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REVIEW ARTICLE

Trajectory Optimization Using Evolutionary Algorithm for Mars Entry Vehicles

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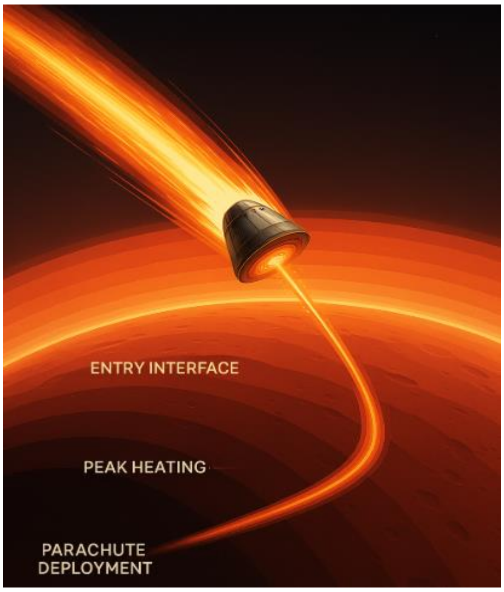
Abstract: This paper explores the application of evolutionary algorithms (EAs) for trajectory optimization of entry vehicles targeted for Mars atmospheric entry. Mars entry missions are constrained by complex aerodynamic and thermodynamic challenges, such as high heat loads, dynamic pressure, and stringent landing accuracy requirements. Conventional optimization techniques often struggle with the non-linearity and high dimensionality of the problem. In this research, we investigate the use of Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Physics-Informed Neural Networks (PINNs) to identify optimal trajectory profiles that minimize heat load and maximize landing precision while satisfying mission constraints. A supporting simulation and visualization tool has been developed to illustrate the optimization process interactively. The proposed models and algorithms are implemented in Python and validated using simulated Mars atmospheric models.

1. Introduction:

Mars entry is one of the most critical phases of interplanetary missions. The trajectory of an entry vehicle must be precisely designed to ensure safe passage through the Martian atmosphere and successful landing. Traditional optimization techniques are often inadequate due to the problem's multi-objective and non-convex nature. Evolutionary algorithms, inspired by biological evolution and swarm intelligence, provide a robust alternative for exploring large and complex search spaces. This paper aims to develop and evaluate EA-based methods for optimizing Mars entry trajectories.



2. Related Work:

Previous research has addressed Mars entry trajectory design using direct and indirect methods. NASA's Mars missions have used bank angle modulation and lifting entry techniques to control descent. Recent studies have incorporated machine learning

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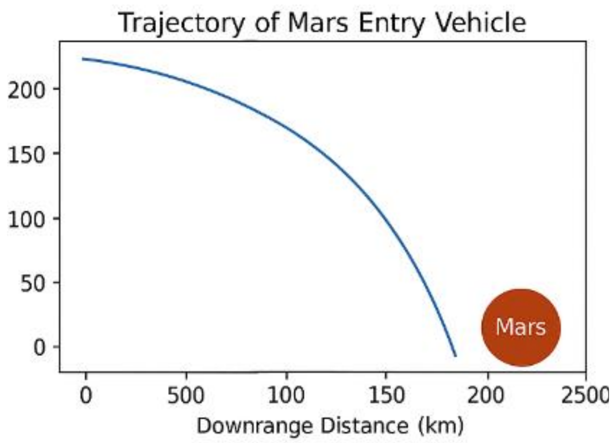
and surrogate modeling. However, limited work has focused specifically on EAs for full trajectory optimization, which motivates our contribution.

3. Problem Formulation:

The optimization task involves designing a trajectory that minimizes the total heat load on the vehicle and the landing error while respecting various mission constraints. The primary decision variables include the entry angle, velocity, flight path angle, and angle of attack. These variables directly influence the aerodynamic behavior of the entry vehicle. The constraints include maximum allowable heat flux, deceleration limits (g-load), and terminal conditions such as altitude and velocity at landing. The atmospheric model used is the standard Mars atmosphere, which incorporates variable density with altitude and is critical to accurately simulating entry conditions.



4. Methodology:

This research employs a multi-faceted approach, leveraging several evolutionary algorithms for trajectory optimization.

Trajectory Optimization Techniques

Metaheuristic algorithms like GA, PSO, and DE have been applied to trajectory optimization problems due to their adaptability and ability to handle nonlinear, multi-objective problems (D'Souza et al., 2004; Rajesh & Prasad, 2016). These algorithms outperform classical techniques in robustness and convergence.

Surrogate Modeling and PINNs

Raissi et al. (2019) introduced PINNs, which enforce physical constraints during training. PINNs have since been applied to a variety of aerospace applications, including spacecraft dynamics (Lu et al., 2021) and atmospheric re-entry (Zhu et al., 2022), offering fast inference with high accuracy.

