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Surrogate Based Simulation in Multidisciplinary Design Optimization of a Space Transportation System

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ABSTRACT

Keywords*:Space Transportation Systems (STS), Multidisciplinary Design Optimization (MDO), Surrogate-based Optimization, Multidisciplinary Design Feasible (MDF), Systems Engineering, Complex Systems*

Recently, engineering systems are quite large and complicated. Conceptual design process of Space Transportation Systems (STSs) is a multidisciplinary task which must take into account interactions of various disciplines and analysis codes. Current approach for the conceptual design of STSs requires the evaluation of a large number of different configurations and concepts. With existing legacy codes, estimating the performance of all design combinations becomes very time consuming and computationally expensive. A possible solution to this problem could be employing surrogates during design tasks. This paper describes an effort to optimize the design of an entire STS to achieve a low Earth orbit, consisting of multiple stages using an efficient surrogate-based Multidisciplinary Design Optimization (MDO) framework with the goal of minimizing vehicle weight and ultimately vehicle cost. Furthermore, a combination of Response Surface Methodology (RSM) and Kriging surrogates has been used for building surrogate models. The disciplines of aerodynamics, propulsion, trajectory simulation, geometry, and mass properties, have been integrated to produce an engineering system model of the entire vehicle. In addition, the system model has been validated using the existing design data of STS's trajectory and their subsystems. For the design optimization, in order to ensure that the payload achieves the desired orbit, a hybrid algorithm has been used to minimize the deference between the actual and the desired orbital parameters. The objective function of the optimization problem is to minimize the overall system mass, thus minimizing the system cost per launch. The proposed design and optimization methodology provides designers with an efficient and powerful approach in computation during designing space transportation systems and can also be developed for more complex industrial design problems with comparable characteristics.

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Introduction

The design of complex products requires extensive investigations regarding the response of the product due to external loads. This could be done by physical experiments or computer simulations.In recent years, increased focus has been put on detailed computer simulations. However, these simulations can be very demanding from a computational point of view. Therefore, in many situations, e.g. during optimization of product performance, there is a need for a simplified model that could provide an efficient representation of the detailed and costly model of the product. These simplified models are called surrogate models. If the model is a surrogate for a detailed simulation model it is called a surrogate. Since this document focuses on optimization based on simulations, the term surrogate will be used throughout the text. Surrogates are created by a mathematical description based on a dataset of input and the corresponding output from the detailed simulation model. The mathematical description, i.e. meta-model type, suitable for the approximation could vary depending on the intended use or the underlying physics that the model should capture. Different datasets are appropriate for building different meta-models. The process of where to place the design points in the design space, i.e. the input settings for the dataset, is called Design of Experiments (DOE).

Traditionally, the meta-models have been simple polynomials, but other meta-models that are better at capturing complex responses are increasing in popularity. Space Transportation Systems (STSs) are among the most considerable segments in planning of space missions. Conceptual design phase of these systems is an interdisciplinary field. The last goal of this process is to manufacture a STS that fulfils the requirements of the customers. The conceptual design phase contains various interactions between specialized disciplines such as propulsion, aerodynamics, cost, and trajectory simulation to mention a few, which sometimes faces conflicting objectives and constraints. Conceptual design of STSs is a complex and decision making process which aims at choosing from a collection of choices implying an irrevocable allocation of resources. Recently, emphasis has been on the advances that can be achieved through the interaction between two or more disciplines. Thus, it is fundamentally a multidisciplinary process.

Multidisciplinary engineering systems are complex systems whose interconnected subsystems belong to different physical domains. Traditional design methodologies for such systems rely on subsystem partitioning, and hence they often result in more iterations and less desirable outcomes. Whereas traditional design methodologies suffer from the aforementioned drawback, a concurrent approach emphasizes the physical integration and communication amongst the subsystems. As research on Multidisciplinary Design Optimization (MDO) has matured, the number of methods available to solve a given problem has increased. These methods can be divided into two classes: monolithic formulations and multilevel formulations. Monolithic formulations that include All-At-Once (AAO) [1], Multidisciplinary Design Feasible (MDF) [2], Individual Discipline Feasible (IDF) [3], and Simultaneous Analysis and Design (SAND) [4] architectures, apply a single system-level optimizer to the whole problem. Also, distributed formulations such as Collaborative Optimization (CO) [5], Concurrent Subspace Optimization (CSSO) [6], Analytical Target Cascading (ATC) [7], and Bi-level Integrated Systems Synthesis (BLISS) [8], use subspace optimizations to promote discipline autonomy.

There have been many studies on the literature that propose systematic design optimization methodologies to solve a space system design problem [9-14]. In the past two decades, approximation methods and approximation-based optimization have attracted intensive attention. These types of approaches approximate computation intensive functions with simple analytical models. The simple model is often called meta-model; and the process of constructing a meta-model is called meta-modelling. With a meta-model, optimization methods can then be applied to search for the optimum, which is therefore referred to as Meta-model-Based Design Optimization (MBDO) [15] and also general framework for surrogate-based numerical optimization is presented [16]. Some applied articles related to multidisciplinary escalator simulation [17], optimal design [18], probabilistic optimization [19], optimization using improved response surface methodology [20], and vortex breakers effectiveness in launch vehicle mass/energy capabilities [21]. In the last method the concept of a modular surrogate can be easily coupled with any optimization method. Furthermore, a multi-objective, multidisciplinary design optimization methodology for the conceptual design of a spacecraft bi-propellant propulsion system is developed [22]. Shafaee et al. [23] proposed a mass-based model to improve the geometrical and performance parameters of space propulsion systems. They investigated a mass-based model for optimization process. Their method used a hybrid GA sequential quadratic programming as an optimizer. The mass-based formulation problem was solved using a hybrid optimization algorithm with a GA as the global optimizer and sequential quadratic programming as the local optimizer starting from the solution given by the GA. Xuan and Lam [24], have studied the Multidisciplinary Design Optimization (MDO) using RSM, GA, and also simulated annealing. The article developed a novel framework for MDO. In terms of optimization algorithms, RSM, GA, and simulated annealing are utilized to get a global optimum. Naseh et al. [25] developed an adaptive multi-objective multi-disciplinary robust design optimization framework. From the literature, it was seen that there is limited work on multi-objective optimization of STS. Hence, in the present work, an attempt has been made to optimize a STS using the integration of the MDF and DOE. Thus, the presented methodology can be developed using the surrogate in design framework and choosing the number and the types of the disciplines, objectives, and applications in the MDO framework and in conclusion reducing process time by using surrogate.

