Pages: 11-30 / Vol.16/ No.2 / Summer- Fall 2023

Journal of Aerospace Science and Technology

www:jast.ias.ir

Scientific-Research Article

# The Success of the Hybrid Genetic and Particle Swarm Algorithm for a Return Spacecraft from the Atmosphere with an Optimal Trajectory Design Approach to Reduce Aerodynamic Heat Transfer

**Alireza Ekrami Kivaj[1] , Aireza Novinzadeh[2]*, Farshad Pazooki[3], Ali Mahmoodi[4]**

1- 3- 4- Department of aerospace Engineering, Science and Research branch, Islamic Azad University, Tehran, Iran

2-Department of Aerospace Engineering K. N. Toosi University of Technology, Tehran, Iran

## ABSTRACT

**Keywords:** Multidisciplinary design optimization, optimal trajectory design, uncertainty, suborbital flight, optimization algorithm

*This study aims to investigate the spacecraft returning from the atmosphere. Due to high speed, prolonged flight duration, and numerical sensitivity, returning from the atmosphere is regarded as one of the more challenging tasks in route design. Our suborbital system is subjected to a substantial thermal load as a result of its return at high speed and the presence of uncertainty. In addition, the current study aims to lessen the thermal load in the system to meet the needs of the initial and final conditions through multi-subject optimization, comparison of the two fields of aerodynamics and flight dynamics, assistance from optimal control theory, and consideration of uncertainties The heat load in the sub-orbital system could be reduced by around 9.6% using these algorithms and optimal control theory. Artificial bee colonies, genetic algorithms, and the combined genetic algorithms and particle swarm algorithms were utilized as exploratory optimization techniques. The objective of the flight mechanics system is also to create the best trajectory while taking into account uncertainty and minimizing thermal load. The conduction law based on heat reduction is described in the search for the ideal trajectory. We reduced the heat rate during the first part of the spacecraft's return journey from the atmosphere by concentrating on the angle of attack. By more accurately specifying the angle of attack and the angle of the bank in the second stage of the split guidance legislation, the ultimate return requirements could be achieved significantly. A certain cost function must be minimized in each stage. As a result, many optimization techniques have been applied and contrasted. Also, the new suggested strategy can lower heat without affecting the results.*

## Nomenclature

| | |
|---|---|
| $\alpha$ | Angle of attack |
| $\beta$ | Bank angle |
| $\gamma$ | Flight trajectory angle |
| $\varphi$ | Longitude |

---

1 PhD. Candidate

2 Associate Professor ,(Correspondence Author) Email: novinzadeh@kntu.ac.ir

3 Assistant Professor

4 Associate Professor

DOI: 10.22034/jast.2023.375858.1138

Submit: 08.12.2022 / Accepted: 07.05.2023

Print ISSN:1735-2134 Online ISSN: 2345-3648

| | |
|---|---|
| u | Control vector |
| x | State vector |
| X0 | Initial conditions |
| g | Algebraic constraints |
| w | Weight function |
| F | Differential equations of motion |
| $x_f$ | Final conditions |
| D | Aerodynamic drag force |
| g | Magnitude of gravitational acceleration |
| $g_0$ | Magnitude of gravitational acceleration at sea level |
| h | Altitude with respect to sea level |
| J | Objective function(s) |
| L | Aerodynamic lift force |
| M | Mach number |
| m | Vehicle mass |
| $P_a$ | Atmospheric pressure |
| Q | Heat flux |
| $Q_{max}$ | Maximum heat flux |
| $q_{max}$ | Maximum dynamic pressure |
| v | Velocity in inertial frame |
| MDO | Multidisciplinary design optimization |

## Introduction

Over the past couple of decades, trajectory optimization problems have attracted a large amount of attention due to their increasing significance in industry and military fields [1], [2]. Generally, this type of problem aims to find the optimal state and control sequences to optimize the predefined performance index. Relative works on this topic can be found in various scientific and engineering applications such as agent/robot trajectory planning [3], [4], autonomous vehicle optimal trajectory design [5], and spacecraft optimal control systems [6]–[8]. More precisely, in [2] the author proposed a time-optimal trajectory generation strategy for a multi-body car model. Pritesh et al. [1] solved a fixed-wing unmanned aerial vehicle trajectory planning problem by embedding human expert cognition. In addition, the trajectory generation problem for a class of wheeled inverted pendulum vehicles was studied and reported in [9]. Besides, an optimal spacecraft Sun-Earth orbital transfer trajectory was designed by applying a hybrid invariant manifold method [6]. Similarly, the low computational cost orbital transfer trajectory was generated by Peng and Wang in [7], wherein an adaptive surrogate optimization technique was constructed. In their follow-up research [8], an emergency transfer trajectory design mission was considered and solved via a fast surrogate-based optimization method. Although many optimization strategies have been designed for trajectory planning problems, it is still challenging to generate the optimal or near-optimal state and control trajectories under a highly constrained environment. Space travel involves dealing with physical, technical, and scientific difficulties; space is a hostile and unfriendly environment without air or gravity and with high levels of ionizing radiation. Our planet, Earth, is surrounded by air composed of nitrogen, oxygen, and other gases, called the atmosphere. Upon entering the atmosphere, the spacecraft experiences drag, which exerts mechanical stress and compression of the air in front of the spacecraft, which in turn causes heating. Good design, such as optimizing the shape of a re-entry spacecraft with considering the amount of heat flux, can reduce the overall mass and cost of a mission and reduce the risk of passenger injury or loss, where applicable. In space operations documents (Returning from Space: Re-entry) published by the Federal Aviation Administration (FAA), all space-mission planning begins with a set of requirements that we must meet to achieve mission objectives. The re-entry phase of a mission is no different, and one must delicately balance three often competing requirements, namely deceleration, heating, and accuracy of landing or impact. Once all trajectory possibilities have been exhausted, one can turn to options for vehicle design, where two ways to meet mission requirements exist, i.e., vehicle size and shape, and thermal protection systems (TPS). The re-entry vehicle's size and shape help determine the ballistic coefficient (BC) and the amount of lift it will generate (most re-entry vehicles are considered non-lifting due to the added complexity of lift in the re-entry analysis). The most challenging component of BC to determine for re-entry vehicles is the drag coefficient, $C_D$, which depends mainly on the vehicle's shape. In addition, it is essential to notice how varying BC changes a re-entry vehicle's deceleration profile and affects the maximum heating rate. A more streamlined (high-BC) vehicle reaches maximum deceleration much lower in the atmosphere than a blunt (low-BC) vehicle (i.e., effects of vehicle shape), and the atmosphere can also significantly decrease re-entry accuracy. Therefore, the designers want the vehicle to spend as little time in the atmosphere as possible, which makes a streamlined vehicle desirable for better accuracy, even though one must accept more severe heating rates. Thermal protection systems can deal with this heating. Effects of vehicle shape on the re-entry corridor are also another factor to be considered as the corridor's upper or overshoot boundary depends on the minimum deceleration for atmospheric capture [10].

Spacecraft optimization design involves a variety of disciplines, including aerodynamics, aerothermodynamics, guidance and control, structure, and cost. Considering the difficulties in its progress, it has been evident from the start that the design of such systems requires a compromise between numerous domains of knowledge. Many efforts have been made in this area, the most recent of which are summarized and briefly discussed in the following section. The problem of re-entry spacecraft shape optimization has been addressed in several publications. The problem of re-entry spacecraft shape optimization has been addressed in several publications. The multidisciplinary optimization of re-entry spacecraft has been discussed by Tava and Suzuki [11], considering four crucial disciplines, namely geometric shape, weight, aerodynamics and flight dynamics, The authors accentuated the complexity of the disciplines and their conflicts; however, less emphasis was made on their optimization method, the accuracy of modeling the disciplines, and their chosen approach—multidisciplinary design feasibility (MDF), a time-consuming and costly method. Mor and Livne [12] investigated the trajectory and the thermal protection system (TPS) for a flight vehicle using the multidisciplinary optimization method. The article highlighted the interdisciplinarity of disciplines and their conflicts. The MDO of a re-entry capsule was presented by Nosratollahi et al. [13], with structure, aerodynamics, and aerothermodynamics modules in place. The authors compared their results using two optimization methods: the multiobjective optimization method and a new optimization approach based on a genetic algorithm. The objective function used in [13] is the mass reduction of the entire system in terms of aerothermodynamics and aerodynamics constraints. Finally, several nose-shape designs were achieved by increasing the weight of each module and adjusting their factor of importance in optimization. Nosratollahi et al. [14] proposed an optimized design of the aerodynamic structure for a capsule to reduce the heat absorption and drag coefficient. They proposed a feasible region so that the designer can decide without having to solve the problem to find the best solution. Later, Adami et al. [15] performed the optimum design of the aerodynamic structure for the same capsule presented by Nosratollahi et al. [14], where they added the structure's discipline, simultaneous minimization of drag coefficient, heat absorption, and mass in their model. Like in the previous work, Adami et al. [15] used the search method to perform the optimization of the design. Later, Nosratollahi et al. [16] provided the optimized design of a controllable re-entry capsule using a multidisciplinary optimization and search method, where the minimum landing speed and minimum mass were selected as the objective function. The MDO of a manned capsule was also addressed by Adami et al. [17], considering the geometric shape and re-entry trajectory, with the criterion of minimizing the vehicle's mass and adhering to the heat flux, aerodynamic, structural, and flight trajectory constraints, frequently observed in the all-at-once (AAO) method. In the book by Dirkx and Mooij [18], multidisciplinary optimization methodology was established and applied to the shape optimization of two classes of re-entry vehicles: a low lift-over-drag or blunt capsule (such as the Apollo); and a winged vehicle, such as the Space Shuttle.