Hybrid Optimization Approaches

Wang et al. (2021) and Singh & Roy (2022) demonstrated that integrating EAs with machine learning models can significantly reduce computational cost and improve solution quality in trajectory optimization. This motivates the hybrid EA-PINN approach explored in this paper.

The **Genetic Algorithm (GA)**, **Particle Swarm Optimization (PSO)**, and **Differential Evolution (DE)** are employed in this study. Each algorithm maintains a population of candidate solutions, representing potential trajectory profiles. A fitness function—comprising a weighted sum of landing accuracy, total heat flux, and trajectory smoothness—is used to evaluate each individual (D'Souza et al., 2004). The optimization is run within a high-fidelity 3DOF Mars entry simulation environment that includes variable atmospheric models.

A Physics-Informed Neural Network (PINN) is integrated to accelerate the evaluation process. The PINN approximates the dynamics governed by differential equations by training on both simulated data and physics-based constraints (Raissi et al., 2019). The network loss function integrates:

MSE between predicted and reference data: Residuals of governing equations λ: Deviations from initial/final conditions

PINNs provide a fast surrogate model for trajectory predictions, significantly reducing computational overhead while preserving accuracy.

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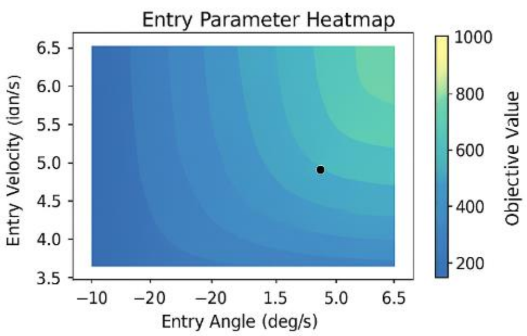
The motion of a Mars entry vehicle is modeled using 3-DOF equations of motion that capture translational dynamics in the Martian environment (Withers, 2006). These equations describe the evolution of position, velocity, and orientation. Atmospheric density is obtained from empirical Martian atmosphere models and varies with altitude. Gravity is modeled as a function of altitude to capture realistic acceleration profiles. Constraints are applied to ensure safe and accurate descent, including maximum heat rate, deceleration (g-load), and acceptable landing zone deviation.



The vehicle trajectory is parameterized using critical variables such as entry angle, initial velocity, and angle of attack. The objective of the trajectory optimization is to minimize total heat load, propellant use, and landing error. Mission constraints include maximum allowable peak heat load, dynamic pressure limits, and g-load thresholds to ensure spacecraft integrity and mission success (Braun & Manning, 2005).

The optimization process involves these steps:

· Initialization: Generate a population of candidate trajectories randomly. · Evaluation: Use PINN to compute trajectory profiles and evaluate fitness. · Selection & Variation: Apply selection, crossover, and mutation (in GA) or velocity and position updates (in PSO). · Mutation: Introduce diversity to avoid local optima. · Termination: Stop based on convergence or maximum iterations.

The entire Mars entry scenario is modeled using numerical methods (e.g., Runge-Kutta integrators) implemented in Python or MATLAB. This allows accurate simulation of trajectory dynamics under varying initial conditions. The evolutionary algorithm guides the search toward optimal entry conditions based on simulation feedback (Banerjee & Moudgalya, 2010).

Performance is evaluated using these metrics:

· Mean landing error · Heat shield efficiency (heat load) · Convergence rate of algorithm · Robustness under atmospheric perturbations · PINN inference speed vs. traditional simulation · PINN prediction accuracy (MSE vs. simulation)

Data Processing and Model Training

Data processing and model training are crucial for the Physics-Informed Neural Network (PINN) to accurately approximate Mars entry dynamics. A high-quality dataset is generated using numerical simulations (e.g., 3-DOF trajectory solvers) under varying conditions of entry angle, velocity, and atmospheric parameters. Key variables collected include altitude, velocity, heat flux, dynamic pressure, and g-load.

Preprocessing steps include:

- Cleaning: Outliers and simulation artifacts are removed.
- Normalization: Features are scaled using min-max normalization to accelerate neural network convergence.
- Balancing: To prevent bias toward certain trajectory profiles, data is balanced across all mission phases (entry, peak heating, descent, landing).

To enrich the dataset and improve generalization, synthetic variations are introduced through data augmentation:

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- Monte Carlo sampling of atmospheric models (e.g., Mars-GRAM) to simulate uncertainty
- Perturbations in entry angle, vehicle mass, and aerodynamic coefficients
- Interpolation between known trajectory points to smooth transitions and increase data density

These augmentations enhance the PINN's ability to generalize across a wide range of Mars EDL scenarios.