In the past few years, new developments in meta-modelling techniques have been continuously coming forth in the literature.

So far little attention has been paid to the surrogate-based design optimization of the STSs. This paper describes an effort to optimize the design of an entire STS to achieve a low Earth orbit, consisting of multiple stages using an efficient surrogate-based MDO framework with the goal of minimizing vehicle weight and ultimately vehicle cost. Furthermore, a combination of Response surface methodology (RSM) and Kriging meta-models has been used for building surrogate models. The paper continues on section 2 which introduces the design problem. Section 3 presents the optimization methodology. Section 4 shows the implementation of the design problem in a MDO framework. Finally, the conclusions are drawn.

System modelling

Problem definition

In recent years, there has been an increasing demand for higher performance STSs for future space missions. In order to improve the performance of these types of systems, a design process integration approach is presented to optimize the design process. To demonstrate that STS conceptual design problem can be formulated as an MDO problem and to develop a suitable MDO architecture, conceptual design of a Two Stage STS is considered for studies. The mission is to deliver 1400 kg payload (satellite) to a circular low earth orbit (400 km) at an inclination of 55 degrees. Propulsion system in each stage is liquid propellant engine. Though the number of stages may also be one of the design variables, however, in this study it is fixed as two. The payload weight and volume requirements are specified in problem definition before the optimization is computed. Also, for the current study, two stage liquid propellant STS have been validated against a real-world example. The real-world example chosen to validate the design model was the Kosmos STS. Given the known parameters for the real-world examples (payload mass, types of propellants, etc.), the system model was manipulated in an attempt to match the physical properties and the performance characteristics of the real-world example. The known parameters used were the payload mass to orbit, the desired altitude and velocity, the individual stage geometry (diameter and length), and the individual stage propellants.

The disciplines are weight-sizing, combustion analysis, propulsion, aerodynamic, and trajectory analysis. The disciplines participating in the MDO problem are represented as modules (codes) for which inputs and outputs are identifiable. It should be noted that the design process is limited to technological and geometrical constraints. For example, diameter of the thrust-chamber and fuel and oxidizer tanks radius (allowed by the installation in the upper stage) are geometrical constraints, which are considered based on overall system specifications. Modelling of the design process consists of employing a suit of analysis modules based on a combination of physical and empirical models. Furthermore, over one hundred of variables (including design variables, coupling variables, state variables) and parameters were used in modelling the conceptual design of the presented system, and the most important ones are briefly described as follows.

Combustion

Modeling and simulation of the combustion process, is one of the most important requirements in determining the performance of a bi-propellant propulsion system. In this research, NASA Glenn's computer code CEA (Chemical Equilibrium with Applications) is applied to determine the properties of the combustion products. CEA is a fast and accurate combustion code, which is usually used to analyze and validate combustion processes [26]. Minimization of free energy approach to chemical equilibrium calculations has been used in all versions of this program [27]. In this analysis module chemical equilibrium analysis was performed for modeling an adiabatic combustion. Three main inputs of the combustion discipline are oxidizer and fuel type, combustion chamber pressure, and oxidizer to fuel ratio. These design variables are the key aspects in designing bi-propellant systems. Combustion chamber pressure affects the size and the specific impulse (I_{sp}) of the engine.

Generally, the propellant type and the optimum oxidizer to fuel ratio are determined based on many major factors (i.e. propellants density, cooling considerations, and start capability). It is obvious that deviations from these values will penalize vehicle performance. In this study, a response surface model (RSM) has been applied as a combustion analyzer based on data generated by CEA code. For example, the variation of combustion temperature, computed in the RSM with respect to oxidizer to fuel ratio and combustion chamber pressure for N_2O_4/UDMH is shown in Fig. 1.

Engine design

The engine design analysis code uses gas dynamics equations to calculate propulsion system characteristics. During the preliminary design, allocations and assumptions were considered to simplify the design process. The most important assumptions are adiabatic combustion, complete combustion, and homogeneous mixing during combustion. Inputs of this discipline consist of a set of design variables, design parameters, and coupling variables. In this discipline, specific impulse, engine geometry, and other performance specifications are computed. The design of the nozzle is influenced by many design considerations such as weight, performance, manufacturing, geometry constraints, etc. The final design would be based on a tradeoff among the benefits of improved performance and penalties of increased weight and greater complexity. In this research, parabolic geometry approximations [28] were used to estimate the bell-nozzle dimensions. This technique works well enough and its accuracy is acceptable in the conceptual design phase. Moreover, characteristic length method was used to estimate the chamber geometry. This method is based on engine test data and gas-dynamic considerations. In the current study, for calculating the real I_{sp}, several I_{sp} losses (e.g. combustion and nozzle) based on empirical and statistical data have been considered. The engine design module has been validated using design data of the liquid propulsion systems. Validation results for the vacuum I_{sp} are shown in Fig. 2 and Fig. 3.

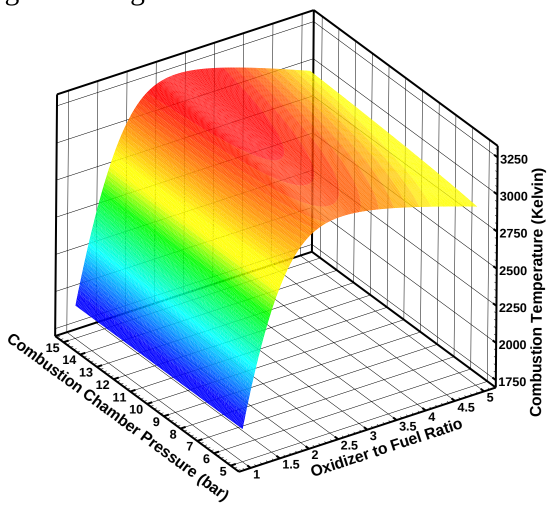

Fig. 1. Combustion temperature versus oxidizer to fuel ratio and combustion chamber pressure for N2O4/UDMH