The emphasis is put on cubic Hermite splines and spline surfaces when using the multiobjective particle swarm optimization (MOPSO) algorithm. The re-entry trajectory optimization problem for hypersonic vehicles in this paper has been studied recently by Yu et al. [19]. The authors indicate that two drawbacks exist to this topic. Firstly, there is no consideration for navigation errors caused by blackout zones in re-entry trajectory optimization models. Second, a solitary methodology is regularly applied to enhance the re-entry trajectory, which neglects to cover its deficiency by consolidating it with different approaches. To this end, a hybrid particle swarm optimization (PSO)–Gauss pseudo-method (GPM) algorithm, specifically the mixed PSO-GPM calculation, is proposed to optimize the re-entry trajectory in this paper. The authors suggested combining other metaheuristic algorithms and pseudospectral methods to solve more complicated optimization problems. Upon completion of the review of several articles on re-entry spacecraft presented in the previous section, in what follows, the MDO of a re-entry spacecraft or a space capsule is implemented in a combined and innovative method. The all-at-once (AAO) approach to the MDO of a re-entry capsule-shape spacecraft with a low lift-to-drag ratio (L/D) is achieved using the RPM optimization method, where a semi-ballistic trajectory, considering the geometry and shape, aerodynamics, and aerothermodynamics disciplines are used. Considering variables, constraints, and various parameters and maximizing the re-entry spacecraft's cross-range as the objective function, the optimized dimensions leading to the reduction in the mass of the capsule are achieved and presented. The MDO method is validated using the available data for the Apollo re-entry capsule. The optimal solution is reached through several iterations to ensure that optimality conditions are satisfied. It is found that the mass of the optimal capsule generated using the proposed method is more than 17% lower than Apollo's. To the author's best knowledge, the application of the AAO-RPM approach to the MDO of a re-entry capsule-shape spacecraft has not been reported in the open literature, which could be considered the main contribution of this paper. Reference [20] has presented a methodology for optimizing the main design parameters of a multi-stage liquid-fuel carrier satellite in the conceptual design phase to minimize the weight of the carrier satellite by satisfying the design constraints. In this article, using the genetic algorithm, the parameters affecting the weight of the satellite carrier have been optimized. Reference [21-22] is the development and evaluation of an optimization software based on aerodynamic/structural design to optimize the configuration of the missile and the shape of the missile's wings. This article specifically deals with the optimization of the beam geometry to minimize the hinge moments of the beam as well as the aeroelastic design of the beams. In reference [23], the author has described a multi-objective optimization problem for the aerodynamic shape of the rocket in the conceptual design phase using the multi-objective genetic algorithm. The objective functions of this problem are to maximize the lift-to-drag ratio and to minimize the radar cross-section. Since the missile's aerodynamic performance (lift-to-drag ratio) is in opposition to the radar cross-section, to increase the efficiency of the optimization in the conceptual design phase, solutions have been obtained in the form of a beam front. Reference [24] has tried to reduce the cost of genetic algorithm calculations by using neural network concepts and to evaluate this hybrid algorithm, a comparison between the number of evaluations to achieve the maximum advance ratio of a subsonic missile between the basic genetic algorithm and the hybrid algorithm was done.

This aerodynamic optimization is done on wing, body and tail parameters as design parameters and for specific flight conditions (fixed speed and angle of attack). Reference [25] deals with the optimization of the design parameters of a folding bow-shaped wing on the body for supersonic missiles to achieve the maximum lift-to-drag ratio. The purpose of this optimization is to maximize the lift-to-drag ratio in a certain flight mode (angle of attack and constant flow speed) to achieve the maximum range. The lift and drag coefficients are also obtained from the numerical solution of the flow around the bird using Euler's equations.

## Multidisciplinary design optimization (MDO)

Engineering system optimization is regarded as a component of design. Multidisciplinary design optimization (MDO) methods have been created to reach the global optimum. That is, with MDO, every component and how it interacts with other sub-systems are analyzed concurrently. Therefore, the ideal design may be attained after some repetitions by optimizing the multi-subject design. To create the ideal system, this technique actively modifies the design factors. The following describes how optimization frameworks are categorized:

### Single-level Multidisciplinary design optimization

### MDF (Multidisciplinary Feasible):

The MDF architecture (2-subspace example) is depicted in Figure 1 single system-level optimizer is used, and from the perspective of the optimizer MDF is no different than a general design problem. A system analyzer coordinates all of the subspace analyzers. The optimizer supplies the system analyzer with a design x, and the system analyzer supplies the optimizer with the appropriate response functions, f, g, and h. MDF maintains the structure of non-hierarchical problems. MDF refers to any complex system optimization strategy that performs a complete system analysis at every optimization iteration, regardless of the analysis method. In industries that deal with coupled systems, Fixed Point Iteration is regularly employed as the analysis tool. However, other analysis tools may be used within an MDF approach.

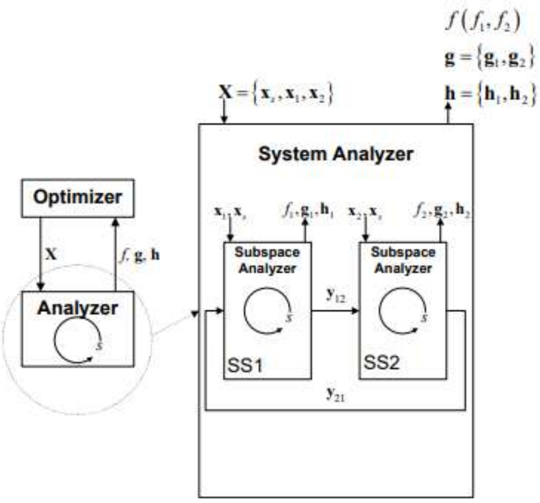


**Figure 1:** MDF structure [28].

## IDF (Individual Disciplinary Feasible):

To address some of the limitations of the MDF formulation, the Individual Disciplinary Feasible approach was developed. IDF is also known as Simultaneous Analysis And Design (SAND) or Single-SAND-NAND. Like MDF, an analyzer for each subspace is employed (solving for state variables if required), and a single system-level optimizer is used. The key difference is that the optimizer coordinates the interactions between the subspaces, rather than relying on the simple iterative scheme of Fixed-Point Iteration, or some other analysis tool. This enables parallelization, improves convergence properties, and drives the design toward better solutions if multiple analysis solutions exist. The IDF architecture is illustrated in Figure 2 The system optimizer gains additional responsibility for the solution process over the MDF approach. In addition to deciding the appropriate values for the design variables, the system optimizer must also control the values for the coupling variables y. Rather than relying on simple iteration to determine the next coupling variable values, an optimization algorithm efficiently performs this task instead, improving convergence speed and probability of convergence. IDF has notably improved robustness over MDF. IDF maps to a design organization with a single project manager, making all of the design decisions and guiding the analysis groups into an agreement. In both a computational and an organizational context the parallel nature of IDF has an advantage over the sequential MDF approach. If parallel analysis tools (multiple analysis groups or parallel processors) are available, IDF can offer a significant compression of the design process. If a high level of centralization is acceptable, then IDF may be an ideal design strategy.

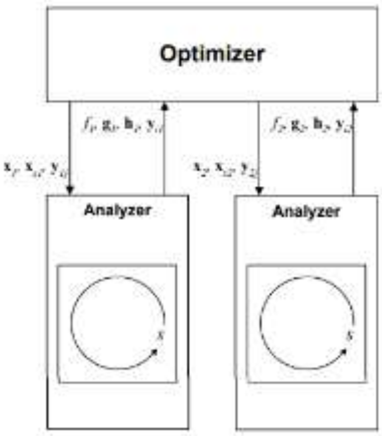


**Figure 2:** IDF structure [28].

## AAO (All At Once):

In this article, for the Multidisciplinary design optimization of the considered system, the Multidisciplinary design optimization design method known as the “all at once” step has been used. the most fundamental single-level MDO architecture is inapplicable to huge and intricate engineering systems. The last of the three fundamental single-level MDO approaches covered in this thesis is the All-At-Once strategy (AAO). It is also referred to as Single-SANDSAND, and sometimes just SAND. Occasionally the term AAO is erroneously used to refer to the MDF approach; it is important to make the distinction between the two formulations. AAO is a highly centralized approach. Instead of utilizing analyzers to complete the analysis for each subspace, evaluators are used that compute only the residuals of the governing equations. The system optimizer is now saddled with three sets of decision variables: the original design variable X, the coupling variable y, and the state variable s. AAO centralizes both design and analysis but still distributes evaluation of governing equations. This high degree of centralization offers impressive efficiency in some situations, yet is sometimes difficult to map to many organizational structures due to its centralization and specialized structure. Figure 3 illustrates how MDF and AAO may be viewed as opposite extrema concerning the number of decision variables the system optimizer explicitly controls. IDF is an intermediate occupant of this spectrum.

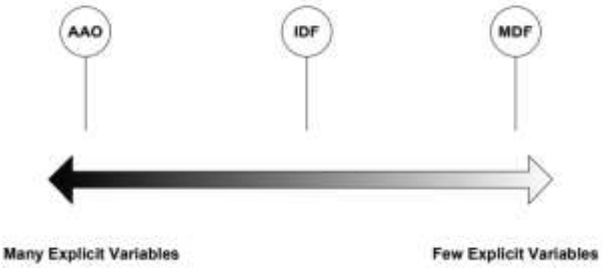


**Figure 3:** Classification of single-level formulations based on number of explicitly controlled decision variables [28].

The AAO architecture is illustrated in Figure 4. It is similar to the IDF formulation but includes an additional auxiliary constraint to ensure zero residuals at problem convergence. The optimization is performed concerning the design variables X, the coupling variables y, and the state variables s. This approach is truly All-At-Once, since the design, system analysis, and subspace analysis are all performed simultaneously.

