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Multidisciplinary Design of Air-launched Satellite Launch Vehicle Using Particle Swarm Optimization

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Abstract: Launch vehicle design is a complex, multidisciplinary engineering activity that requires making difficult compromises to achieve a balance among competing objectives for the vehicle, including safety, reliability, performance, operability, and cost. Significant work has been done in recent years to advance the design, analysis and optimization of launch vehicles. In the present research effort we propose the application of Particle Swarm Optimization (PSO) in devising a Multidisciplinary Design and Optimization (MDO) strategy for designing a multistage Air-launched Satellite Launch Vehicle (ASLV) with a solid fueled propulsion system. The detailed modules for propulsion characteristics, aerodynamics, mass properties and flight dynamics have been integrated to produce a high fidelity multidisciplinary model of the entire vehicle. Design and optimization of an ASLV is a challenging undertaking and differs from conventional ground launched SLVs. A major difference is in the launch phase, that is, it has to be carried on a mother aircraft to a certain altitude and then launched in a horizontal direction (Flight Path Angle (FPA) = 0 deg). Another difference is in the aerodynamics, that is, ASLV has aerodynamic lifting surfaces in order to improve stability and to provide lift during both the launch phase and within atmospheric flight. A lack of availability of literature on MDO for an ASLV makes our problem even more complex and difficult. PSO is a relatively recent heuristic search method whose mechanics are inspired by swarming or collaborative behavior of biological populations. Simplicity of coding and relatively less computational cost makes PSO a very attractive choice for our problem. PSO has been used as a global optimizer to achieve an optimal solution for attaining a minimum Gross Launch Weight (GLW) while remaining within the set constraints and ensuring delivery of the payload to the desired orbit. The objective of this paper is to develop a design strategy based on PSO that proves to be effective (finding the true global optimal solution) with much better computational efficiency (least computational time) and facilitates system design and optimization of ASLV at the preliminary design level. Use of PSO in system design and optimization of the ASLV makes the present research innovative. The design approach is meant for initial design sizing purposes with minimum basic vehicle data but gives a quick insight on the vehicle performance prior to detailed design.

Keywords: *Multidisciplinary design and optimization, air launched satellite launch vehicle, particle swarm optimization*

1. INTRODUCTION

The design of an ASLV carrying a payload to LEO is a complex problem that must balance competing objectives and constraints. It involves teams of specialists working separately on individual system components. These groups typically work toward their specialized design components (like aerodynamics, propulsion, structure, guidance etc.) separately albeit coordinated through a system level set of design requirements such as physical size or weight. This type of segmented design process requires much more iterations and invariably leads to design compromise as system-level engineers work to make each component of the total launch vehicle system compatible with each other. This leads us to think *"out of the box"* and devise the strategy for MDO of ASLV with the use of an artificial intelligence learning tool that can control the design of each component simultaneously. With the MDO process, the design engineer is able to set broad system-level goals and then turn the design optimization process completely over to an optimizer. This unique approach to launch vehicle system design frees the engineers to improve their component level models (like aerodynamics, weight and sizing, trajectory) while letting the computer do what it does best: tirelessly trying thousands of designs while learning which design features work against a particular threat and which ones do not.

The Genetic Algorithm (GA) has been the most favored choice of designers in MDO of SLVs. Significant research has been performed in rocket-based vehicle design optimization using GA (e.g. Anderson et al., 1998, Bayley et al., 2007, Bayley et al., 2007, Rafique et al., 2008, Bayley et al., 2008). PSO has been applied due to its high adaptability to continuous problems: certain structural problems (e.g. Fourie and Groenwold, 2002, Schutte and Groenwold, 2003, Venter and Sobieski, 2003); optimizing Proportional Integral (PI) controller coefficient which is used to meet the different performance needs in a single-area and a two-area interconnected power system (Fei and Xue-bo, 2006) and multidisciplinary optimization problems (Venter and Sobieski, 2004). Hassan et al. (2005) have applied both GA and PSO on component level design and optimization of satellites and proved that both GA and PSO have the same accuracy of results. The above mentioned literature and much more leads us to conclude that researchers have not yet gauged the potential of applying PSO in the highly complex and non-linear multidisciplinary problem of SLV.

This paper is organized in four major sections. First, the multidisciplinary design analysis of ASLV is described. Integrated disciplines are discussed in this section. The optimization process is presented in section two along-with the design objectives, the design variables and the constraints of the integrated disciplines. Performance results and conclusions are presented in the last two sections.