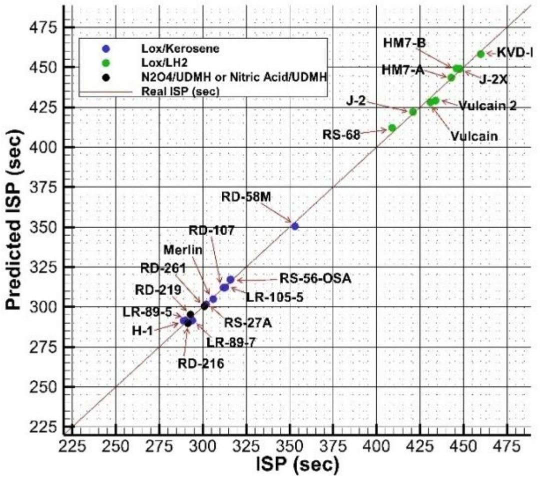

Fig. 2. Accuracy of the design model for predicting vacuum I_{sp} for gas generator cycle

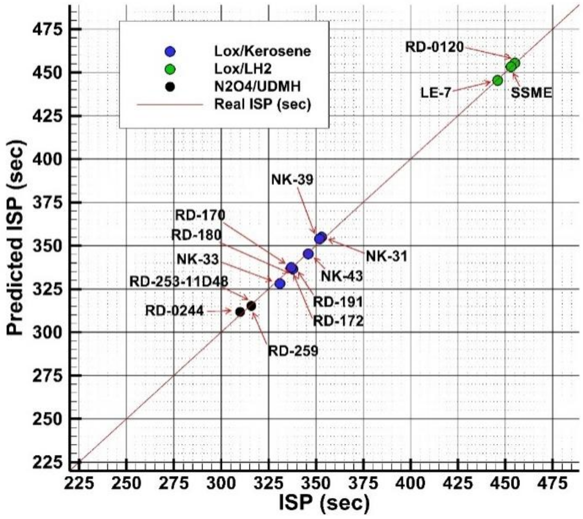

Fig. 3. Accuracy of the design model for predicting vacuum I_{sp} for staged combustion cycle

Aerodynamics

The aerodynamics model computes aerodynamic properties of the flight vehicle during mission phases. In the present paper, US Air Force Missile DATCOM [29] code is used to estimate aerodynamic coefficients of different configurations. It is capable of rapidly and economically computing the aerodynamics of a wide variety of vehicle configurations and it has the predictive accuracy appropriate for the conceptual design phase. In this discipline based on flight condition, vehicle configuration, etc., aerodynamic tables are generated and transferred to the trajectory discipline. Axial force coefficient and normal force coefficient versus angle of attack and Mach number for a specific configuration are illustrated in Fig. 4. In the design process, for optimizing the shape of STS, several fairing configurations could be considered as discrete design variables. The effect of fairing shape on drag coefficient is shown in Fig. 5. As can be seen from Fig. 5, fairing shape has a big impact on the aerodynamic coefficients of flight vehicle.

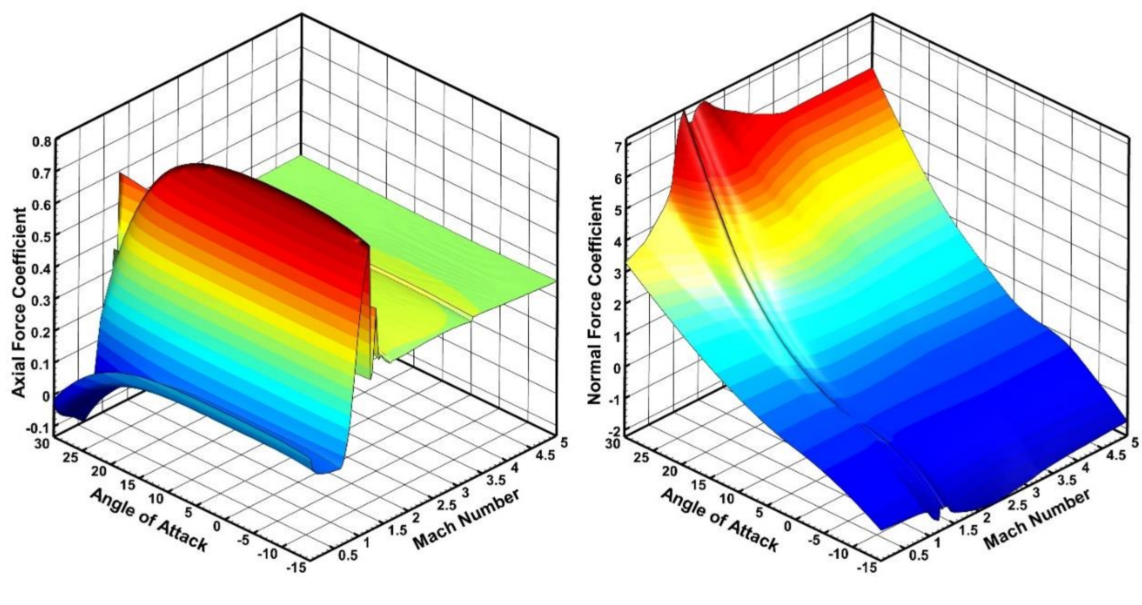

Fig. 4. Axial force coefficient and normal force coefficient versus angle of attack and Mach number for a specific configuration