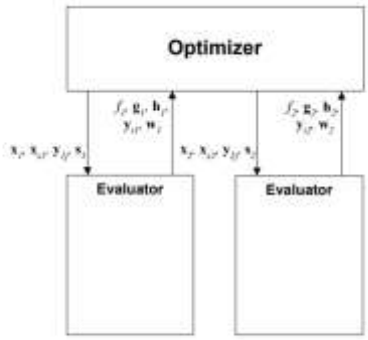


**Figure 4:** AAO structure [26].

In this article, for the Multidisciplinary design optimization of the considered system, the Multidisciplinary design optimization design method known as the at-once step has been used. Regardless of the optimization method, a general optimization problem can be defined as follows:

Min : $f(x, u(x))$
Subject to : $g(x,u(x)) \leq 0$ and $h(x,u(x)) = 0$

In which $x = \{ x_1 , x_2 , x_3,..., x_n\}$ is the vector of design variables and $u = \{ u_1 , u_2 , u_3,..., u_n$ is the vector of current variables of the system, f is the objective function (In this article, reduction of aerodynamic heat transfer) and g, h are the equality and inequality constraints of the problem. Now, to solve the optimization problem, this mathematical logic should be implemented in the form of a multi-objective optimization method, and the optimization process should be implemented. Table 1 shows the comparison between single-level methods:

**Table 1:** Comparison of single-level MDO formulation characteristics [28].

| | AAO | IDF | MDF |
|---|---|---|---|
| ▷Use of legacy analysis tools | None | Full | Full, requires coupling |
| ▷Satisfaction of governing eqns. | Only at convergence | At each opt. iteration | At each opt. iteration |
| ▷System consistency | Only at convergence | Only at convergence | At each opt. iteration |
| ▷Optimizer decision variables | $\mathbf{X} = \{\mathbf{x}, \mathbf{x}_s\}, \mathbf{y}, \mathbf{s}$ | $\mathbf{X} = \{\mathbf{x}, \mathbf{x}_s\}, \mathbf{y}$ | $\mathbf{X} = \{\mathbf{x}, \mathbf{x}_s\}$ |
| ▷Expected speed | Fast | Medium | Slow |
| ▷Robustness | Unknown | High | Medium |

## Multi-level Multidisciplinary design optimization

Complex issues may now be solved thanks to multilayer MDO optimization algorithms that offer a variety of capabilities. Here, four multilayer MDO techniques are presented: (Refer Table2)

### Collaborative optimization (CO)

Collaborative optimization (CO) is a bilevel architecture designed to provide discipline autonomy while maintaining interdisciplinary compatibility. The optimization problem is decomposed into several independent optimization subproblems, each corresponding to a discipline. Each disciplinary optimization is given control over its (local) design variables and is responsible for satisfying its constraints.

## Bi-Level Integrated Synthesis System (BLISS)

BLISS is a method for the optimization of engineering systems by decomposition. It separates the system-level optimization, having a relatively small number of design variables, from the potentially numerous subsystem optimizations that may each have a large number of local design variables. The subsystem optimizations are autonomous and may be conducted concurrently. Subsystem and system optimizations alternate, linked by sensitivity data, producing a design improvement in each iteration. Starting from the best guess initial design, the method improves that design in iterative cycles, each cycle comprised of two steps. In step one, the system-level variables are frozen and the improvement is achieved by separate, concurrent, and autonomous optimizations in the local variable subdomains.

### Concurrent Subspace Optimization (CSS)

Concurrent Subspace Optimization (CSSO) is one of the main decomposition approaches in Multidisciplinary Design Optimization (MDO). It supports a collaborative and distributed multidisciplinary design optimization environment among different disciplinary groups. The CSSO method allows a complex couple system to be decomposed into smaller, temporarily decoupled subsystems, each corresponding to different disciplines (subspaces). Each subspace optimization minimizes the system objective function subject to its constraints as well as constraints contributed by the other subspaces. Each subspace optimization uses its high-fidelity analysis tools as well as given surrogate models or low-fidelity analysis tools provided by the other subspaces for analysis. Subsequently, the subspace optimizations can be performed concurrently. The system-level coordination optimization will be implemented completely based on approximation analysis tools. The subspace optimizations and the coordination optimization will be alternatively performed until results are finally decided by the coordination optimization. Therefore, the CSSO method is particularly suited to applications in a design organization where tasks are distributed among different design groups.

### Analytical Cascade Target optimization (ATC)

Analytical Target Cascading (ATC) is a method for solving large-scale distributed optimization problems. It can be applied to multidisciplinary design optimization (MDO) problems. A very simple example problem was chosen so that the ATC solution process could be illustrated without requiring much effort to understand the underlying optimization problem. The benefits of ATC are not realized when solving this or other small problems; ATC is helpful for large optimization problems with sparse dependence structures that are suitable for decomposition.

The computational cost of analysis in each of the subjects and the abundance of design variables and restrictions are some of the characteristics that define the most significant issues with the multi-subject design optimization approach in general and collaborative optimization in particular. In comparison to single-subject optimization, the multi-subject design optimization approach requires a greater computing effort due to the inter-subject interaction and the increased design variables that result from the addition of each subject. The system must be optimized by the interaction of analytical codes from each subject. These situations ultimately result in extremely expensive processing expenses and organizational challenges that lower the performance of even the most sophisticated systems. We may use evolutionary algorithms to describe the categories of optimization techniques that can provide global optimization.

**Table 2:** Advantages and disadvantages of optimization frameworks [28].

| Advantages and disadvantages<br>Optimization framework | Advantages | Disadvantages |
|---|---|---|
| CO<br>framework | 1- Easily usable for distributed sub-systems (Distribute Sub-system)<br>2- Industrial application due to the distribution of sub-systems | 1- Low convergence<br>2- Unusable for coupled sub-systems |
| CSS framework | 1- Increasing convergence compared to CO<br>2- Can be used for distributive sub-systems<br>3- Can be used for coupled sub-systems | 1- Usability for distributive sub-systems compared to less CO<br>2- Less convergence than BLISS |
| BLISS framework | 1- High convergence compared to the previous two frameworks<br>2- Can be used for coupled sub-systems | 1- Unusable for distributive sub-systems<br>2- Lack of industrialization |
| ATC framework | 1- Easily usable for distributed sub-systems (Distribute Sub-system)<br>2- Can be used for coupled sub-systems | 1- Low convergence<br>2- Lack of industrialization |

### Heuristic optimization algorithms

Popular population-based meta-heuristic algorithms include evolutionary algorithms. Here are some examples of evolutionary algorithms:

### Artificial Bee colony algorithm (ABC)

Different approaches have been presented for the particular intelligent behavior model of the honey bee swarm and applied to address hybrid issue types. The application of bee collective intelligence in the creation of artificial systems to resolve complicated traffic and transportation issues has been advocated by Theodore Vas. Theodore Voss further asserted that meta-heuristic bee colony optimization is capable of deterministically resolving both uncertain and combinatorial issues. In the natural world, bees and food sources make up a bee colony. In the artificial bee colony algorithm, bees include three groups: Worker, searcher, and forerunner bees.

For the first time, worker bees make up half of the bee swarm in the artificial bee algorithm, while searcher bees make up the other half. There is just one worker bee per food source. In other words, the amount of food sources around the hive equals the number of worker bees. A worker bee that has had its food supply depleted by other bees turns into a precursor bee. An essential control parameter of the bee colony algorithm is the threshold value, which is equivalent to the number of attempts to give up a food source. Exploration and exploitation operations must be carried out in tandem throughout a thorough search. In the bee colony algorithm, the precursors govern the discovery process, while the worker and search bees are involved in the exploitation process in the search space.

### Genetic algorithm (GA)

Based on the notion of natural selection, the genetic algorithm is a technique for addressing limited and unconstrained optimization problems (the process that drives the evolution of biology). The power and endurance of the genetic algorithm make it superior to other AI-based techniques. The evolutionary algorithm does not quickly collapse with slight changes in input values or with considerable levels of noise in the system, in contrast to prior artificial intelligence systems. Additionally, the use of genetic algorithms has many more advantages over traditional search methods in other optimization techniques, such as linear programming, random search, depth-first, surface-first, or praxis search methods, in search of a large state space, multimodal state space, or a multidimensional procedure [44]. (For use in this article)

**Table 3:** Adjustable parameters of GA algorithm [43]

| explain | values | parameters |
|---|---|---|
| population | 100 | $N_{pop}$ |
| Crossover ratio | 1.2 | $R_{crs}$ |
| Scale parameter | 0.1 | $a_{Mut}$ |
| Shrink parameter | 0.5 | $b_{Mut}$ |
| Probability of mutation | variable | $p_{Mut}$ |
| The possibility of crossover | variable | $p_{crs}$ |

### Particle Swarm Optimization algorithm (PSO)

An efficient metaheuristic method for non-linear continuous function optimization is the particle swarm optimization algorithm or PSO algorithm. The particle swarm optimization method, often known as the PSO algorithm, was inspired by the idea of particle intelligence (also known as swarm intelligence), which typically occurs in groups of animals like herds and packs of animals. The particle swarm method, commonly known as the PSO algorithm or the traditional form of this technique, was first introduced in 1995. The Linear-Decreasing Inertia Weight of the Constriction Factor Weight factor, hybrid models, or even quantum-inspired optimization techniques applied to the PSO algorithm have been described as variations of the classical approach.

### Genetic hybrid algorithm and GA-PSO particle swarm algorithm

The suggested model is used as the basis for the implementation of the genetic algorithm, which first optimizes the model. The output of this method is then considered as the first position of the swarm, and the particle swarm optimization technique is used to enhance the results. When the stopping condition is met, and the optimal solution has been found, the end location from the particle swarm algorithm is then considered as the beginning swarm for the genetic algorithm [39]. (For use in this article)

**Table 4:** Optimizer parameters of GA+PSO algorithm [43]

| Parameters | Values |
|---|---|
| Number of optimization parameters | 12 |
| Number of generations | 150 |
| population | 1500 |
| Retention percentage | 0.3 |
| Cross percentage | 0.2 |
| Mutation percentage | 0.05 |

### Optimal Control Problems Solution Method

The approaches to tackling optimum control issues may generally be split into two groups:

### Indirect methods

In these procedures, state and control variables are first calculated utilizing certain extra variables and parameters that are subsequently retrieved. The great sensitivity of the solution to pseudo-state variables is one of the most significant issues when using the indirect technique to solve optimal control problems. Since these factors have no physical significance, a reliable first guess cannot be considered for them. Dividing the integration time interval into numerous smaller intervals is one of the basic methods for reducing sensitivity. This strategy is known as multiple shooting. In this scenario, the initial values in each time sub-interval are considered optimization variables, and the equality constraint is applied between the final values of each interval and the initial values of the following interval to ensure that these values are equal after the solution and that a continuous solution of the variables is obtained. The most accurate approach to solving optimum control issues is the indirect method (route optimization).

## Direct methods

In these techniques, state and control variables are determined directly without the need for other parameters and extra variables. There are now three primaries, traditional ways for resolving optimum control issues: [27]

- Indirect method of maintaining dynamics
- Direct Shooting Method of maintaining dynamics
- Direct Collocation Method, dynamic removal

Other approaches to solving optimum control issues are developed versions of one of these three approaches and have some connection to it. As a result, it's critical to understand each method's capabilities, advantages and disadvantages to propose fresh approaches to the problem.