2. MULTIDISCIPLINARY DESIGN OF ASLV

Many practical MDO methods have been widely applied in aerospace for overall designs of aircraft and space transportation vehicles. MDO processes allow an evaluation of the constraints for multiple disciplines from the early stages of the design, thus the expense of making approximations or corrections is reduced.

Multidisciplinary design of a SLV is an iterative process, requiring a number of design iterations to achieve a balance of emphasis from the diverse inputs and outputs. A MDO strategy is envisaged for multistage ASLV analysis which includes: (a) Propulsion module (b) Mass module (c) Aerodynamics module and (d) ASLV Trajectory module. A flow chart of the multidisciplinary design approach followed is given in Figure 1.

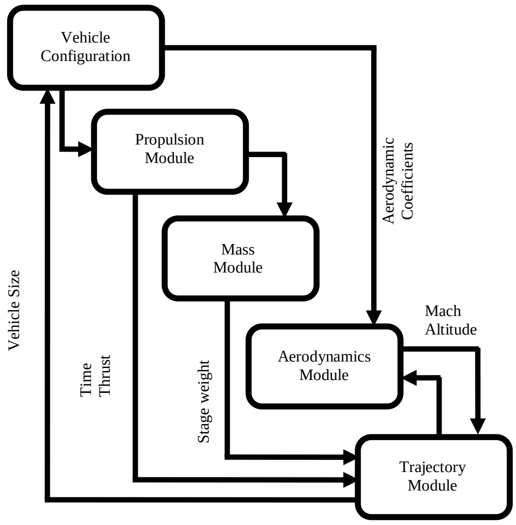


Figure 1. Multidisciplinary design approach.

2.1. Propulsion Module

Propulsion analysis describes important parameters like thrust, burn time, mass flow rate and nozzle parameters (Sutton and Oscar, 2001). The chamber pressure (p_c) is an important design variable which has an affect on the solid rocket motor (SRM) specific impulse. Increasing the p_c will reduce the losses at the nozzle exit and increase the specific impulse. The p_c, however, also affects the burning rate of the propellant, combustion stability, size of the expansion nozzle and the thickness of the casing materials to withstand the pressure stresses. Burning surface area of the propellant grain *(S_{ri})* mainly dictates the performance of the propulsion system in a SRM. The design and performance of the SRM and Grains is discussed in detail in Douglass, et al., 1970, Douglass, et al., 1971, Douglass, et al., 1972. However in this analysis, we are not restricted to a particular shape of grain at the conceptual design level, rather a variable grain shape factor (k_{si}) is used to represent the burning surface area of grain as a function of grain length (L_i) and diameter (D_i). Simplified analytical expressions and empirical formulations are used for the propulsion system sizing.

In order to calculate the average specific impulse (I_{sp}^{a}), the process of a real SRM should be simplified and abstracted to be an ideal SRM. Some assumptions are needed:

- The grain is burnt perfectly in the combustion chamber and its exhaust flow is an ideal gas, that is, the specific heat ratio (γ) of the gas is constant during expansion.
- Average expansion, that is, there are no velocity-lag and temperature-lag between the gas phase and condensed phase.
- One dimension flow, that is, the exhaust is parallel to the longitudinal axis of the SRM.
- Zero viscosity, that is, no friction loss and heat dispersion loss between the gas flow and the internal wall.

Under the same conditions, the relationship of thrust (F), vacuum specific impulse (I_{sp}^{vac}) and mass flow rate of propellant $\dot{m}_{gni}$ w.r.t. design parameters are used, as described by LinShu (2004);

$$F_{1..N} = I_{sp}^{vac}\,\dot{m}_{gni} - p_a A_{ei} \tag{1}$$

$$I_{sp}^{vac} = I_{sp}^{a} + \left(p_e / p_c \right)^{\frac{\gamma-1}{\gamma}} R_c T_c / g_o^2 I_{sp}^{a} \tag{2}$$

$$\dot{m}_{gni} = \rho_{gni} u_i S_{ri} = \rho_{gni} u_i K_{si} \lambda_{gni} D_i^2 \tag{3}$$

where N is number of stages, p_a is atmospheric pressure, A_{ei} is nozzle exit area, p_e is exit pressure, R_c is gas constant, T_c is temperature in combustion chamber, g_o acceleration due to gravity, ρ_{gn} is density of grain, u_i is burning rate of grain and λ_{gni} is the fineness ratio of grain.