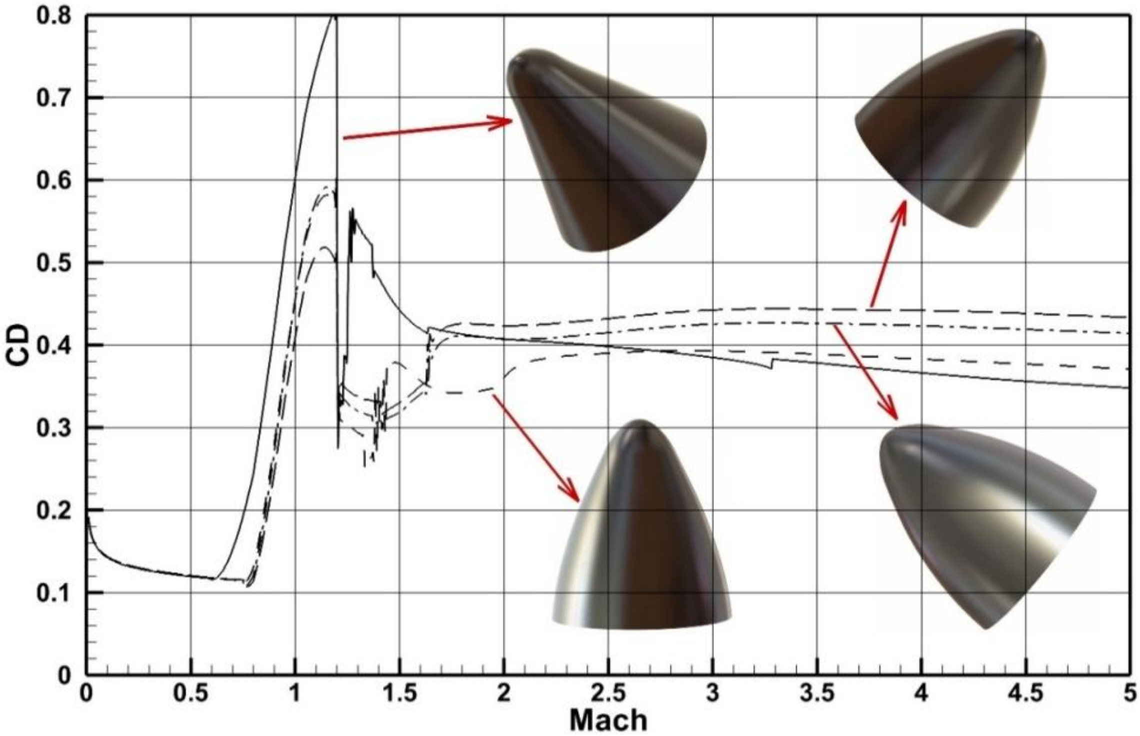

Fig. 5. Different fairing configurations for predicting aerodynamic properties

Weights and sizing

This sub-section describes the weight/sizing model programmed for the STS design problem. The STS weight is of prime importance for optimization procedure. There are two main models to estimate the weight of a vehicle that are analytical models and statistical models. Analytical models are not easy to develop for estimating the weight of STS due to complexity and lack of sufficient data in conceptual design phase. In addition, the development of these models needs to use some assumptions that can make the problem easy to simulate. Because the statistical models need to establish a database for estimating the weight of subsystems, the weight of components is estimated as total system weight. In the present paper a combination of analytical and statistical models has been used in order to estimate the weight of the STS. Sizing model calculates areas and volumes for the major components of the vehicle, which are inputs to the aerodynamic module and also Mass Estimating Relationships (MERs) in the weights tool. The mass of a stage can be calculated as:

$$\mathrm{M_{stage}} = \mathrm{K_C}(\mathrm{M_{Body\ Group}} + \mathrm{M_{Propulsion\ Group}} + \mathrm{M_{Other}}) \tag{1}$$

$$\begin{aligned}\mathrm{M_{Body\ Group}} = \mathrm{K_S}\big(&\mathrm{M_{tanks}} + \mathrm{M_{antivortex}} \\ &+ \mathrm{M_{slash\ baffles}} + \mathrm{M_{intertank}} \\ &+ \mathrm{M_{interstage}} + \mathrm{M_{forward\ skirt}} \\ &+ \mathrm{M_{aft\ skirt}} \\ &+ \mathrm{M_{engine\ compartment}} \\ &+ \mathrm{M_{thrust\ structure}}\big)\end{aligned} \tag{2}$$

$$\begin{aligned}\mathrm{M_{Propulsion\ Group}} = &\mathrm{M_{engines}} + \mathrm{M_{engine\ installation}} \\ &+ \mathrm{M_{engine\ subsystem}} \\ &+ \mathrm{M_{thrust\ vector\ control}} \\ &+ \mathrm{M_{propellant\ purge}} + \mathrm{M_{feed}} \\ &+ \mathrm{M_{pressurization\ system}}\end{aligned} \tag{3}$$

$$\begin{aligned}\mathrm{M_{other}} = &\mathrm{M_{reaction\ control\ system}} + \mathrm{M_{Avionics}} \\ &+ \mathrm{M_{Primary\ Power}} \\ &+ \mathrm{M_{Hydraulic\ Systems}} \\ &+ \mathrm{M_{Residual\ Propellants}} \\ &+ \mathrm{M_{Ascent\ Reserve\ Propellants}}\end{aligned} \tag{4}$$

Where $\mathrm{K_C}$ and $\mathrm{K_S}$are the technology level factor denote structure and propellant type coefficient. Furthermore, it should be noted that the $\mathrm{K_C}$ depends on the material alloy type that for aluminum alloy is considered equal to 1. In the case of $\mathrm{K_S}$ depends on fuel and oxidizing (propellant) types. For storable propellant, $\mathrm{K_S}$ is considered to be 1 and for hydrogen fuel is considered to be 2. In this paper, the engine weight as function of the pressure expansion ratio and thrust is calculated by an efficient RSM (Fig. 6). The feasible area, the scattering (accuracy) of applied model is shown in Fig. 7. In the design optimization process, state variables for Sizing tool can be updated at each iteration of the design loop. Geometry updates of the design loops enable high-fidelity tracking of configuration and aerodynamic effects on vehicle closure.

