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Solar Sail Interplanetary Transfer: Part I - Earth-Mars Rendezvous Using Evolutionary Neural Network

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Abstract Solar sail technology has been very attractive for an interplanetary mission exploration offering a green propulsion method of continuous thrust without any propellant consumption and potentially good cost advantages for long duration missions. Finding an optimal solution for the solar sail trajectory optimization problem remains challenging due to the natural behaviour of nonlinearity and complexity of low-thrust trajectories. This paper presents an alternative way of solving the optimal control problem via the neural network approximation method combined with an evolution algorithm for parameter tunings. This method allows a better convergence of a high dimensional optimization problem as it provides a wider exploration of the solution space. The proposed method is demonstrated via a coplanar Earth-Mars rendezvous with different sail performances and solver configurations

1. Introduction

Solar sail, a compelling alternative to conventional chemical and electric propulsion systems has emerged through continuous acceleration from the solar radiation pressure enabling extended mission durations, higher payload ratios and potentially unlimited delta-V capability [1], [2], [3], [4]. Through an innovative approach to deep space exploration, this technology reached a significant milestone with the launch of Japan's IKAROS mission in 2010 which successfully validated the solar sail concept for attitude controls and power generation [5], [6]. In 2019, planetary Society's Lightsail 2 has successfully achieved controlled maneuvers and Earth orbit raising [7]. Followed by the development of 2022 NASA's Near-Earth Asteroid Scout CubeSat with 86 m² solar sail for reconnaissance [8]. Recently, there's a development of 1633 m² Solar Cruiser where it demonstrated its scalable booms and membranes via ground testing [9]. Despite these advancements, optimizing solar sail trajectories remain a difficult challenge due to the highly nonlinear system dynamics, very strict constraints on thrust vector orientation and the huge computational demands required perform realistic long duration transfers with external gravitational disturbances. [3], [10], [11], [12]. As such, the research exploration of robust and computationally efficient optimal control steering for solar sail remains a key research focus to transform the technology for advanced deep space missions[12]. Primarily, low thrust trajectory optimization problems such as solar sails are categorized into two approaches which are indirect method and direct methods where the indirect method is essentially needs to satisfy the necessary optimality conditions based on Pontryagin's minimum principle where the process often faces struggles associated with boundary value problems and poor initial costate guesses which lead towards a local solution convergence [11], [12]. Pseudospectral collocation and multiple shooting of direct methods use the transformation of a nonlinear programming problem from a continuous optimal control problem, where although it offers larger convergence basins, the accuracy of the complex multi revolution trajectories accuracy may be compromised and the process may potentially require heavy computational resources [3], [11]. A recognized need to overcome the local optimality of traditional methods via global optimization algorithms exists as these algorithms can explore extensive search space in solar sail trajectory optimization problems [13]. Modern techniques such as artificial intelligence and machine learning techniques have increasingly emerged as effective approaches in recent years not only in the low thrust trajectory optimization but also across the wider field of spacecraft dynamics [11], [14], [15], [16]. These techniques address the constraints of dependence on precise initial guesses and the vulnerability to local optima entrapment by exhaustively expanding into multimodal parameter spaces which would converge into a robust global solution that is amenable to onboard implementation under gravitational perturbations[12], [15], [17]. The evolutionary algorithm is a global solver that uses population stochastic method that is based on natural evolutionary principles similar to Darwinian evolutionary mechanisms where a group of candidate solutions undergoes iterative survival of the fittest through mutation, selection and crossover [15], [16]. Neural network computational method is modelled on layers of artificial neurons that have the characteristics of a biological neural system that is able to generate approximation of spacecraft steering policies by learning nonlinear mapping functions from inputs to outputs such as spacecraft states and mission targets through adjustable parameters such as weights and activation functions [4], [11], [14]. By using the global search capability of an evolutionary algorithm, the adjustable neural network parameters can be trained and optimized to approximate the solar sail steering strategy more efficiently while maintaining the solution selection

under target mission constraints and guide the large search space to converge towards a well fitted solutions that can be evaluated using mission parameters. This paper will provide a simplified evolution neural network setup that is able to solve the solar sail coplanar interplanetary trajectory optimization problem. Set of solutions are demonstrated through different mission and algorithm parameters to showcase the effectiveness of the solver with a low computational power and training data points.

2. Simulation model

In this section, numerical procedures and constraint formulations used to simulate and optimize the ephemeris based heliocentric transfer trajectory for an interplanetary mission of a solar sail to Mars are outlined as an example.

2.1. Solar radiation pressure force model

The perfectly reflecting solar sail, modelled as an ideal sail experiences solar radiation pressure (SRP) that generates a force $\mathbf{F}_{SRP}$ acting on the sail's flat surface. This force is exerted through the momentum transfer of incident solar photons which is directed along the sail's normal vector $\mathbf{n}$. The orientation of the sail is described using two-unit vectors, the sail normal vector, $\mathbf{n}$ which is perpendicular to the sail plane and pointing away from the Sun and the sail tangential vector, $\mathbf{t}$ which is parallel to the sail plane. By taking the cross product of $\mathbf{n} \times \mathbf{t}$ a unit vector pointing "out of the page" is defined. This defines the sail cone angle β , sometimes called the pitch angle, which is illustrated in Fig. 1.