2.2. Mass Module

Using a combination of physics-based methods and empirical data, the weight of the major components for the solid stages is determined from LinShu (2004). The total mass of a multistage ASLV includes the masses of propellants and their tanks, related structures and payload mass. The mass equation for a multi-stage SLV can be written as:

$$m_{01} = m_{PAY} + \sum_{i=1}^{n} (m_{gni} + m_{sti} + m_{svi} + m_{asi} + m_{fei} + m_{fsi}) \tag{4}$$

Where m_{01} is gross mass of the i^{th} stage vehicle; m_{gni} is mass of the i^{th} stage SRM grain; m_{sti} is mass of the i^{th} stage SRM structure; m_{svi} is mass of control system, safety self-destruction system, servo, and cables inside the i^{th} stage aft skirt; m_{asi} is mass of the i^{th} stage aft skirt including shell structure, equipment rack, heating protect structure, and directly subordinate parts for integration; m_{fei} is mass of equipment and cables inside the i^{th} stage forward skirt; m_{fsi} is mass of the i^{th} stage forward skirt including shell structure, equipment rack, and directly subordinate parts for integration. The mass of the payload m_{PAY} is known from the design mission. Skirt mass ratio N_i, and propellant reserve coefficient K_{gni} have small dispersions which can be selected from statistical data (LinShu, 2004, Sutton and Oscar, 2001). Relative mass coefficient μ_{ki} of effective grain is given below in Equation 2. It is a design parameter which should be optimized.

$$u_{ki} = \frac{m_{gni}^{e}}{m_{oi}} \tag{5}$$

Structure mass fraction (α_{sti}) is the main parameter for designing a multistage SLV. It is dependent upon structural material, grain shape, as well as the parameters of internal ballistics of SRM. This structure mass fraction is the ratio of the sum of the chamber case mass (m_{cc}), cementing layer mass (m_{cl}), nozzle mass (m_n) and insulation liner mass (m_{in}) to the grain mass (m_{gni}), as shown in Equation (6):

$$\alpha_{sti} = \frac{m_{cc} + m_{cl} + m_n + m_{in}}{m_{gni}} \tag{6}$$

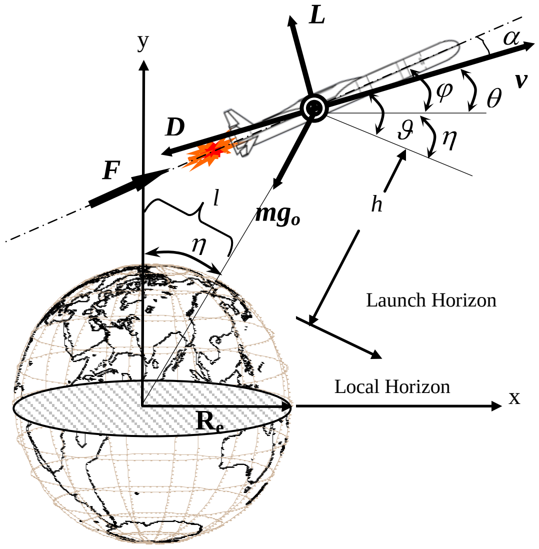
2.3. Aerodynamics Module

In the preliminary design phase of a SLV, rapid and economical estimations of aerodynamic stability and control characteristics are frequently required. The extensive application of complex automated estimation procedures is often prohibitive in terms of time and cost in such an environment. Thus a need arises for the use of time-efficient computer software that can predict the aerodynamic properties over a range of flight conditions. For this purpose U.S. Air Force Missile DATCOM 1997 (digital) (Blake, 1997) has been widely used in aerospace industry. DATCOM is capable of quickly and economically estimating the aerodynamics of a wide variety of design configurations and in the different flow field regions that the SLV encounters during atmospheric flight.

The aerodynamic analysis for the current study of a SLV was performed for a sub-orbital trajectory. The flight path was assumed to follow a trajectory from 40,000 ft to an altitude of about 80 km, from Mach 0.8 at launch to Mach 8.0 at altitude. Force coefficients were calculated for eighteen particular Mach numbers in the specified range, at fourteen angles of attack for each Mach number, ranging from -4 degrees to +22 degrees. The output of the aerodynamics calculation is then used as input to the trajectory module.