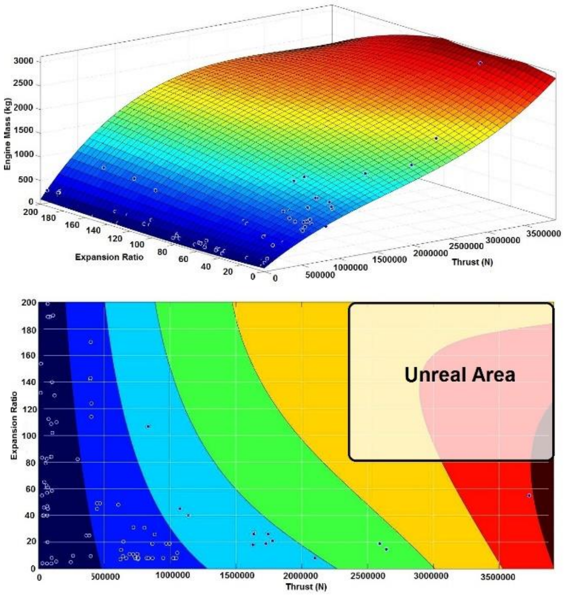

Fig. 6. Response surface model for predicting engine mass

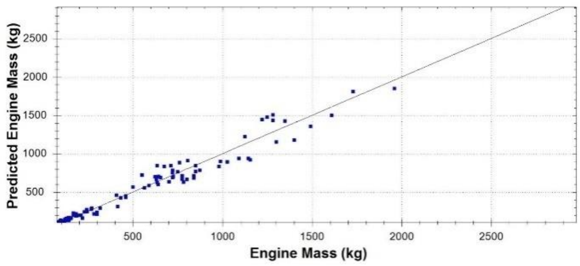

Fig. 7. Scattering and accuracy of statistical data fitting

Trajectory analysis

In a typical STS design optimization problem, the main outputs of the trajectory module are the constraints of the problem. These constraints are intermediate constraints and final orbit constraints. The final orbit constraints are usually specified by the customer depending on the payload mission. The final position and velocity constraints are specified in terms of orbital elements (apogee altitude, perigee altitude, inclination, perigee argument and etc.). The intermediate constraints are either linked to environment loads that the launcher or the payload can stand (maximum dynamic pressure, heat flux or acceleration), or to operational requirements.

The trajectory model used in this study is derived from the following classical 3D dynamics equations, written in an Earth-centered, Earth-fixed referential.

$$\dot{r} = V sin\gamma \tag{5}$$

$$\dot{V} = \frac{T cos(\theta-\gamma) - D}{m} - g(r)\sin(\gamma) + \omega^2 r cos\varphi(\sin\gamma cos\varphi - \cos\gamma sin\varphi cos\psi) \tag{6}$$

$$\dot{\gamma} = cos\mu \frac{L + T cos(\theta-\gamma)}{mV} + \left(\frac{V}{r} - \frac{g(r)}{V}\right)\cos\gamma + 2\omega sin\psi cos\varphi + \frac{\omega^2}{V} r cos\varphi(\cos\gamma sin\varphi - \sin\gamma sin\varphi cos\psi) \tag{5}$$

$$\dot{\lambda} = \mathrm{V}\frac{\cos\gamma sin\psi}{r cos\varphi} \tag{6}$$

$$\dot{\varphi} = \mathrm{V}\frac{\cos\gamma sin\psi}{r} \tag{7}$$

$$\dot{m} = q \tag{8}$$

Where

r	radius (m)
V	Norm of velocity vector(ms^{-1})
γ	Flight path angle (rad)
φ	Latitude(rad)
λ	Longitude(rad)
ψ	Flight path heading (rad)
μ	Bank angle (rad)
θ	pitch angle (rad)
ω	Earth angular Velocity($rads^{-1}$)
T	Thrust (N)
D	Drag (N)
L	Lift (N)
$g(r)$	Gravity acceleration ($\mathrm{m}^2\mathrm{s}^{-1}$)
m	Mass (kg)
q	Mass flow rate (kgs^{-1})

The trajectory module cannot generate correct trajectories for each set of input. Since there is hardly any detailed data at the beginning of STS conceptual design, it is computationally expensive to use 6-DOF trajectory simulation during this phase. Therefore, in this study a three-degree-of-freedom (3-DOF) trajectory analysis was used. State variables are altitude, velocity, and flight path angle. Pitch rate is the control variable, which is determined by the optimizer. The trajectory analysis computes state variables by integrating ordinary differential equations of motion with given design variables and examining constraints conditions during the flight [30].

Optimization approach

Multidisciplinary Feasible (MDF) framework

In general, MDO problems, three main categories of variables are defined. Design variables are independent quantities that are controllable from the designer's point of view. Typically, design variables can be classified into continuous, discrete (including integer and categorical), and Boolean types. In the MDO frameworks, they are always under the explicit control of an optimizer. State variables represent analysis results of the disciplinary analysis, and depend on the design variables and state equations. In the MDO process, analysis modules are connected with each other by coupling variables. An MDO problem can be formulated in a standard form as [13]:

$$\begin{aligned} &Minimize && f(x.y.z) \\ &Subject\ to && g(x.y.z) \leq 0 \\ & && h(x.y.z) = 0 \\ & && \forall i.\, R_i(x_i.y_i.z_i) = 0 \\ & && \forall i.\forall j \neq i.\, y_i = \{c_{ji}(x_j.y_j.z_j)\}_j \\ & && i = 1.\dots.n \\ &With\ respect\ to && x = \{x_{sh}.\bar{x}_k\} \end{aligned} \tag{9}$$

Where x is the vector of design variables. x_{sh} symbolizes the variables which are shared between different subsystems (global variables) and $\bar{x}_k$denotes the variables which are specific to one subsystem (local variables). z is the vector of the state variables; y is the vector of the coupling variables; Also, $f(.)$ is the objective function (i.e. cost function). The inequality constraints are described by $g(.)$, and $h(.)$ represents the equality constraints. $c_{ji}(.)$symbolizes coupling functions which calculate the coupling variables from the subsystem i to the subsystem j. $R_i(.)$ characterizes the residual functions for the subsystem i, which quantify the satisfaction of the state equations, and n is the number of the subsystems. $(.)_i$ represents functions or variables that apply to subsystem i. Selection of proper MDO architecture depends on many factors such as the nature of design problem. In the presented design problem, because of strong coupling between disciplines, MDF was selected for solving the optimization problem.

MDF is the most general MDO formulation and has a comprehensive industry acceptance. The MDF, moreover known as fully integrated optimization and "all-in-one (AiO)" solves the optimization problems with different subsystems, simultaneously. In this framework, a system analyzer coordinates all of the subspace analyzers and the system level optimizer controls the design process, ensuring that the global objective is achieved while the design constraints are satisfied. In design problems that deal with coupled systems, some analysis methods (i.e. Fixed Point Iteration and Newton-Raphson) are regularly employed within an MDF approach. Compared with other monolithic formulations, the major benefit of MDF framework is that the dimension of optimization problem is as small as it can be for a monolithic formulation. Another advantage of this framework is that in each optimization iteration, MDF returns a solution that always satisfies the consistency constraints, but it may be time-consuming. The MDF architecture for the STS design problem and coupling relationships of the disciplines are described with a Design Structure Matrix (DSM) shown in Fig. 8. Coupling variables definition is presented in Table 1.

