of the components that make up the vehicle. The total uncertainty is defined in the range shown in Fig. 16. The sensitivity of the individual components that make up the total uncertainty is shown in Fig. 17. The maximum and minimum values for uncertainty are presented based on the 95th percentile case. The absolute minimum and maximum values are

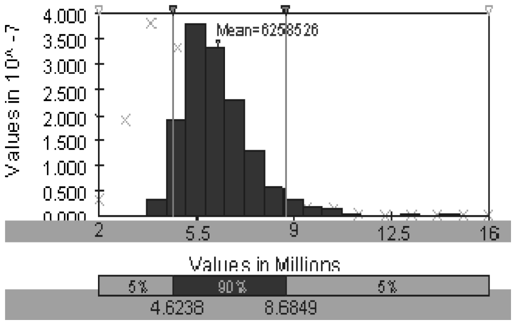

Fig. 18 Distribution for GLOW/weight.

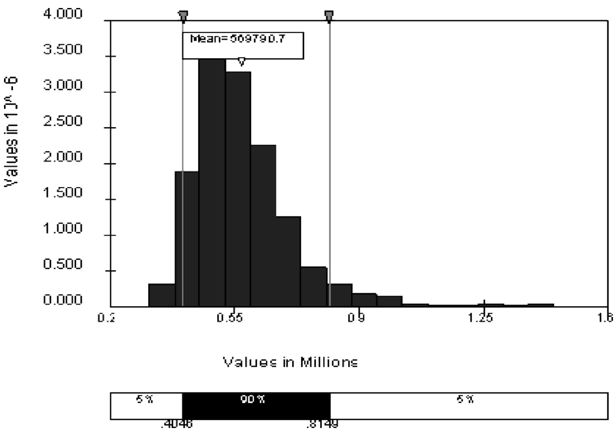

Fig. 19 Distribution for dry weight.

decidedly outside the bounds of acceptable engineering estimates. This is the benefit of using the 95th percentile case to describe the bounds of the DDTE cost uncertainty. The data define the lower and upper values of uncertainty at −45–76% of the mean value of DDTE cost. The results show that there is a significant level of uncertainty in the cost based on the uncertainty in component weights and on the NAFCOM uncertainty.

In a manner similar to that in the preceding section, the distributions are developed for each of the vehicle components (wings, tail, tanks, etc.). The SE is calculated using power series regression curves. Taking each of the component weights and multiplying the weight by the uncertainty in weight computes the uncertainty vehicle weight. Equation (9) is used to calculate the component weight uncertainty and will be used to determine the total uncertainty in the weight for a specified component (wings, tail, tanks, etc.).

The total uncertainty is defined in the range shown in Fig. 18 for the GLOW and Fig. 19 for the dry weight. The maximum and minimum values for uncertainty are presented based on the 95th percentile case. The results show that there is a significant level of uncertainty based on the uncertainty in component weights.

IV. Conclusions

Using the Cequel code for thermochemical outputs, by inputting P_c, $\AE$ and OF, provided a methodology that has not been used in previously designed tools attempting to optimize a closed-loop system. The Cequel output and input structure designed in the linkages proved that a true closed-loop system produces the results in a significantly more efficient way. The alternatives to integrating thermochemical results into the model are to use databases and extrapolate the results for a given input condition.

A key aspect of the model was the method to determine engine mass based on parameters of the system or propulsion variables produced in the design process. Design synthesis of the proposed propulsion parameters and the goodness of the engine mass models led to the optimum design being chosen that closely matched the theoretical optimum vehicle. The engine mass modeling approach is open to updates based on any new and/or improved methods to estimate the mass using design parameters. The ability to have the engine mass, parameters used to determine engine mass, and the vehicle weight and cost integrated together in an optimized fashion is the essence of CLO. The model outputs are only as good as the data being used to formulate the model. This point must not be overlooked, and an emphasis must be made toward higher-fidelity modeling in future efforts where CLO is attempted.

The integrated model output defined that the GLOW and dry weight was 67% higher for the DDTE cost minimization case when compared to the weights determined from the minimization of GLOW case. This is driven by the nature of the parameters tendency toward making the optimized value in each case as small as possible. In a likewise manner, The DDTE cost was 53% higher using the GLOW minimization case when compared to the case for minimization of the DDTE cost. Again, this was an expected result due to the higher cost for the case where weight is being optimized. These variables provide valuable insight into program management trades where cost and vehicle weight are involved.

The uncertainty of the model results are defined using the lognormal distributions based on the power series regression curves and SE values for each component weight and SE values for the NAFCOM regression curves. When the lognormal distributions were used, the data being used in the Monte Carlo runs were significantly more accurate than a triangular distribution or normal distribution. This was true because the lognormal curves represent the log space distribution of the power curve data that are plotted on logarithmic scale axis. The model output for DDTE cost uncertainty was approximately 76% above the mean value for the 95th percentile upper limit. According to feedback from NASA and academia experts, this closely matches the 80% value used for program planning purposes. The dry weight uncertainty output reflected a 95th percentile uncertainty upper range that was +90.2% above the model output for the minimized dry weight (428,123 lb). Likewise, the GLOW uncertainty output had a value of 81.3% above the model output for minimized GLOW (4,635,904 lb).

The model output for the core propulsion parameters was a significant result of the optimization effort. The chamber pressure for the optimum GLOW and dry weight are 2713 and 2465 psi, respectively, and compare to the 2994 psi for the block 2 SSME. The likelihood of these optimized values being the true optimized values can be clarified by further efforts in engine mass studies.

The $\AE$ for optimum engine design, for the minimization of dry weight (case 2), was 86.7. The conclusion can be drawn that the $\AE$ for SSTO systems could be slightly higher than the SSME is currently designed and significantly higher than the first-stage engines used in expendable launch vehicles. A more accurate trajectory model would aid in confirming these results.

The OF was the most sensitive component of the propulsion parameters due to its significant impact on the propellant weight and tank volume. This was due to propellant mass significance to the GLOW and the propellant volume significance to the dry weight. The GLOW was most impacted by the propellant weight. Another driving force behind the OF was that the maximum specific impulse occurs at the ratio of 5.2. When these driving factors were used, the optimum OF for fuel weight was defined 6.87 for the GLOW optimization case involving the engine with T_{vac} equal to 800,000. The optimum OF for the SSME thrust level of 500,000 lbf was defined at 6.63.

The importance of the TFs and CIFs cannot be underestimated in determining the optimum system with respect to cost and weight. The base technology represented by the Boolean code one does not improve the optimum system weight but does make the system cheaper to design and test. The technology improvements and weight savings represented by Boolean codes two and three are significant weight reducers but do increase the overall DDTE cost. The CIFs have no direct impact on these cost cases. Their only influence is with the input weights and DDTE cost provided by the model components. A comparison of the optimization cases show that system tradeoffs can be made to improve the cost of the system at the expense of vehicle weight. This was also true for the reverse. The improvement in overall vehicle weight resulted in significant increases in the cost of the system. The key component of trading cost and weight proved to be the technology and CIFs resulting from the inclusion of new technologies. The engine design parameters have some impact on the overall system optimization, but the effects are minimal in comparison the TFs.

Acknowledgments

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