2.4. Trajectory Module

Since detailed data are not available at the beginning of conceptual design, it is inappropriate to use a 6 Degree-of-Freedom (DOF) trajectory simulation. Therefore, this study implements a 3 Degree-of-Freedom (3DOF) trajectory analysis (see, Zipfel, 2007). Therefore, a 3DOF model was developed and simulated in SIMULINK to analyze the flight path. A trajectory simulation obtained from 3DOF model is computationally efficient and serves the purpose. The trajectory analysis depends on inputs from the aerodynamic, mass and propulsion modules. The flight program and results obtained from the other disciplines are used to compute the flight trajectory. In this investigation the ASLV is treated as a point-mass, and flight in 2D over a spherical non-rotating earth is assumed, which implies that the Coriolis and centrifugal pseudo forces are negligible. Forces acting on ASLV along with the governing equations of motion are given in Figure 2.



$$\frac{dv}{dt} = \frac{F\cos\alpha - D}{m} - g_o \sin\vartheta$$

$$\frac{d\vartheta}{dt} = \frac{F\sin\alpha + L}{mv} - \frac{g_o\cos\vartheta}{v} + \left(\frac{v}{R_e + h}\right)\cos\vartheta$$

$$\frac{dh}{dt} = v\sin\vartheta$$

$$\frac{dl}{dt} = \left(\frac{R_e}{R_e + h}\right) v\cos\vartheta$$

$$\alpha = \eta + \varphi - \vartheta$$

$$\eta = \frac{l}{R_e}$$

$$\varphi = \varphi_{pro}(t)$$

$$L = C_L \frac{1}{2}\rho v^2 S_{ref}$$

$$D = C_D \frac{1}{2}\rho v^2 S_{ref}$$

Figure 2. Forces acting on an ASLV

Where, $\boldsymbol{v}$ is velocity, m is mass of the vehicle, F is thrust force, g_o is acceleration due to gravity, ϑ is flight path angle, α is angle of attack, η is range angle, θ is trajectory angle, R_e is radius of Earth, h is height about ground, l is range, L is lift force and D is drag force, S_{ref} is surface area.

3. OPTIMIZATION PROCESS

The optimization strategy is shown in Figure 3. In this case a set of design variables with upper and lower bounds is passed to PSO which creates an initial random population and then performs further operations. These candidate design vectors are then passed to weight and sizing, propulsion and trajectory analyses modules. The constraints are calculated and handled by an external penalty function. The algorithm runs in a closed loop via an optimizer until an optimal solution is obtained.

3.1. Particle Swarm Optimization

Particle swarm optimization is a stochastic, population-based computer algorithm for problem solving. It is a kind of swarm intelligence that is based on social-psychological principles and provides insights into social behavior, as well as contributing to engineering applications. PSO was invented in the mid 1990s by Kennedy and Eberhart (1995) while attempting to simulate the choreographed, graceful motion of swarms of birds as part of a socio-cognitive study investigating the notion of "collective intelligence" in biological populations. In PSO, a set of randomly generated solutions (initial swarm) propagates in the design space towards the optimal solution over a number of iterations (moves) based on a large amount of information about the design space that is assimilated and shared by all members of the swarm. PSO is inspired by the ability of flocks of birds, schools of fish, and herds of animals to adapt to their environment, find rich sources of food and avoid predators by implementing an "information sharing" approach, hence, developing an evolutionary advantage. A complete chronicle of the development of the PSO algorithm from merely a motion simulator to a heuristic optimization approach is described by Kennedy and Eberhart (2001). PSO was originally aimed at treating nonlinear optimization problems with continuous variables. Moreover, PSO has been expanded to handle combinatorial optimization problems and both discrete and continuous variables as well. Efficient treatment of mixed-integer nonlinear optimization problems (MINLPs) is one of the most difficult problems in practical optimization. Moreover, unlike other optimization techniques, PSO can be realized with only a small program and it can also handle MINLPs with only a small program. This feature of PSO is one of its advantages compared with other optimization techniques. Apart from this PSO is simple to code and has a small computational cost. A MATLAB based PSO tool box that has been developed by Birge (2003) has been used for our problem. Its working is summarized as:

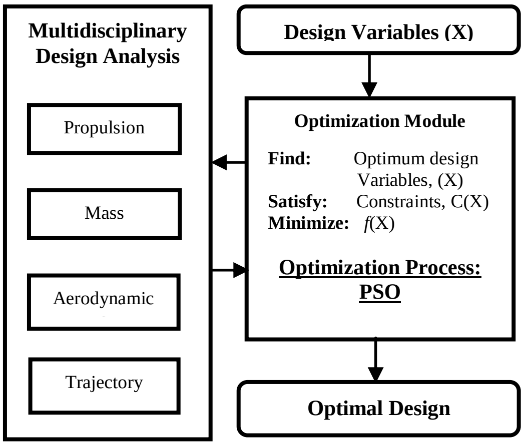


Figure 3. Optimization strategy

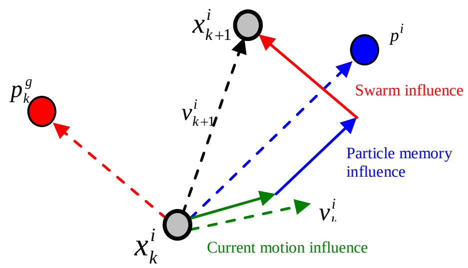


Figure 4. Depiction of velocity and position updates in PSO

- Define problem to search and develop solution criteria.
- Initialize population via random initial positions and random initial velocities.
- Determine global best position.
- Determine personal best position.
- Update velocity and position equations.

PSO algorithm is given as:

$$v^i_{(k+1)} = \phi v^i_k + a_1\left(\gamma_{1i}\left(p^i - x^i_k\right)\right) + a_2\left(\gamma_{2i}\left(p^g_k - x^i_k\right)\right) \quad (7)$$

Where, i is the particle index, k is discrete time index, v is the velocity of the i^{th} particle, x is the position of the i^{th} particle, p^i is the best position found by the i^{th} particle (personal best), $\gamma_{1,2}$ are random numbers on the interval applied to the i^{th} particle, Φ is the inertia function and $a_{1,2}$ are acceleration constants.

Position update is the last step in each iteration. The position of each particle is updated using its velocity vector as shown in Equation 8 and depicted in Figure 4.

Table 1. Discipline-wise design variables

Design variable	Discipline	Symbol	Units
Relative mass coefficient of grain	Structure Propulsion	μ_{ki}	Ratio
Body diameter	Structure Propulsion Aerodynamics	D_i	m
Chamber pressure	Structure Propulsion	p_{ci}	Bar
Exit pressure	Structure Propulsion	p_{ei}	Bar
Coefficient of grain shape	Structure Propulsion	K_{si}	
Grain burning rate	Propulsion	u_i	mm/sec
Max angle of attack	Aerodynamics Trajectory	α	deg
Launch maneuver variable	Aerodynamics Trajectory	a	

$$x^i_{(k+1)} = x^i_k + v^i_{(k+1)} \quad (8)$$

The above mentioned steps of PSO are repeated until a desired convergence criterion is met.

3.2. Design Objective

In aerospace vehicle design minimum launch weight concepts have traditionally been sought. This is because weight (or mass) is a strong driver on vehicle performance and cost, and so takes a central role in the vehicle design process. For the present effort, the design objective is to minimize the GLW (kg) of the entire vehicle under the mission constraints. The baseline design is launched from 40000 ft at Mach number of 0.8. This is intended as a representative number taken from launch conditions of similar ASLVs (Isakowitz, 1999). The mission of the ASLV is to deliver 200 kg payload to LEO. The propulsion system is solid fuelled Solid Rocket Motor (SRM) and number of stages is fixed as three.

3.3. Design Variables

The system design variables for each stage with their respective disciplines are shown in Table 1. There are a total of 19 design variables that govern the whole design and optimization problem.

Table 2. Optimum values of design variables

Design variable	LB	UB	Optimum Value (PSO)
μ_{k1}	0.60	0.75	0.70
μ_{k2}/μ_{k1}	0.95	1.05	1.00
μ_{k3}/μ_{k2}	0.95	1.05	1.00
D_1	1.25	1.35	1.30
D_3	0.80	0.95	0.85
p_{c1}	55.0	75.0	70.0
p_{c2}	55.0	75.0	60.0
p_{c3}	55.0	75.0	70.0
p_{e1}	0.12	0.16	0.14
p_{e2}	0.10	0.16	0.15
p_{e3}	0.08	0.12	0.10
u_1	5.00	8.00	7.00
u_2	5.00	8.00	7.00
u_3	5.00	8.00	7.00
K_{s1}	1.50	2.50	2.30
K_{s2}	1.50	2.50	2.30
K_{s3}	1.50	2.50	1.60
α_m	1.00	22.0	21.9
a	0.01	0.10	0.02