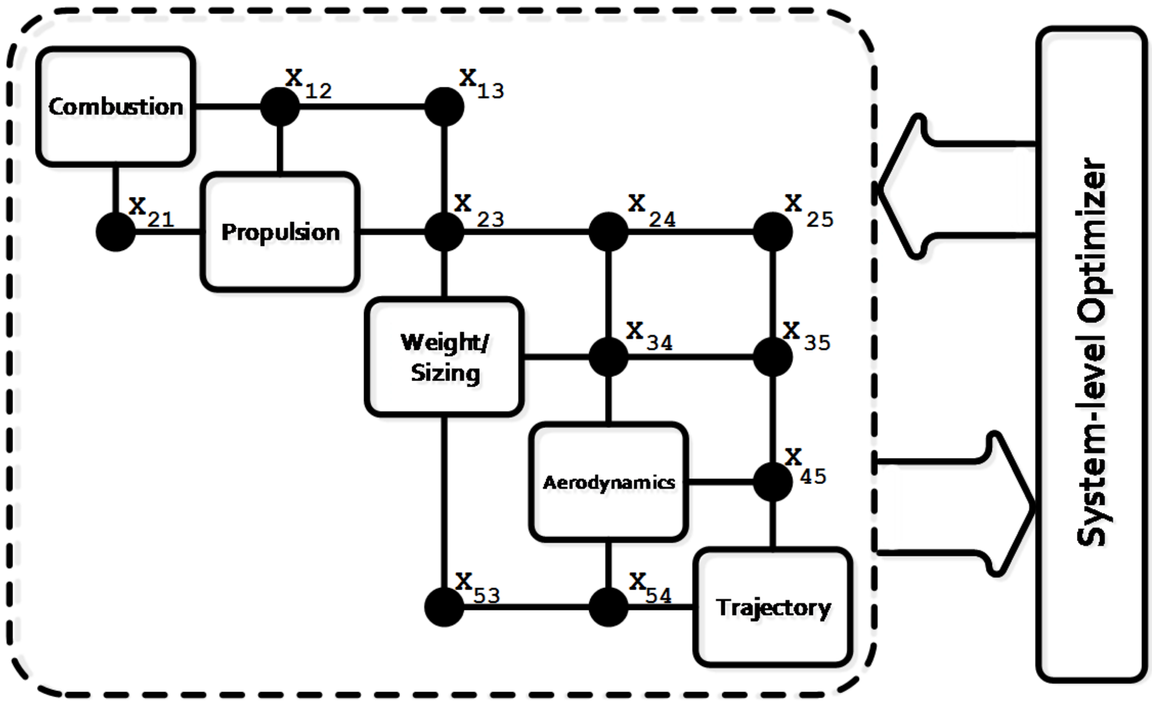

Fig. 8. MDF architecture for the STS design problem

Table1. Coupling variables definition

Coupling	definition	Coupling	definition
X_{12}	Propellant Thermo-chemistry Properties	X_{34}	Geometry, CG
X_{13}	Propellant Mass and Density	X_{35}	Geometry, CG, System Mass
X_{21}	Chamber Properties(P_{CC}, T_{CC})	X_{45}	Aerodynamic Properties
X_{23}	Engine Geometry, Chamber Properties(P_{CC}, T_{CC})	X_{53}	Environmental load
X_{24}	System Geometry	X_{54}	Environmental load
X_{25}	I_{sp}	-	-

Surrogate-based design optimization

The detailed simulation models used for STS design are often computationally too expensive to calculate. Surrogate-based design optimization, in which surrogate is used for the evaluations, can then be an efficient approach to decrease the required computational effort. [15] This is in contrast to direct optimization where the evaluations are conducted using the detailed simulation models directly. The detailed models used in direct optimization are often computationally expensive to evaluate, which is a challenge when many evaluations are required, as when performing optimization studies. The idea of surrogate models originates from fitting a surrogate model to a series of designed physical experiments.

In the present paper an efficient surrogate-based design optimization framework for designing the space transportation systems is presented. The mentioned approach uses Design of Experiments (DOE) methods and the intelligent use of response surface methodology and Kriging models for problem analysis and optimization.

3.2.1. DOE

Latin hypercube sampling (LHS) is a popular choice for Design of Experiments (DOE) [11, 12]. In the simplest version of LHS, each design variable is divided into intervals with equal marginal probability, and the unique sample values are randomly matched across all the variables to form all sample points by randomly permuting each factor column in the design. The samples generated by this sampling method are distributed uniformly in the design space.

LHD was used in this study. Samples were repetitively generated for the meta-models evaluation and testing the surrogate models.

Finally all surrogate models passed the minimum 98% Root Mean Squared Error (RMSE).

3.2.2. Surrogate modeling

Response surface methodology (RSM) approaches were originally developed to evaluate the results of experiments and generate empirically-based equations of the obtained response data. In the RSM methodology the number of coefficients to be calculated is determined by the number of design variables involved and the order of polynomial. In the practical application of RSM, it is essential to develop an approximate model for the true response surface. The second-order (quadratic) response surface model is the most frequently applied one because it is the most economic non-linear model [31]. The quadratic RSM predictor $\hat{y}(x)$ for k factors can be defined as:

$$\hat{y}(x) = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i=1}^{k} \sum_{j=1}^{i-1} \beta_{ij} x_i x_j \quad (10)$$

Where β_0, β_i, β_{ii}, and β_{ij} are unknown coefficients to be estimated, x_i and x_j are design variables. In this paper, the RSM approach (quadratic and cubic predictors) is used to create approximations of complex and or long running models. The resulting response surface executes much quicker than the actual analysis codes used to create the response surface and is therefore more practical for design optimization frameworks which may require hundreds if not thousands of function evaluations.

Kriging has been widely used in recent years for surrogate-modeling of computationally expensive simulations. Kriging models provide a statistic prediction of a simulation model by minimizing its Mean Squared Error (MSE). Prediction of the standard error is a major advantage of Kriging over other surrogate-modeling techniques. [32] This allows the surrogate to be dynamically updated based on the responses during a given optimizing procedure. The major disadvantage of the Kriging process is that model construction can be very time-consuming. Kriging provides a statistic prediction of an unknown function by minimizing its Mean Squared Error (MSE). It can be equivalent to any order of polynomials and is thus well suited for a highly-nonlinear function with multi extremes [33].