## Methodology

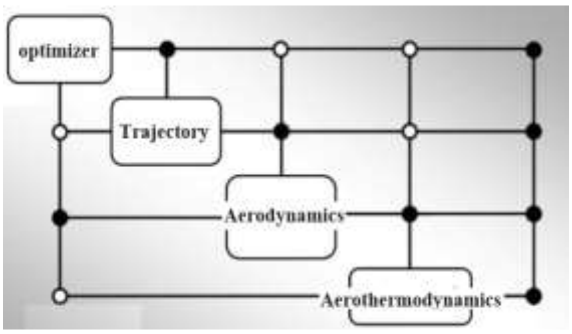


**Figure 5.** Design structure matrix (DSM) of AAO architecture for re-entry spacecraft [39].

The design of multidisciplinary systems (e.g., aircraft, spacecraft, automobiles) often requires an iterative cycle that includes a design initialization, a system analysis, a sensitivity analysis, and design optimization. The name of this standard design cycle in the field of MDO, often referred to as the multiple-discipline-feasible (MDF) approach, stems from the fact that complete multidisciplinary feasibility is maintained in each design cycle. The MDF, however, can be a costly procedure. Alternate means for posing and subsequently solving the multidisciplinary design problem have therefore been developed. The simultaneous analysis and design (SAND) and all-at-once (AAO) approaches treat the entire multidisciplinary design cycle as one large optimization problem, whereas the individual-discipline-feasible (IDF) approach exhibits characteristics that lie in between the two extremes exemplified by MDF and AAO. IDF assures that each discipline is feasible on every design cycle while driving the entire system (all disciplines) towards multidisciplinary feasibility. The all-at-once (AAO) approach is deemed to be the most efficient, fastest, and least costly method in comparison with IDF and MDF methods for enormous and sparse problems, as also stated by Cramer et al. An overview of the AAO architecture used in this paper is presented in Figure 5 above.

The steps in this research are as follows:

- Three global optimization algorithms are used to establish the ideal bank angle and angle of attack profiles (ABC, GA, and GA-PSO).
- Optimal route design aims to decrease the heat rate while preserving excellent ultimate conditions.
- The heat rate can be reduced by concentrating on the angle of attack during the early part of the return flight from the atmosphere [28].
- To satisfy the last requirements, the proposed guideline law's second stage includes a specific description of the bank angle and angle of attack.
- A particular cost function needs to be reduced at each stage.
- Various optimization techniques have been used and contrasted (including genetic algorithm, bee algorithm, and combination of genetic algorithm and particle population).
- The ideal trajectory has been determined based on the optimization criteria in both phases for several cost functions, including first: overall heat rate; second: maximum heart rate; and third: final conditions.

The aerodynamic and flight mechanics sub-systems will be examined in greater detail, and the structure sub-system will also be considered since the major goals are to build an ideal trajectory for a sub-orbital system and create a structure with a focus on uncertainty.

Additionally, only dimensions are retrieved from the structural system, and aerodynamic coefficients are derived from it. There are two ways to define Ben Abrayan. Aerodynamic heating and sub-systems are included in the first level. The sub-system for flight mechanics is at level two. Designing the best trajectory while considering uncertainty and minimizing thermal load is the aim of flight mechanics. It is assumed in this section that an ideal offline route design will be completed first. As a result, the system's motion equations are calculated using material points while taking input from aerodynamic and aerothermal sources.

## Design Trajectory Optimization

The best layout for an SRV's re-entry trajectory was covered in this section. The steps in work are as follows:

- A novel approach to improving the well-known optimum control will first be described.
- Then, in the second part, the guiding law is divided into two separate parts by presenting an innovative method [29-32].
- Then, using the above method, the optimal combined trajectory is created. The importance of the proposed method is to provide all the requirements of the route with certain restrictions.

## Optimal trajectory method

The system dynamics can be considered as the following equation:

$$\dot{\vec{x}} = f(\vec{x}(t), \vec{u}(t), t) \qquad t_0 < t < t_f \qquad (1)$$

The above non-linear system is described with a state vector $\vec{x} \in R^n$ and control variable vector as is given as $\vec{u} \in R^m$.

According to the optimal control theory, the cost function may be used to express the best trajectory as follows: [26].

$$J=\Phi[\vec{x}(t_f),t_f] + \int_{t_0}^{t_f} L[\vec{x}(t),\vec{u}(t),t]dt \qquad (2)$$

Where $t_f$ is the final time for the problem of spacecraft return from the atmosphere, Also, $\Phi$ represents the final criterion is the penalty function or the penalty function for the previous states. The Hamiltonian function is also described as $H(\vec{x},\vec{\lambda},\vec{u},t)$ by the integral of the cost function $L(\vec{x},\vec{u},t)$ along with a multiplication of the common states of Equation (4) and the dynamic equations of the system, that is $f(\vec{x},\vec{u},t)$, as follows:

$$H(\vec{x},\vec{\lambda},\vec{u},t) = L(\vec{x},\vec{u},t) + \vec{\lambda}^T f(\vec{x},\vec{u},t) \qquad (3)$$

$$\dot{\vec{\lambda}}^T = -\partial H/\partial \vec{x} \qquad (4)$$

In this way, the optimization conditions by $(\partial H/\partial \vec{u}) = 0$ are obtained given the reference [46].

Accordingly, SRV and optimal conditions are considered based on the angle of attack $\alpha(t)$ and the bank angle $\beta(t)$, which have the following boundary conditions:

$$(\partial H/\partial \alpha) = 0 , (\partial H/\partial \beta) = 0$$

The combination of an indirect approach using unique series like the 4th order Rang Kata and optimization techniques is the primary emphasis of this study [47].

Three optimization techniques, including GA-PSO, GA, and ABC, have also been researched for this study. GA replicates a human population. The collection of genes describes the properties of the GA technique [26].

On this population, operators like recombination and selection are used. A portion of a gene is changed at random through mutation [48].

Combining two individuals results in a mixture while choosing the individual who performs worse than the other results in elimination.

The population of the highest fitness gets increasingly homogenous when more of a set of initial random individuals are subjected to these operators. An optimization algorithm may be used to describe this procedure [49].

The swarm-based Artificial Bee Colony (ABC) algorithm imitates the honey bee colony's exploring activity. Colony size, limit, and maximum cycle are three crucial control factors in ABC [50, 51].

It is possible to predict the angle of attack and bank angle by combining sinusoidal and polynomial functions. To provide oscillatory activity, polynomial functions are defined as base functions and sinusoidal functions. To create optimal control of control inputs $\alpha(t), \beta(t)$ is defined as the functions below:

$$\alpha(t) = \sum_{i=1}^{N} \tau_i (t+\kappa)^i + \eta_i \sin\left(\xi_i (t+\kappa)\right) \quad (5)$$

$$\beta(t) = \sum_{i=0}^{M} \zeta_i (t+\kappa)^i + \upsilon_i \sin\left(\varepsilon_i (t+\kappa)\right) \quad (6)$$

Where $\tau_i$, $\eta_i$, $\xi_i$, $\zeta_i$ , $\upsilon_i$,$\varepsilon_i$ are constants that are estimated by optimizers.

$\kappa$ is the time division, which will be further explained in the following sections.

(N=1, 2, 3, …) and (M=1, 2, 3, …)

Equations 7 and 8 and 9 may be used to define the SRV's aerodynamic heating and The original cost function, which is provided as a function of height (h) and velocity (v) [35]. According to the average heat rate and the overload heat rate along the whole trajectory, these equations are considered for the cost function [26].

$$Q = q_0 \left(\sum_{i=0}^{3} c_i \alpha^i\right) \sqrt{\rho}.(v)^{3.07} \quad (7)$$

$$J_{mh} = \max\left[q_0 \left(\sum_{i=0}^{3} c_i \alpha^i\right) \sqrt{\rho}.(v)^{3.07}\right] \quad (8)$$

$$J_Q = \int_0^{T^*} Q(t)dt \quad (9)$$

Where represents the division time. Additionally, the optimizer employs the penalty function to guarantee the fulfilment of the following final conditions:

$$J_P = \sum_{k=1}^{5} r_k \left(X_k(T) - X_k^{nominal}(T)\right)^2 \quad (10)$$

Consequently, it is recommended that the total cost function be expressed as follows:

$$J_{total} = J_P + J_Q + J_{mh} \quad (11)$$

Where $X_i(T)$ k $= [1, \dots, 5]$ are the dynamic system modes for SRV, i=1 indicates height, i=2 expresses velocity, i=3 shows the angle of the flight trajectory, i=4 demonstrates azimuth, and i=5 represents latitude. The weight coefficients $r_k$ are used to normalize the parameters in the same order [26, 33]. The conventional method's algorithm is shown in Figure 3. Equations (5) and (6) are used by the optimizer in this research's computational technique to first estimate the bank angle and angle of attack profiles for the SRV problem (6). The iso values after the journey are likewise calculated by the optimizer. The state and isolate equations are then produced by integrating the system of differential equations under the provided boundary conditions [26]. Optimal requirements ( $\partial H/\partial\alpha$ ,$\partial H/\partial\beta$) and the cost function $J_{total}$ are calculated at the end. Equation 8's maximum heat, Equation 9's total heat along the trajectory, and Equation 10's ultimate needs make up the cost function's sub-criteria (Equation 10). The best solutions are those that fulfil both optimum control and optimization criteria according to an examination of the optimization conditions [52]. The optimizer attempts to minimize the cost function to meet the thermal and final criteria if the convergence process of all algorithmic components is satisfactory (for instance, non-singularity) [26].