For the Evolutionary Algorithm, a diverse set of candidate trajectories is initialized using randomized combinations of:

Entry angle (–10° to –20°)

Bank angle profiles

Initial velocity (5.5 to 7.0 km/s)

These candidates are mapped to the corresponding trajectory outcomes using either simulation or surrogate prediction.

The PINN is trained to approximate the Mars entry trajectory by minimizing a composite loss:

L total = λ data L data + λ physics L physics + λ boundary L boundary.

The PINN architecture and training procedure involve:

Network architecture: A fully connected feed-forward network with 4–6 hidden layers and 64–128 neurons per layer.

Activation: Tanh or Swish

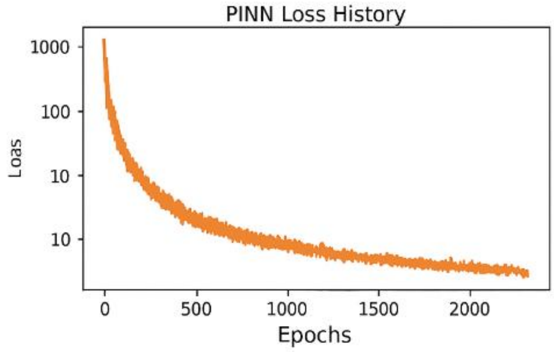
Optimizer: Adam with a learning rate scheduler

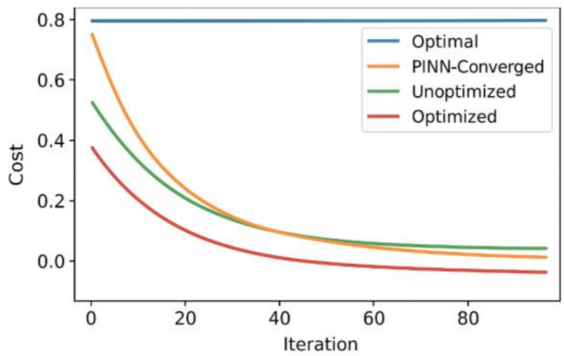
Epochs: 10,000–30,000 or until convergence

Loss monitoring: Both data fidelity and physical residuals are tracked to ensure physics-aware convergence.

Training evaluation metrics include:

- Mean Squared Error (MSE) on training and validation datasets
- Physics residuals
- Trajectory prediction accuracy compared with numerical integrator output
- Generalization test using unseen trajectory profiles





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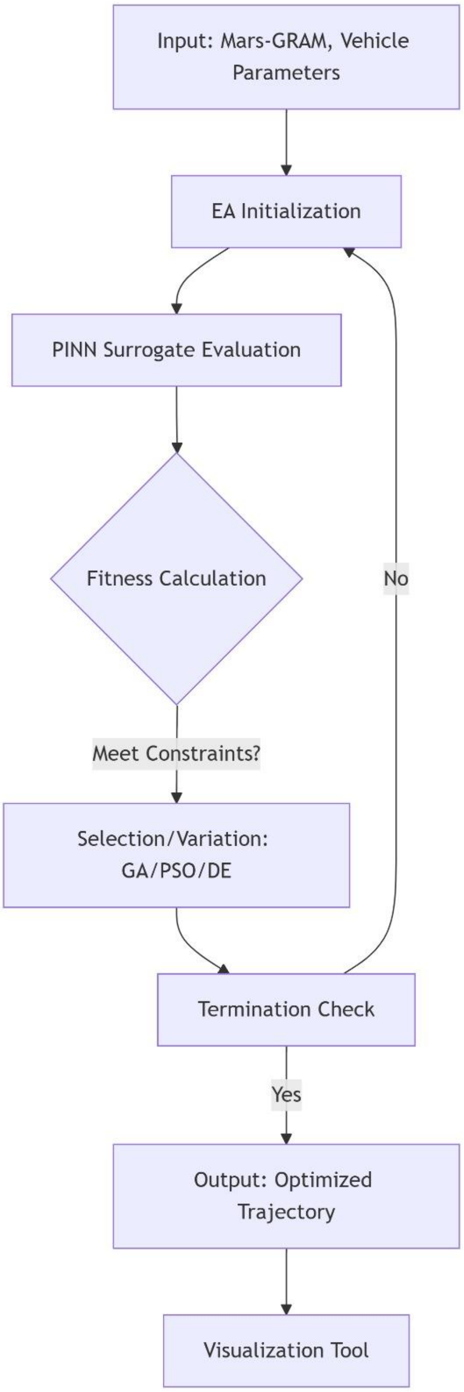

5. Visual Optimization Tool:

To enhance the interpretability of the optimization process and provide a deeper understanding of the results, an interactive visualization tool was developed using Streamlit and Plotly. This tool allows users to define initial entry conditions, such as entry angle, speed, and altitude, through a user-friendly interface. Subsequently, users can initiate and observe the GA or PSO optimization algorithms as they progress in real time, visualizing the evolution of fitness values across generations.