3.4. Design Constraints

Mission velocity *(V)* and corresponding altitude *(H)* are formulated as trajectory constraints. The overall structure of the system should be extremely strong to survive the high g-loads. Therefore an axial overload (O_x) constraint is implemented to restrict loads below 12g for 1st and 2nd stage. During the launch maneuver; the maximum angle of attack (α_m) is constrained to be below 22 deg and to ensure that it is zero during the transonic phase. Nozzle exit diameters are constrained to be less than stage diameters. 1st and 2nd stage diameters are constrained to be equal. If any of these conflicts occur, the program is set to send back extremely poor performance values in each goal area so that it will learn not to try these designs in the future. A dynamic penalty function is used to handle in-flight and terminal constraints.

4. PERFORMANCE RESULTS

Optimum values of the design variables obtained by PSO and performance graphs of optimized configuration are shown in Table 2 and Figure 5 respectively.

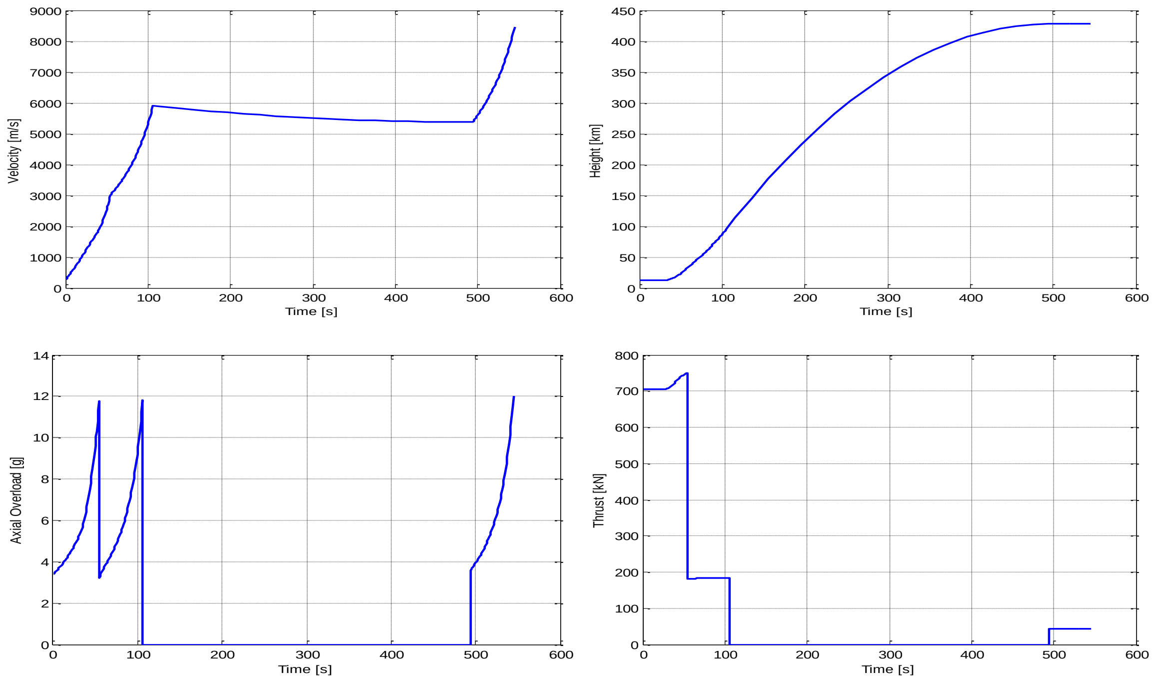


Figure 5. Performance graphs of optimized configuration

5. DISCUSSION AND CONCLUSIONS

An integrated design and optimization methodology to perform MDO of multistage air launched satellite launch vehicle was successfully implemented using Particle Swarm Optimization. It proved capable of providing a preliminary design considering propulsion, mass features, aerodynamics and trajectory performance objectives and constraints. Figure 5 shows the required velocity to reach required altitude, that is, LEO and axial overloads are also within structural limit of 12g. Moreover the thrust requirement is also shown in Figure 5. The optimum values of all the interdisciplinary design variables are provided in Table 2 showing that they are within the lower and upper bounds. The method described in this paper provides the designer with a simple and powerful approach for preliminary design. Simple analytical expressions are used for propulsion system sizing, which can be easily replaced by highly accurate code with more capabilities. Such a design strategy will allow vehicle designers to rapidly consider a number of fully converged design alternatives in a very short time without sacrificing design detail, thus improving the quality of whole design process.