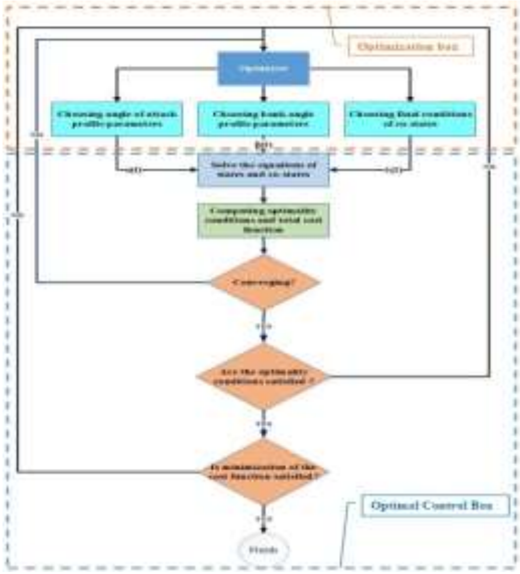


**Figure 6:** Schematic diagram of the main algorithm.

## Proposed and developed conduction law

The suggested and developed method's major objective is to lower the heat rate while keeping the final conditions [26]. The flying trajectory is divided into half to accomplish this. The first stage of the conduction law challenge focuses primarily on reducing the heat rate caused by the carrier's high velocity. (Machine speed of around 25; see reference [35]). A combination of total heat and maximum heat can be used to define the cost function at the first step of the trip.

$$J_{phase1} = r_1 Max\,(Q) + r_2 \int_0^{T^*} Q(t)dt \quad (12)$$

Where $r_1$ and $r_2$ are chosen as 1 and 0.0001, respectively, based on the skill level gained from this attempt. From equation (21), the characteristics of the angle of attack may be defined as follows [26]:

$$\alpha(t) = (\tau_1 t + \tau_2) + \eta_1 \sin(\xi_1 t) \quad (13)$$

The following cost function is the major concern in the second stage of the journey to meet the requirements in full:

$$J_{phase2} = J_P \quad (14)$$

Finding the history of the bank angle and the attack angle is crucial for obtaining the objective function. As a result, using Eq, the proposed angles of bank and attack for SRV are as follows.

$$\beta(t) = (\tau_3(t+\kappa) + \tau_4) + \eta_2 \sin(\xi_2(t+\kappa)) \quad (15)$$

$$\alpha(t) = (\tau_5(t+\kappa) + \tau_6) + \eta_3 \sin(\xi_3(t+\kappa)) \quad (16)$$

Consequently, the split conduction schematic is displayed in Figure (4) for improved understanding. The illustration demonstrates the transfer to the second phase of the results of the main algorithm stage from Figure (3), which include the following:

- Boundary circumstances
- The initial phase's attack angle and bank angle
- At the final calculation time, which is the second phase's beginning values, state and quasi-state variables are passed to the second phase's main algorithm.

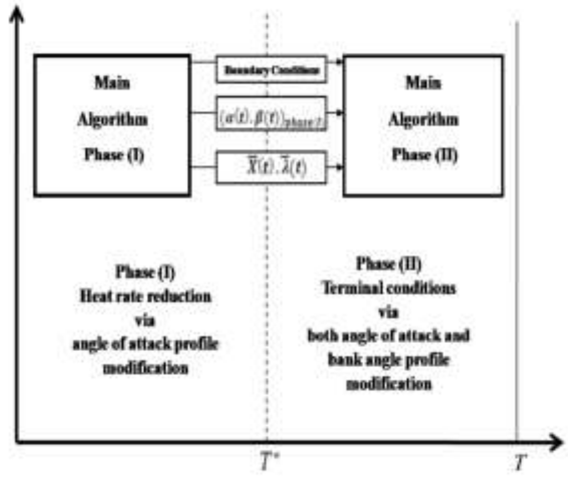


**Figure 7:** Schematic of the split routing method.

## Modeling spacecraft returning from the atmosphere

The chosen instance involves enhancing a spacecraft's return route from the atmosphere. Two significant variables that contribute to the difficulty of the task involved in the spacecraft's return to the atmosphere are:

- Extremely sensitive to equations being solved numerically
- Prolonged flying time after leaving the spacecraft's atmosphere

The space entrance vehicle's equations of motion are as follows [26, 35]:

$$\dot{h} = \mathrm{v}\sin(\gamma) \quad (17)$$

$$\dot{v} = -\frac{D(\mathrm{h,v,\alpha})}{m} - \mathrm{g}(h)\sin(\gamma) \quad (18)$$

$$\dot{\gamma} = \frac{L(\mathrm{h,v,\alpha})}{\mathrm{mv}}\cos(\beta) + \cos(\gamma)\left(\frac{v}{R_e + \mathrm{h}} - \frac{g(h)}{v}\right) \quad (19)$$

$$\dot{\theta} = \frac{v}{R_e + \mathrm{h}}\cos(\gamma)\cos(\psi) \quad (20)$$

$$\dot{\psi} = \frac{L(\mathrm{h,v,\alpha})}{\mathrm{mv}\cos\gamma}\sin(\beta) + \frac{v}{R_e + \mathrm{h}}\cos(\gamma)\sin(\psi)\sin(\theta) \quad (21)$$

$$\dot{\phi} = \frac{v}{R_e + \mathrm{h}}\cos(\gamma)\sin(\psi)/\cos(\theta) \quad (22)$$

The system states are altitude h, velocity v, flight trajectory angle γ, azimuth ψ, latitude θ, and longitude φ. Since the bank angle β(t) and the angle of attack α(t) are two control variables, the equations of lift force and drag force are obtained as of the angle of attack [26, 35]:

$$L(\mathrm{h,v,\alpha}) = \frac{1}{2} C_L(\alpha) \times \rho(h) \times \mathrm{v}^2, \text{where } C_L(\alpha) = \mathrm{a}_0 + \mathrm{a}_1 \alpha \quad (23)$$

$$D(\mathrm{h,v,\alpha}) = \frac{1}{2} C_D(\alpha) \times \rho(h) \times \mathrm{v}^2, \quad C_D(\alpha) = \mathrm{b}_0 + \mathrm{b}_1 \alpha + \mathrm{b}_2 \alpha^2 \quad (24)$$

The aerodynamic coefficients $C_D$ and $C_L$ are described as functions that rely only on the angle of attack at high

speeds, and it is anticipated that they will remain roughly constant as the Mach number varies. According to the atmospheric model, air density and gravity simply depend on height, as seen below [35]:

$$g(h)=\mu/(R_e+h)^2, \rho(h)=\rho_0 \exp[-h/h_r] \quad (25)$$

The constant values of the parameters in the above equation are based on [26, 35].

**Table 5:** Constant coefficients (No technical specifications of the study item (shuttle)).

| Symbol | Value | Symbol | Value | Symbol | Value |
|---|---|---|---|---|---|
| $\mu$ | 398,603.2 [$Km^3/s^2$] | $\rho_0$ | 1.225 [$Kg/m^3$] | $R_e$ | 6,371.2 [Km] |
| $h_r$ | 7.25 [Km] | $S$ | 249.91 [m2] | $m$ | 2,861.96 [Kg] |
| $a_0$ | -0.20704 | $a_1$ | 1.675557 | $b_0$ | 0.07854 |
| $b_1$ | -0.352896 | $b_2$ | 2.039962 | $c_0$ | 1.06723181 |
| $c_1$ | -1.1018767 | $c_2$ | 0.698787 | $c_3$ | -0.19029629 |

The initial condition of the vehicle when returning is as follows [26]:

$$h(0) = 79.248(Km) \quad \phi(0) = 0(deg)$$
$$v(0) = 28{,}090(Km/h) \quad \theta(0) = 0(deg)$$
$$\psi(0) = 90(deg) \quad \gamma(0) = -1(deg)$$

According to this definition of aerodynamic heating in a returning spaceship as a function of angle of attack, altitude, and speed [35]:

$$q_r(\alpha, h, v) = q_0\left(\sum_{i=0}^{3} c_i \alpha^i\right)\sqrt{\rho(h)} \cdot (v)^{3.07} \quad (26)$$

Where $q_0 = 3.7156 \times 10^{-8}\left(\sqrt{kg/m^3}\right)$. To validate it, the methodology of this study was compared with reference [35]. As can be observed, the results for all modes are in perfect consistency with the results of the reference [26, 35]. Consequently, the present study's optimization approach and dynamic flight model are both reliable.

**Table 6:** Space carrier parameters at the final time.

| Parameters | Values at the final time |
|---|---|
| Height($h$) | 24062 (m) |
| Velocity($v$) | 751(m/s) |
| Flight trajectory angle ($\gamma$) | -0.104 (rad) |
| Azimuth ($\psi$) | 0.1471 (rad) |
| Latitude ($\theta$) | 0.601 (rad) |

## Simulation Results

A novel definition of the flight trajectory of a spacecraft that travels through two major stages before returning is the primary objective of this research. One of the characteristics of this research is the trajectory's division into two parts. The goal of the first step, referred to as "heat reduction," is to minimize the heat rate by taking the cost functions' impact into account. The following step involves meeting the last requirements, with an emphasis on the bank angle. κ parameter optimization techniques, including genetic algorithms (GA), artificial bee colonies (ABC), and GA-PSO. The results of each technique are contrasted with those of other techniques and references [35]. The parameter displays the trajectory splitting time, which is set at 1000 seconds in this research. Figures (8) displays the simulation results:

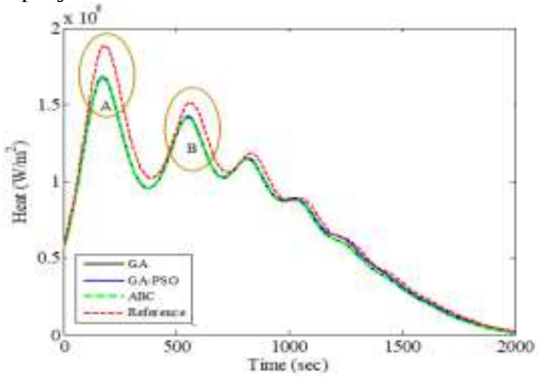


**Figure 8a:** Heat transfer – time.

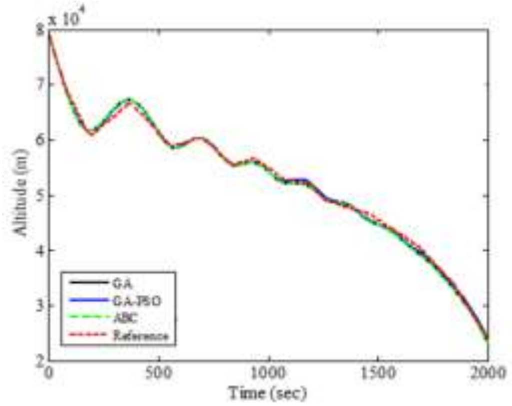


**Figure 8b:** Altitude-time.

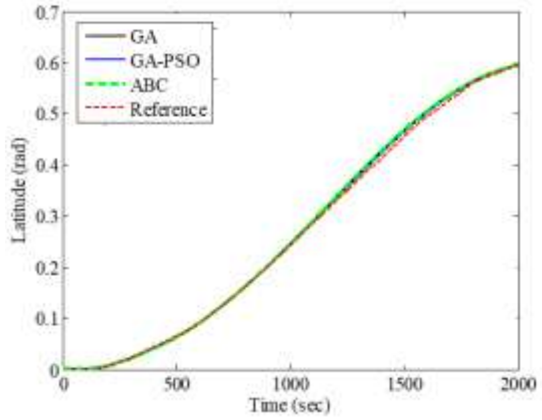

**Figure 8c:** Latitude angle – time.

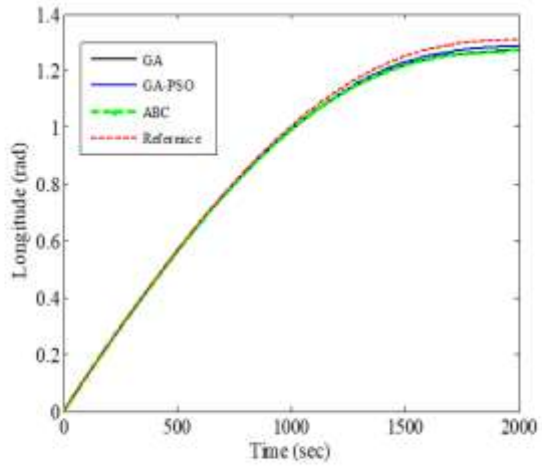

**Figure 8d**: Longitude-time.

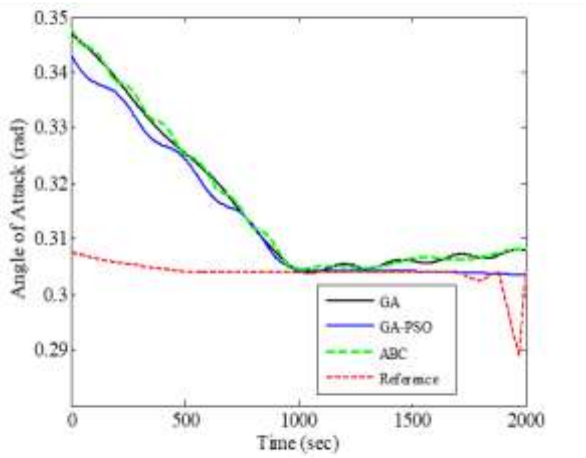

**Figure 8e:** Attack angle – time.

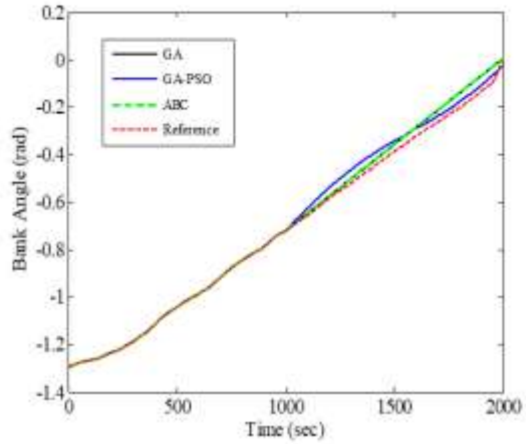

**Figure 5f:** Bank angle – time.

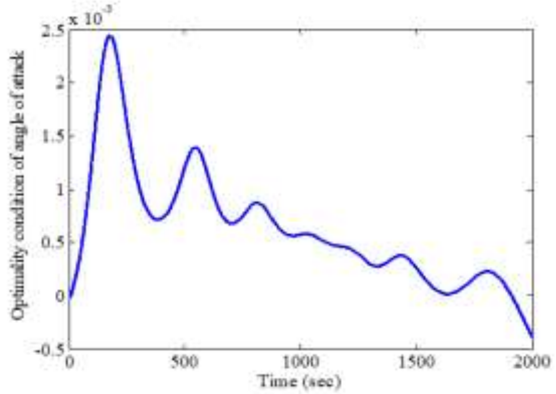

**Figure 5g:** Optimality condition for angle of attack.

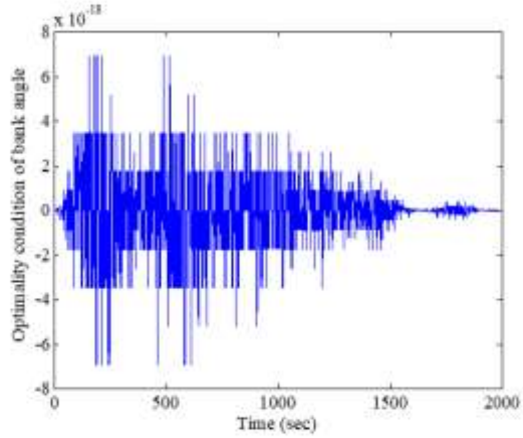

**Figure 5h:** Optimality condition for bank angle.

The trajectory resulting from each method is shown in Figure 9:

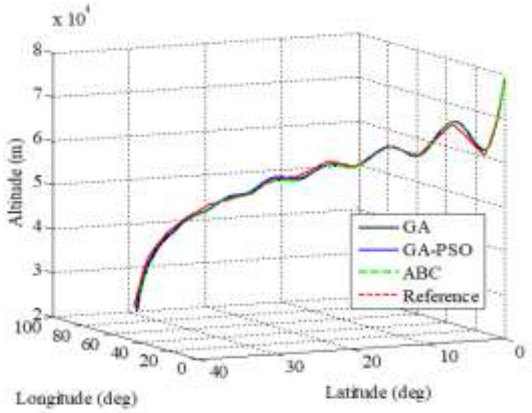


**Figure 9:** 3D trajectory by three optimizers.

Figure 8 (a) demonstrates that the two sections, A and B, have a significant impact on lowering the heating rate. In sections, A and B, the area under the heating diagram and the maximum value of the heat rate are both minimized. It is clear from Figures 8(g) and 8(h) that both optimization criteria $(\partial H/\partial \alpha) = 0\,, (\partial H/\partial \beta) = 0$ are appropriately met as a result of values being near zero. Therefore, using the suggested method of this study, all of the chosen optimization approaches are effective in handling the SRV optimum control problem. They may all lower the heat rate and adjust to the demands of the situation. Two-phase conduction is the term used to describe these two benefits of 1- decreasing heat and 2- completing the final requirements. GA-PSO, on the other hand, has the most results and the least amount of inaccuracy.

Tables 7 to 10 make it very evident that the GA-PSO strategy yields the best results. Using the previously shown technique, the overall heat is lowered by 5.03%. Because the period (140–250 seconds) is the ablation period in the Juke SRV's re-entry phase, heat reduction during this part of the flight was crucial. As a result, both the maximal heat rate and the overall heat fall by around 9.6% between 140 and 250 s. The final specifications are precisely satisfied, and the biggest inaccuracy in terms of speed is only approximately 2.5%. Other optimization techniques often lower heat transmission as well, but neither of these approaches achieves the desired results. For instance, the azimuth error in GA is around 11.76%, but the error in ABC is approximately 25.5%. Finally, it can be said that the aforementioned algorithm and GA-PSO optimization approach yield the greatest results for minimizing heat and fulfilling the final requirements.

**Table 7:** Comparing the GA-PSO method and reference values.

| Parameter | GA-PSO | Reference [35] | Percent of difference |
|---|---|---|---|
| Overall Heat (W.s/m2) | 1.17435897e+09 | 1.23661173e+09 | -5.03%* |
| Overall Heat [140-250 sec] (W.s/m2) | 1.7718467e+08 | 1.960612781e+08 | -9.6% |
| Max Heat(W/m$^2$)** | 1.7081681e+06 | 1.88791064e+06 | -9.5% |
| Final Latitude [rad] | 0.5945 | 0.5963 | -0.3% |
| Final altitude [m] | 23989.814 | 24062 | -0.3% |
| Final Velocity [m/s] | 728.47 | 751 | -3% |
| Final Flight Trajectory Angle[rad] | -0.1017 | -0.104 | -2.2% |
| Final Azimuth [rad] | 0.1463 | 0.1471 | 0.5% |

Note: The negative sign in the percentage column indicates the reduction percentage.

**It should be noted that the maximum heat transfer occurs in about 180 seconds.

**Table 8**. Comparison of the ABC method and the reference values.

| Parameter | ABC | Reference [35] | Percent of difference |
|---|---|---|---|
| Overall Heat (W.s/m2) | 1.16779193e+09 | 1.236611737e+09 | -5.5% |
| Overall Heat [140-250 sec] (W.s/m2) | 1.76896373e+08 | 1.960612781e+08 | -9.7% |
| Max Heat(W/m$^2$) | 1.70527533e+06 | 1.88791064e+06 | -9.6% |
| Final Latitude [rad] | 0.5960 | 0.5963 | -0.05% |
| Final Altitude [m] | 23891 | 24062 | -0.71% |
| Final Velocity [m/s] | 754.84 | 751 | -5.1% |
| Final Flight Trajectory Angle[rad] | -0.1032 | -0.104 | -1.769% |
| Final Azimuth [rad] | 0.1095 | 0.1471 | -25.5% |

**Table 9**. Comparison of the GA method and the reference values.

| Parameter | GA | Reference [35] | Percent of difference |
|---|---|---|---|
| Overall Heat (W.s/m2) | 1.1519646e+09 | 1.236611737e+09 | -6.8% |
| Overall Heat [140-250 sec] (W.s/m2) | 1.7300106e+08 | 1.960612781e+08 | -11.76% |
| Max Heat(W/m$^2$) | 1.6760813e+06 | 1.88791064e+06 | -11.22% |
| Final Latitude [rad] | 0.5959 | 0.5963 | -0.067% |
| Final Altitude [m] | 23323 | 24062 | -3.07% |
| Final Velocity [m/s] | 691 | 751 | -7.98% |
| Final Flight Trajectory Angle[rad] | -0.1177 | -0.104 | -13.17% |
| Final Azimuth [rad] | 0.1298 | 0.1471 | -11.76% |