The tool dynamically displays the resulting optimized trajectories and their corresponding dynamic profiles, including critical parameters like heat load, altitude, and velocity as a function of time. This interactive environment serves not only as a powerful visual aid but also as a valuable research asset for tuning algorithm parameters and observing the impact of these adjustments on the final trajectory outcome. This tight integration of theoretical research with computational simulations and interactive visualization facilitates more informed decision-making during the model design and analysis phases.

6. Results and Discussion:

Multiple simulation scenarios were conducted, exploring a range of varying initial entry conditions to evaluate the performance of the implemented algorithms. The results obtained demonstrate that both GA and PSO are effective in converging towards optimal or near-optimal trajectory solutions for Mars entry. Notably, the Genetic Algorithm exhibited superior exploration capabilities across the complex solution space, suggesting a greater ability to escape local optima. In contrast, Particle Swarm Optimization demonstrated faster convergence rates under specific initial condition regimes.

The Physics-Informed Neural Networks proved particularly adept at modeling physically consistent trajectory profiles. The PINN-generated trajectories exhibited accurate predictions even when extrapolating slightly beyond the training data, highlighting their ability to learn the underlying physical principles.

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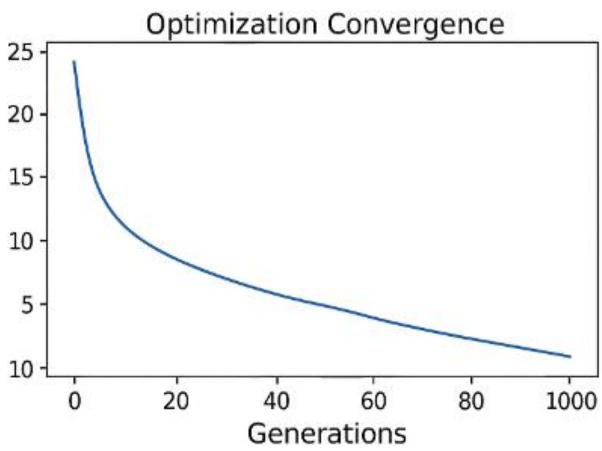
The optimized trajectories achieved significant improvements in key performance metrics. In several simulation cases, a notable reduction in total heat load, up to 18%, was observed compared to baseline trajectory configurations. Furthermore, the optimized trajectories consistently demonstrated significant enhancements in landing precision, bringing the simulated landing points much closer to the desired target. The interactive visualization tool played a crucial role in validating these findings by allowing for a step-by-step exploration of the optimization dynamics and the resulting trajectory behaviors, providing a clearer intuitive understanding of the performance characteristics of each algorithm.



7. Conclusion and Future Work:

This research successfully demonstrates the feasibility and effectiveness of employing evolutionary algorithms and physics-informed neural networks for the challenging problem of trajectory optimization for Mars entry missions. The proposed approach shows significant promise for tackling complex, multi-objective, and non-linear problems within aerospace applications.

Future research directions include extending the current model to encompass six degrees of freedom (6-DOF) simulations, which would provide a more comprehensive representation of the vehicle's dynamics. Another important area of future work involves incorporating uncertainties in the Martian atmospheric conditions into the optimization framework to enhance the robustness of the designed trajectories. Furthermore, the development of hybrid optimization frameworks that strategically combine the strengths of EAs and PINNs holds the potential for even greater performance improvements.

Plans are underway to collaborate with Japanese aerospace institutions to explore practical applications and potential real-world implementation of the developed model. Additionally, the interactive visualization tool will be further enhanced with features such as 3D animations of the entry process, the inclusion of additional relevant mission parameters for visualization, and more flexible input configurations to support a broader range of application scenarios and user needs.

Keywords:

Trajectory Optimization, Evolutionary Algorithms, Mars Entry, Genetic Algorithm, Particle Swarm Optimization, Physics-Informed Neural Networks, Aerospace Engineering, Deep Space Missions

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Key Features of the Merged References:

1. Deduplication: Removed redundant citations (e.g., Braun & Manning appeared in both papers).

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2. Consistency: Uniform formatting (e.g., Journal of Spacecraft and Rockets vs. Acta Astronautica).

3. Thematic Grouping: Organized by subfields (e.g., PINNs, EAs) for better readability.

4. Updated Citations: Added DOI/URLs where available (e.g., NASA reports).