The results of this preliminary design can be used as a basis for detailed design. The optimization results are to be considered as preliminary (proof-of-concept) only, but they can be compared to existing systems and can be applied in the conceptual design of similar systems.

REFERENCES

Anderson, M.B. (1998), Design of a missile interceptor using genetic algorithms, Dissertation, Auburn University, Alabama.

Bayley, D.J., Hartfield, R.J., Burkhalter, J.E. and Jenkins, R.M. (2007), Design optimization of a space launch vehicle using a genetic algorithm, 3rd AIAA Multidisciplinary Design Optimization Specialist Conference.

Bayley, D.J. and Hartfield, R.J. (2007), Design optimization of space launch vehicles for minimum cost using a genetic algorithm, 43rd AIAA Joint Propulsion Conference and Exhibit.

Bayley, D.J., Hartfield, R.J., Burkhalter, J.E. and Jenkins, R.M. (2007), Design optimization of a space launch vehicle using a genetic algorithm, *Spacecrafts and Rockets*, 45(4), 733–740.

Birge, B. (2003), PSOt, A particle swarm optimization toolbox for Matlab, IEEE Swarm Intelligence Symposium Proceedings.

Blake W.B. (1997), Missile DATCOM: User's manual-1997 FORTRAN 90 revision, U.S. Air Force Research Lab/ Air Vehicle Directorate.

Douglass, H.W., Collins, J.H., Whitfield, H.K. and Keller, R.B. (1970), Solid rocket motor metal cases, space vehicle design criteria, NASA-70-sp8025.

Douglass, H.W., Collins, J.H., Miller, W.H. and Keller, R.B. (1971), Solid rocket motor performance analysis and prediction, space vehicle design criteria, NASA-71-sp8039.

Douglass, H.W., Collins, J.H., Brooks, W.T. and Keller, R.B. (1972), Solid propellant grain design and internal ballistics, space vehicle design criteria, NASA-72-sp8076.

Fei, M. and Xue-bo, C. (2006), Application of varying population size particle swarm optimization algorithm to AGC of power systems, 6th world congress on intelligent control and automation, June 21-23.

Fourie, P.C. and Groenwold, A.A. (2002), The particle swarm optimization algorithm in size and shape optimization. *Structural and Multidisciplinary Optimization*, 23(1), 259–267.

Hassan, R., Cohanim, B., Weck, O.D. and Venter, G. (2005), A comparison of particle swarm optimization and the genetic algorithm, 46th AIAA Structures, Structural Dynamics and Materials Conference.

Isakowitz, S. J. (1999), International reference guide to space launch systems, 3rd Edition, AIAA.

Kennedy, J. and Eberhart, R. C. (1995), Particle swarm optimization, Proceedings of the IEEE International Conference on Neural Networks, 1942-1945.

Kennedy, J. and Eberhart, R. C. (2001), Swarm intelligence.

LinShu, H. (2004), Launch vehicle design, Beijing University of Aeronautics and Astronautics, China.

Rafique, A.F., Zeeshan, Q. and LinShu, H. (2008), Conceptual design of small satellite launch vehicle using hybrid optimization, International conference on nonlinear problems in aviation and aerospace, ICNPAA.

Schutte, J.F. and Groenwold, A.A. (2003), Sizing design of truss structures using particle swarm, *Structural and Multidisciplinary Optimization*, 25(4), 261–269.

Sutton, P. and Oscar, B. (2001), Rocket propulsion elements, 7th edition, John Wiley & Sons, New York.

Venter, G. and Sobieszczanski-Sobieski, J. (2003), Particle swarm optimization, *AIAA Journal*, 41(5), 1583–1589.

Venter, G. and Sobieszczanski-Sobieski, J. (2004), Multidisciplinary optimization of a transport aircraft wing using particle swarm, *Structural and Multidisciplinary Optimization*, 26(1), 121–131.

Zipfel, P.H. 2007. Modeling and simulation of aerospace vehicle dynamics, AIAA, Reston.