The combustion chamber temperature surrogate model, one of the combustion subsystem models, is presented in equation 13. In this regard, the combustion chamber temperature is estimated in terms of combustion chamber pressure (P_{cc}(bar)) and oxidant-to-fuel ratio (OF). This model is extracted from 2500 samples with RMSE about 98.7%.

$$\begin{aligned} T_{cc} = {} & -928.7 - 10.7P_{cc} + 3715OF + \\ & .8454P_{cc}^2 - 664.7OF^2 - 3.637P_{cc}OF + \\ & 0.1809P_{cc}^3 - 347.2OF^3 - 4.311P_{cc}^2OF + \\ & 38.46P_{cc}OF^2 - 0.0122P_{cc}^4 + \\ & 143.7OF^4 + 0.1106P_{cc}^3OF + \\ & 0.7665P_{cc}^2OF^2 - 14.28P_{cc}OF^3 + \\ & 0.2378 * 10^{-3}P_{cc}^5 - 14.66OF^5 - \\ & 0.9773 * 10^{-3}P_{cc}^4OF - 0.012P_{cc}^3OF^2 - \\ & 0.034P_{cc}^2OF^3 + 0.489P_{cc}OF^4 \end{aligned} \quad (11)$$

The flowchart of applied surrogate-based design optimization is shown in Fig. 9. As shown in Fig. 9 optimization process begins with executing analysis codes and generating data based on the design of experiments techniques. Once the data from these initial runs has been generated, mathematical approximations (surrogate models) of objectives and each of constraints will be created. When the surrogate models are created, Sequential Quadratic Programming in conjunction with the surrogate models will be used to predict the optimum design(s) for the design problem. For complex design problems, it is likely that the predicted models by the initial data will not exactly correspond to actual results obtained from running the analysis codes. For some problems, in fact, the errors may be quite large. If this is the case, then the optimal designs obtained from the surrogate models were not really optimal after all [34]. Therefore, we need extra data in order to refine surrogate models and to use the newly updated surrogate models. After optimizing surrogate models, the results will be validated. This process continues until the optimum design is achieved.

Results and discussion

The design problem deal with the minimization of the STS mass, considering the design constraints as well as the side constraints on the design variables. Disciplines of the conceptual design model are all strongly coupled to each other in the MDF framework. Generally, performing engineering design optimization needs some information about the design phase, design parameters, design variables (independent variables), constraints, and the design objectives.

Design parameters identify constants that will not change as different designs and are generated during optimization. The design data for the STS design problem including design variables and constraints are presented in Table 1 and Table 3.
In the MDF formulation, five disciplines were used to demonstrate the proposed methodology. Using the MDO architecture presented in Fig. 8 and equation (9), the presented design problem has been solved. In this study, in order to evaluate the accuracy and efficiency of the introduced optimization method, a robust NSGA-II was used to solve the optimization problem. The GA parameters are shown in Table 4. The GA parameters including selection, crossover, and mutation as well as other parameters such as population size were utilized together to enhance the convergence rate of the optimization.

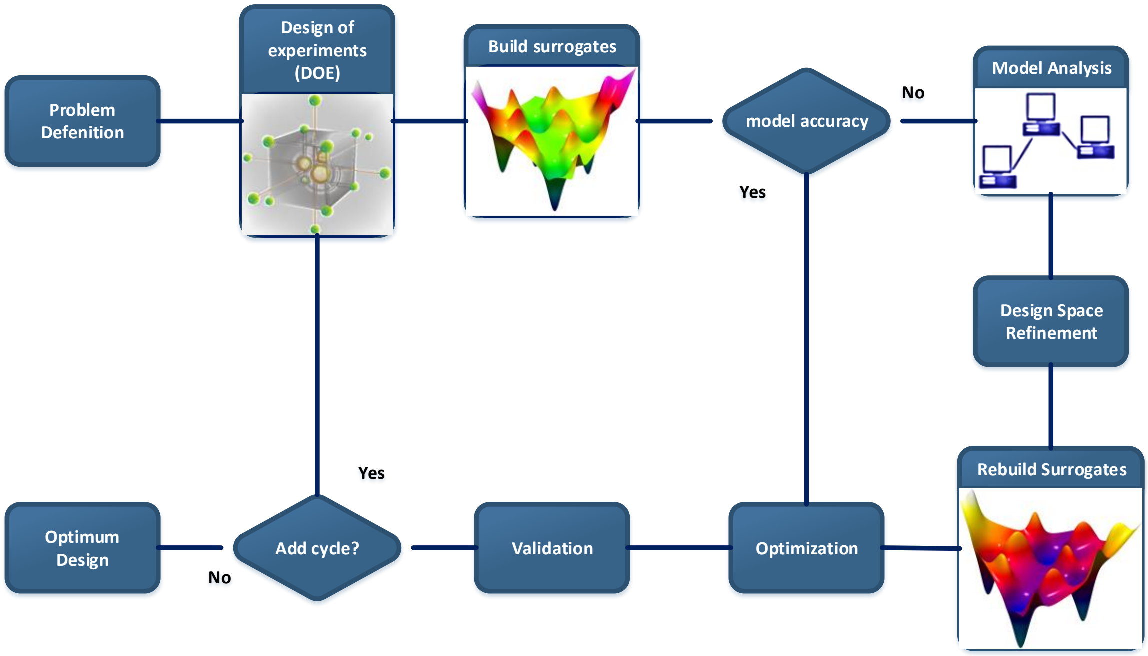

Fig. 9. Flowchart of surrogate-based design optimization

Table 2. Design variables for the STS design problem in the MDF architecture

No.	Design variable	Symbol	Unit	Range
1	Diameter	D	m	2-3
2	Stage one propellant mass	$M_{propellant\ 1}$	kg	40000-100000
3	Stage two propellant mass	$M_{propellant\ 2}$	kg	10000-25000
4	Stage one thrust	$Thrust_1$	N	1400000-2000000
5	Stage two thrust	$Thrust_2$	N	100000-250000
6	Combustion chamber pressure for stage one	P_{cc1}	bar	30-90
7	Combustion chamber pressure for stage two	P_{cc2}	bar	30-90
8	Oxidizer to fuel ratio for stage one	$\left(\frac{O}{F}\right)_1$	-	1.5-3
9	Oxidizer to fuel ratio for stage two	$\left(\frac{O}{F}\right)_2$	-	1.5-3
10	Exit pressure for stage one	P_{e1}	bar	0.05-1
11	Exit pressure for stage two	P_{e2}	bar	0.01-0.5
12	Vertical flight time	t_v	s	6-15
13	Pitch rate at flight stations	$\dot{\theta}_1.\dot{\theta}_2.\dot{\theta}_3.\dot{\theta}_4.\dot{\theta}_5$	$rad/_s$	-0.01-(-0.0005)