**Table 10:** Comparison of three optimizers according to reference [35].

| Parameter | GA-PSO | GA | ABC |
|---|---|---|---|
| Overall Heat (W.s/m2) | -5.03% | -6.8% | -5.5% |
| Overall Heat [140-250 sec] (W.s/m2) | -9.6% | -11.76% | -9.7% |
| Max Heat(W/m2) | -9.5% | -11.22% | -9.6% |
| Final Latitude [rad] | -0.3% | -0.067% | -0.05% |
| Final altitude [m] | -0.3% | -3.07% | -0.71% |
| Final Velocity [m/s] | -2.5% | -7.98% | -5.1% |
| Final Flight Trajectory Angle[rad] | -1.9% | -13.17% | -1.769% |
| Final Azimuth [rad] | 0.5% | -11.76% | -25.5% |

## Uncertainty

The most popular optimization under the uncertainty approach is the probabilistic approach. In the probabilistic approach, an uncertain parameter is assumed as a random number associated with the assumed probability density function (PDF). The PDF is assumed to be based on an expert's opinion or previous statistical data. The probabilistic analysis aims at obtaining the PDF of the output dependent variable based on the variations of the input uncertain independent variable. There are multiple techniques to approximate the output dependent variable's PDF [36-38]. The most common method used is sampling methods like Monte Carlo simulations (MCS) or Latin hypercube sampling (LHS). The major difference between these two sampling methods is that the sampling is completely random in MCS. The method requires a huge number of samples. In the LHS method, the sampling is performed in a more stratified manner, reducing the number of samples required. The other methods are analytical methods, where the variance of the output parameter is estimated around its mean value. The most common analytical-based methods are the first-order reliability method (FORM) and the first-order second moment (FOSM). The parameters for which uncertainty and error are considered are 1) Error in initial conditions (altitude, longitude, latitude, speed, direction angle and heading angle) 2) Uncertainty in Mass 3) Uncertainty in the main and secondary elements of the moment of inertia tensor 4) Uncertainty in atmospheric density 5) Uncertainty in coefficients of drag and drag aerodynamic forces 6) Uncertainty in stability derivatives.

### Monte Carlo simulation

A Monte Carlo simulation is a model used to predict the probability of a variety of outcomes when the potential for random variables is present. Monte Carlo simulations help to explain the impact of risk and uncertainty in prediction and forecasting models. Monte Carlo methods, or Monte Carlo experiments, are a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results. The underlying concept is to use randomness to solve problems that might be deterministic in principle. They are often used in physical and mathematical problems and are most useful when it is difficult or impossible to use other approaches. Monte Carlo methods are mainly used in three problem classes optimization, numerical integration, and generating draws from a probability distribution.

$$\begin{aligned} &\mathrm{h}(0) = 79.248(\mathrm{Km}) && \phi(0) = 0(\mathrm{deg}) \\ &\mathrm{v}(0) = 28{,}090(\mathrm{Km/h}) && \theta(0) = 0(\mathrm{deg}) \\ &\psi(0) = 90(\mathrm{deg}) && \gamma(0) = -1(\mathrm{deg}) \end{aligned}$$

Monte Carlo methods vary, but tend to follow a particular pattern: 1) Define a domain of possible inputs 2) Generate inputs randomly from a probability distribution over the domain 3) Perform a deterministic computation on the inputs 4) Aggregate the results. In this part, the outputs are examined using the Monte Carlo method in which multiple computer runs are use

**Table 11:** Uncertainty model of initial conditions.

| parameter | | Distribution type | Average value | Erorr Max/ Min |
|---|---|---|---|---|
| Initial Condition | Altitude=h | Uniforms | 79248 (Km) | ±140 |
| | Latitude= θ | Uniforms | 0° | ±0.2° |
| | Longitude = φ | Uniforms | 0° | ±0.2° |
| | Velocity=v | Uniforms | 28090 (Km/h) | 75m/s |
| | Flight patch angle= γ | Uniforms | -1° | 0.3° |
| | Azimuth angle= ψ | Uniforms | 90° | ±0.05 ° |

## Conclusion

It is unavoidable for spacecraft carrying precious cargo to return to Earth via the atmosphere. This carrier travels at supersonic speed while re-entering the atmosphere affected by gravity. The carrier becomes warmer as a result of this high speed. Therefore, taking heat protection into account is necessary for spaceship safety. One of the simplest methods to minimize heat is to design the best return trajectory. Trajectory optimization and optimal control problems are common ways to formulate optimization problems in the fields of aviation and astronautics. The ideal trajectory for a space carrier (spacecraft) in the return phase from the atmosphere was analyzed using one of the multi-objective optimal design techniques and optimal control theory under the special presented method and strategy [34,42,45]. The optimum control issue is described in SRV as a test case. Three global optimization strategies are used to find the ideal bank angle and angle of attack (ABC, GA, and GA-PSO). Optimal path design aims to reduce the heat rate while preserving optimum end conditions. The current method to accomplish this involves dividing the journey into two halves. The value of the heat rate may be reduced by designing the angle of attack. The heat rate is particularly important in the first phase. As a result, the angle of the attack profile is parameterized using a series of temporal functions, such as the Rang Kata Mertier series 4. By reducing the cost function, optimizers can reduce the heat rate or a combination of the heat rate and end conditions. The maximal heat plus the heat integral over time make up the cost function in the first phase. The second step's final requirement can be satisfied using either the bank angle or the angle of attack. In terms of producing results based on the results, the GA-PSO approach has shown to be the best and most rational. Using this method, the total heat is decreased by about 5.03%, and the heat transmission in the time [140–250 s] is reduced by around 9.6%. Additionally, the maximum heat rate is decreased by around 9.5% using the present method. All final condition errors are, therefore, below 2.5%. In conclusion, the method adopted in the present study is used to lower an SRV's heating rate without sacrificing the outcome.

## References


[1] P. Narayan, P. Meyer, and D. Campbell, "Embedding human experting cognition into autonomous UAS trajectory planning," IEEETransactions on Cybernetics, vol. 43, no. 2, pp. 530–543, 2013. DOI: 10.1109/TSMCB.2012.2211349

[2] A. Rucco, G. Notarstefano, and J. Hauser, "An efficient minimum time trajectory generation strategy for two-track car vehicles," IEEE Transactions on Control Systems Technology, vol. 23, no. 4, pp. 1505– 1519, 2015. DOI: 10.1109/TCST.2014.2377777

[3] Z. Chen and H. T. Zhang, "A minimal control multiagent for collision avoidance and velocity alignment," *IEEE Transactions on Cybernetics*, vol. 47, no. 8, pp. 2185–2192, 2017. DOI: 10.1109/TCYB.2017.2712641

*[4] A. J. Hausler, A. Saccon, A. P. Aguiar, J. Hauser, and A. M. Pascoal, "Energy-optimal motion planning for multiple robotic vehicles with collision avoidance," IEEE Transactions on Control Systems Technology, vol. 24, no. 3, pp. 867–883, 2016. DOI: 10.1109/TCST.2015.2475399*

[5] L. Paull, C. Thibault, A. Nagaty, M. Seto, and H. Li, "Sensor-driven area coverage for an autonomous fixed-wing unmanned aerial vehicle,"*IEEE Transactions on Cybernetics*, vol. 44, no. 9, pp. 1605–1618, 2014. *DOI: 10.1109/TCYB.2013.2290975*

*[6] H. Peng, B. Chen, and Z. Wu, "Multi-objective transfer to librationpoint orbits via the mixed low-thrust and invariant-manifold approach,"Nonlinear Dynamics, vol. 77, no. 1, pp. 321–338, 2014. https://doi.org/10.1007/s11071-014-1296-2*

*[7] H. Peng and W. Wang, "Adaptive surrogate model based multi-objective transfer trajectory optimization between different libration points," Advances in Space Research, vol. 58, no. 7, pp. 1331–1347, 2016. DOI:* 10.1016/j.asr.2016.06.023

[8] W. Wang and H. Peng, "A fast multi-objective optimization design method for emergency libration point orbits transfer between the sunearth and the earth-moon systems," *Aerospace Science and Technology*,vol. 63, pp. 152–166, 2017. https://doi.org/10.1016/j.ast.2016.12.026

[9] C. Yang, Z. Li, and J. Li, "Trajectory planning and optimized adaptive control for a class of wheeled inverted pendulum vehicle models,"*IEEE Transactions on Cybernetics*, vol. 43, no. 1, pp. 24–36, 2013. DOI: 10.1109/TSMCB.2012.2198813

*[10] J.J. Sellers, Returning from Space: Re-Entry. Understanding Space: An Introduction to Astronautics. 2000. Available online:* https://www.faa.gov/sites/faa.gov/files/about/office_org

*[11] M.Tava,; S. Suzuki, Multidisciplinary design optimization of the shape and trajectory of a reentry vehicle. Trans. Jpn. Soc. Aeronaut. Space Sci. 2002, 45, 10–19.* https://doi.org/10.2322/tjsass.45.10

*[12] M. Mor,; E. Livne, Integrated aeroelastic shape optimization of flight vehicles. In Proceedings of the 46th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference, Austin, TX, USA, 18–21 April 2005. Collection of Technical Papers.*

*[13]* M. Nosratollahi,; M. Mortazavi,; A. Adami,; M. Hosseini, Multidisciplinary design optimization of a reentry vehicle using genetic algorithm. Aircr. Eng. Aerosp. Technol. 2010, 82, 194–203. https://doi.org/10.3390/applmech3040067

[14] M. Nosratollahi,; M. Hosseini,; A. Adami, Multidisciplinary Design Optimization of a Reentry Vehicle's Configuration. In Proceedings of the 8th Aerospace International conference, Isfahan, Iran, 17–19 February 2009. ttps://doi.org/10.3390/applmech3040067

[15] A. Adami,; M. Hosseini,; M. Nosratollahi, Multiobjective Optimization of a Reentry Vehicle's Aerodynamic Shape. In Proceedings of the 17th Mechanic International conference, Tehran, Iran, 19–21 May 2009. https://doi.org/10.3395/applmech3041267

[16] M. Nosratollahi,; M. Hosseini,; A. Adami, Multidisciplinary design optimization of a controllable reentry capsule for minimum landing velocity. In Proceedings of the 51st Collection of Technical Papers—AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference, Orlando, FL, USA, 12–15 April 2010. https://doi.org/10.2514/6.2010-3009

[17] A. Adami,; M. Nosratollahi,; M. Mortazavi,; M. Hosseini, Multidisciplinary design optimization of a manned reentry mission considering trajectory and aerodynamic configuration. In Proceedings of the 5th International Conference on Recent Advances in Space Technologies–RAST 2011, Istanbul, Turkey, 9–11 June 2011. DOI:10.1109/RAST.2011.5966908

[18] D. Dirkx,; E. Mooij, Conceptual Shape Optimization of Entry Vehicles: Applied to Capsules and Winged Fuselage Vehicles; Springer Aerospace Technology; Springer: Berlin/Heidelberg, Germany, 2017.