Table 3. Design constraints for the STS design problem in the MDF architecture

No.	Design constraint	Symbol	Unit	Lower bound	Upper bound
1	Nozzle exit area for stage one	D_{e1}	m	0	0.8×D
2	Nozzle exit area for stage two	D_{e2}	m	0	0.4×D
3	Length to diameter ratio	$\frac{L}{D}$	-	6	15
4	Thrust to weight for stage one	$\left(\frac{T}{W}\right)_1$	-	1.4	2.5
5	Thrust to weight for stage two	$\left(\frac{T}{W}\right)_2$	-	0.4	1
6	Final velocity	V	$m/_s$	7665	7671
7	Final altitude	H	m	398000	402000
8	Flight path angle	$\gamma_{insertion}$	deg	-2	2
9	Maximum dynamic pressure	max_Q	pa	0	70000
10	Maximum axial load	$max_{A\ load}$	g	0	7
11	Maximum Q.Alpha	$max_{Q.Alpha}$	deg.pascal	0	200000
12	Angle of attack at maximum dynamic pressure	$Alpha_{\max Q}$	deg	-1	1
13	Angle of attack at separation	$Alpha_{sep}$	deg	-1	1
14	Pitch rate at separation	$\dot{\theta}_{sep}$	$rad/_s$	0	0

This paper does not intend to address the details of NSGA-II and only presents the results of applying it to compare the efficiency of the proposed methodology. After implementing the optimization problem on the MDF framework, it was solved by the NSGA-II and the proposed method and the convergence history is shown in Fig. 10 and Fig. 11. As shown in these figures the objective function in both situations is converged to a specific value.

Table 3. Genetic Algorithm (GA) parameters for optimization problem

No.	Mode/Parameter	Value
1	Maximum Generations	600
2	Population size	70
3	Crossover	0.9
4	Mutation	0.1
5	Maximum constraint violation	0.01
6	Percent penalty	0.05
7	Stall generation limit	70

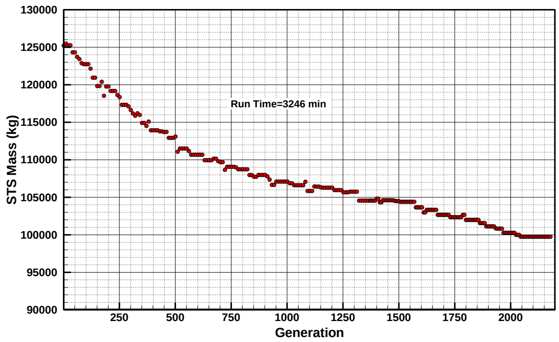

Fig. 10.Convergence history of the objective function in the NSGA-II process

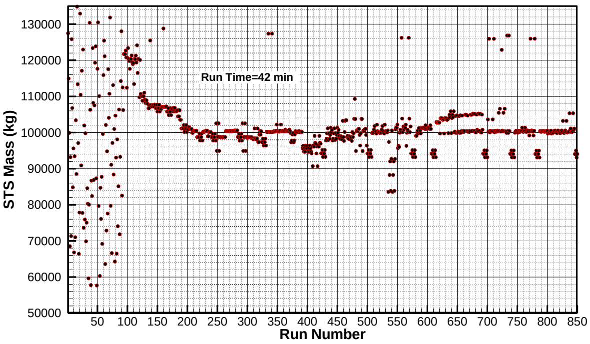

Fig. 11.Convergence history of the objective function in the surrogate-based design optimization process

While in the case of MBO the design problem with less functions evaluation is quickly converged, in the case of using GA, the number of functions evaluation and computation time increased dramatically. The results of optimization with the presented MBO method are presented and compared with a real world example (Table 4). In this method, the STS mass was optimized which was 8.87% lower than the Kosmos total mass. The presented MBO framework provides possibilities for solving complex multidisciplinary design problems such as the design of space transportation systems when using conventional optimization approaches are difficult or very time consuming.

Table 4.design characteristics for the selected optimal design

No.	Description	Kosmos	MBO	Units
1	Total mass	109700	99963.47	kg
2	Stage one fuel mass	81900	77031.25	kg
3	Stage two fuel mass	18700	14277.34	kg
4	Stage one dry mass	5300	5614.56	kg
5	Stage two dry mass	1435	1292.31	kg
6	Diameter	2.4	2.267	m
7	Length	32.4	32.130	m
8	Stage one thrust	1745000	1682421	N
9	Stage two thrust	157000	103808	N
10	Combustion chamber pressure for stage one	75	89	bar
11	Combustion chamber pressure for stage two	98.1	90	bar
12	Oxidizer to fuel ratio for stage one	2.5	2.358	-
13	Oxidizer to fuel ratio for stage two	2.65	2.66	-
14	Stage one ISP	291.3	296.3	s
15	Stage two ISP	303	306.4	s
16	Stage one flight time	130	128.2	s
17	Stage two flight time	330	398.8	s

Conclusion

Space transportation systems exemplify highly integrated systems that suffer from high levels of computation efforts during the design process. The elemental design philosophies for these systems need fundamental changes; each needs to move from a conventional design approach toward a completely integrated approach focused on the system design problem. This paper illustrates MDO’s successful application to a STS design problem. A surrogate based multidisciplinary design optimization framework was applied to conceptual studies of the STS in order to improve the mass and performance capabilities that can fulfil customer and mission requirements. Improving the mass capability means the increasing payload mass capability that can be transferred by the upper stage and also improving the performance capability means increasing the final velocity that can be achieved. Conceptual design of the mentioned system was performed by collaboration of several different analysis modules. The results of this investigation show that, in the MBO, CPU time and function calls are lower than using conventional optimization methods. Furthermore, the presented architecture could potentially mitigate some of the difficulties that arise at later stages of the STS design process, and reduce design complexities. In this article, engineering-level analysis codes were used in the conceptual design phase, which can be replaced by high fidelity analysis modules (such as three dimensional CFD or FEA codes) with more capabilities in the detailed design phase. The proposed design and optimization methodology provides designers with an efficient and powerful approach in computation during designing space transportation systems and can also be developed for more complex industrial design problems with comparable characteristics.

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