[19] Y. Wu,; J. Deng,; L. Li,; X. Su,; L. Lin, A hybrid particle swarm optimization-gauss pseudo method for reentry trajectory optimization of hypersonic vehicle with navigation information model. Aerosp. Sci. Technol. 2021. ttps://doi.org/10.1016/j.ast.2021.107046

[20] Hong Liu, "Multiobjective Evolutionary Computation for Noncircular Missile Shape Optimization", 42nd AIAA Aerospace Sciences Meeting and Exhibit, paper 04-453, 2004.https://doi.org/10.2514/6.2004-453

[21] W. Su1, Y. Zuo and Z. Gao, "Preliminary Aerodynamic Shape Optimization Using Genetic Algorithm and Neural Network", 11th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, paper 06-7106, 2006. https://doi.org/10.2514/6.2006-7106

[22] k. Cui and G.W. Yang, "Shape Optimization for Hypersonic Arc-Wing Missiles", Journal of Spacecraft and Rockets, Vol. 47, No. 4, pp. 694–700, 2010. https://doi.org/10.2514/1.45882

[23] A. Z. Al-Garni, , A. H. Kassem, , and A. M. Abdallah, , "Aerodynamic-Shape Optimization of Supersonic-Missiles Using Monte Carlo", International Review of Aerospace Engineering, Vol. 1, No. 1, 2008. DOI:10.2514/2.3615

[24] O. Tekinalp, , and M. Bingol, , "Simulated Annealing for Missile Optimization: Developing Method and Formulation

Techniques", Journal of Guidance, Control, and Dynamics, Vol. 27, No. 4, pp. 616–626, 2004. https://doi.org/10.2514/1.2103

[25] H . Nobahari, S. Y. Nabavi, S. H. Pourtakdoust, "Aerodynamic Shape Optimization of Unguided Projectiles Using Ant Colony Optimization and Genetic Algorithm", 25th International Congress of the Aeronautical Sciences, ICAS Paper 2006-3.6S, Hamburg,2006. http://dx.doi.org/10.4314/jfas.v8i3s.385

[26] A. Ekrami Kivaj, A. Basohbat Novinzadeh, and F. Pazooki, "Spacecraft reentry trajectory optimization by heuristic optimization methods and optimal control theory," Int. J. Dyn. Control., 2022. https://doi.org/10.1007/s40435-022-01033-0

[27] P. N. Desai, D. T. Lyons, J. Tooley, and J. Kangas, "Entry, descent, and landing operations analysis for the Stardust entry capsule," J. Spacecr. Rockets, vol. 45, no. 6, pp. 1262-1268, 2008.

[28] M. Ghoreyshi, D. Vallespin, A. Da Ronch, K. J. Badcock, J. Vos, and S. Hitzel, "Complex System Optimization: A Review of Analytical Target Cascading, Collaborative Optimization, and Other Formulations," In AIAA Atmospheric Flight Mechanics Conference, 2010.

[29] M. Ghoreyshi, K. J. Badcock, A. D. Ronch, S. Marques, A. Swift, and N. Ames, "Framework for establishing limits of tabular aerodynamic models for flight dynamics analysis," J. Aircr., vol. 48, no. 1, pp. 42-55, 2011.

[30] J. T. Betts, and I. Kolmanovsky, "Practical Methods for Optimal Control using Nonlinear Programming," Appl. Mech. Rev., vol. 55, B68, 2002. https://doi.org/10.1115/1.1483351

[31] P. Gurfil, and N. J. Kasdin, "Niching genetic algorithms-based characterization of geocentric orbits in the 3D elliptic restricted three-body problem", Comput. Methods Appl. Mech. Eng., vol. 191, pp. 5683-5706, 2002. https://doi.org/10.1016/S0045-7825(02)00481-4

[32] A. Da Ronch, M. Ghoreyshi, D. Vallespin, K. J. Badcock, Z. Mengmeng, J. Oppelstrup, and A. Rizzi, "A framework for constrained control allocation using CFD-based tabular data," At the 49th AIAA Aerospace Sciences Meeting, AIAA–2011–925, Orlando, Florida, 2011.

[33] A. Rahimi, K. Dev Kumar, and H. Alighanbari, Particle swarm optimization applied to spacecraft re-entry trajectory. J. Guid Control Dyn., vol. 36, no. 1, pp. 307-310, 2012. https://doi.org/10.2514/1.56387

[34] H. Duan, and S. Li, "Artificial bee colony–based direct collocation for re-entry trajectory optimization of hypersonic vehicle," IEEE Trans. Aerosp Electron Syst., vol. 51, no. 1, pp. 615–626, 2015. https://doi.org/10.1109/TAES.2014.120654

[35] K. Graichen, and N. Petit, Constructive Methods for Initialization and Handling Mixed State-Input Constraints in Optimal Control. J. Guid Control Dyn., vol. 31, no. 5, pp. 1334-1343, 2008. https://doi.org/10.2514/1.33870

[36] M. Samani, M. Tafreshi, I. Shafieenejad, and A. A. Nikkhah, "Minimum-time open-loop and closed-loop optimal guidance with GA-PSO and neural-fuzzy for Samarai MAV flight," IEEE Aerosp Electron. Syst. Mag., vol. 30, pp. 28-37, 2015. https://doi.org/10.1109/MAES.2015.7119822

[37] W. Chen, M. Panahi, H. R. Pourghasemi, "Performance evaluation of GIS-based new ensemble data mining techniques of adaptive neuro-fuzzy inference system (ANFIS) with genetic algorithm (GA), differential evolution (DE), and particle swarm optimization (PSO) for landslide spatial modeling," Catena, vol. 157, pp. 310-324, 2017. https://doi.org/10.1016/j.catena.2017.05.034

[38] H. K. Abdulkhader, J. Jacob, and A. T. Mathew, "Fractional-order lead-lag compensator-based multi-band power system stabilizer design using a hybrid dynamic GA-PSO algorithm," IET Gener Transm. Distrib., vol. 12, pp. 3248-3260, 2018. https://doi.org/10.1049/iet-gtd.2017.1087

[39] Y. Liu, X. Li, P. Jiang, Zh. Du, Zh. Wu, B. Sun, and X. Huang, « Evolutionary multi-objective trajectory optimization for a redundant robot in Cartesian space considering obstacle avoidance," Mech. Sci., vol. 13, pp. 41–53, 2022. https://doi.org/10.5194/ms-13-41-2022

[40] H. Yang, S. Li, and X. Bai, « Fast homotopy method for asteroid landing trajectory optimization using approximate initial costates," J. Guid Control Dyn., vol. 42, no. 3, pp. 585-597, 2019. https://doi.org/10.2514/1.G003414

[41] H. Xu, W. Li, X. Wang, C. Hu, and S. Zhang, "Multidisciplinary reliability design optimization under time-varying uncertainties," Adv. Mech. Eng., vol. 8, no. 11, pp. 1–11, 2016.

[42] L. Jaege, and T. Jorquera, "Uncertainty propagation in multi-agent systems for multidisciplinary optimization problems," In: 10th World Congress on Structural and Multidisciplinary Optimization, Orlando, Florida, USA, May 19 - 24, 2013.

[43] J. Berends, and M. Van Tooren, "MDO Design Support by Integrated Engineering Services within a Multi-Agent Task Environment Framework," In: The 26th Congress of ICAS and 8th AIAA ATIO, 2008. https://doi.org/10.2514/6.2008-8947

[44] I. Shafieenejad, A. B. Novinzadeh, V. R. Molazadeh, "Comparing and analyzing min-time and min-effort criteria for the free true anomaly of low-thrust orbital maneuvers with a new optimal control algorithm," Aerosp Sci. Technol., vol. 4, no. 35, pp. 116-134, 2014. https://doi.org/10.1016/j.ast.2014.03.009

[45] H. Peng, C. Yang, Y. Li, S. Zhang, and B. Chen, "Surrogate-based parameter optimization and optimal control for the optimal trajectory of Halo orbit rendezvous," Aerosp Sci. Technol., vol. 26, no. 1, pp. 176-184, 2013. https://doi.org/10.1016/j.ast.2012.04.001

[46] D. Karaboga, and B. Basturk, "On the performance of artificial bee colony (ABC) algorithm," Appl. Soft Comput., vol. 8, no. 1, p. 687, 2008. http://dx.doi.org/10.1016/j.asoc.2007.05.007

[47] B. Akay, and D. Karaboga, "Artificial bee colony algorithm for large-scale problems and engineering design optimization," J. Intell. Manuf., vol. 23, no. 4, pp. 1001-1014, 2012. https://doi.org/10.1007/s10845-010-0393-4

[48] M. Srinivas, and L. M. Patnaik, "Genetic algorithms: A Survey," Computer, vol. 27, no. 6, pp. 17-26, 1994. https://doi.org/10.1109/2.294849

[49] H. S. Ramadan, A. Fathy, and M. Becherif, "Optimal gain scheduling of VSC-HVDC system sliding mode control via artificial bee colony and mine blast algorithms," IET Gener. Transm. Distrib., vol. 12, no. 3, p. 661, 2017. https://doi.org/10.1049/iet-gtd.2017.0935

[50] Sh. Zhang, "An Optimal Design Scheme of Missile Trajectory," In: Journal of Physics: Conference Series, 2022

International Conference on Automation and Space Science & Technology, 2022. doi:10.1088/1742-6596/2220/1/012012

[51] E. Ta, V. Ar, and L. John, “Costate mapping for indirect trajectory optimization,” Astrodynamics, vol. 5, pp. 359–371, 2021. https://doi.org/10.1007/s42064-021-0114-0

[52] C. R. Hargraves, and S. W. Paris, « Direct trajectory optimization using non-linear programming and collocation,” J. Guid Control Dyn., vol. 10, no. 4, pp. 338-342, 1987.