The solar radiation pressure at a solar distance r can be modelled as $P = P_0(r_0/r)^2$ [18]. The mean solar radiation pressure, P_0 is obtained by dividing solar radiation flux at solar distance r_0 , $S_0 = 1368 \text{ Wm}^{-2}$ by the speed of light, c . This leads to $P_0 = S_0/c = 4.563 \mu\text{Nm}^{-2}$ which provides the final expression of $P = 4.563(r_0/r)^2 \mu\text{Nm}^{-2}$.

Force magnitudes of incident and reflected solar radiation are $\mathbf{F}_i = PA_{\perp} \cos \beta$ and $\mathbf{F}_r = PA_{\perp} \cos \beta$ where P is solar radiation pressure, $A_{\perp}$ is the area of the sail that is perpendicular to the solar radiation where $A_{\perp} = A \cos \beta$ and β is the sail cone angle. Both $\mathbf{F}_i$ and $\mathbf{F}_r$ point in the direction of the sail normal vector, $\mathbf{n}$. The total solar radiation pressure force onto the solar sail is:

$$\mathbf{F}_{SRP} = \mathbf{F}_r + \mathbf{F}_i = 2PA \cos^2 \beta \mathbf{n} \quad (1)$$

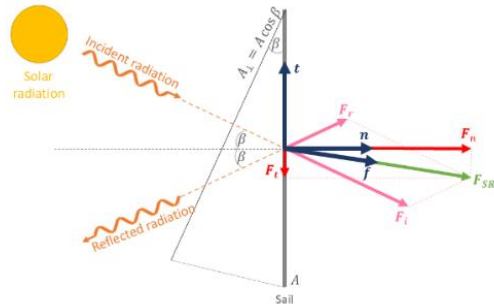


Fig. 1. Solar Radiation Pressure (SRP) acting on ideal sail.

2.2. Sail performance metric

Solar sail performance can be characterized by several key parameters that shape the mission capability. The primary metric used to quantify the sail performance is the characteristic acceleration, a_c which can be defined as the acceleration produced by SRP at Earth solar distance. An ideal sail with mass m will have characteristic acceleration of

$$a_c = \frac{2P_0 A}{m} \quad (2)$$

Lightness number λ can be defined as the ratio of characteristic acceleration to the solar gravitational acceleration at Earth solar distance, given as

$$\lambda = \frac{a_c(r_0/r)^2}{\mu/r^2} = \frac{a_c}{\mu/r_0^2} \quad (3)$$

2.3. Orbital dynamics formulation

The trajectory of a solar sail is affected by multiple perturbing forces in space. This includes the gravitational attraction, SRP forces, finite solar wind disk effects, and the fluctuations in solar radiation. Moreover, practical real sails can undergo some deformation via wrinkling and bending. The analysis conducted for this framework is based on the following assumptions

- i. The solar sail deformation effects on its surface are neglected.
- ii. The environment system is only affected solely by gravitational and SRP forces.
- iii. The Sun is modelled as a point mass and only as a celestial body that emits light as a source.
- iv. The solar sail attitude adjustment is presumed to occur instantaneously.

In this study, the sail motion is modeled in the heliocentric ecliptic reference frame. Newton's second law states that $\mathbf{F} = m\mathbf{a} = m\dot{\mathbf{r}}$ where $\mathbf{F}$ includes all forces acting on the sail. The gravitational force can be described as $\mathbf{F}_g = -\mu m/r^2$. By introducing the characteristic acceleration into the SRP force model, the SRP force becomes $\mathbf{F}_{SRP} = ma_c(r_0/r)^2 \cos^2 \beta \mathbf{n}$. Subsequently, the lightness number λ from Eq. 3 is substituted into the SRP force yields:

$$\mathbf{F}_{SRP} = \lambda \frac{\mu m}{r^2} \cos^2 \beta \mathbf{n} \quad (4)$$

The equations of motion for a solar sail are derived from the gravitational and SRP acceleration components [19], defined a

$$\ddot{\mathbf{r}} = \mathbf{a}_g + \mathbf{a}_{SRP} = \mathbf{F}_g/m + \mathbf{F}_{SRP}/m \quad (5)$$

Substituting $\mathbf{F}_{SRP}$ from Eq. 4 into Eq. 5 yields

$$\ddot{\mathbf{r}} = -\frac{\mu}{r^2} \mathbf{e}_r + \lambda \frac{\mu}{r^2} \cos^2 \beta \mathbf{n} \quad (6)$$

For the coplanar formulation, the motion of the spacecraft is restricted to the heliocentric ecliptic plane and described in polar coordinates using radial distance r and azimuth angle φ . The 2D equations of motion will only use a single control variable of cone angle β , making the spacecraft steering angle control vector defined to $\mathbf{U}_{2D} = [\beta]$. We can define the sail normal vector as $\mathbf{n} = \cos \beta \mathbf{e}_r + \sin \beta \mathbf{e}_t$ which gives the following coplanar equations of motion of an ideal solar sail:

$$\ddot{r} = r\dot{\varphi}^2 + \frac{\mu}{r^2} (\lambda \cos^3 \beta - 1) \quad (7a)$$

$$\ddot{\varphi} = -\frac{2\dot{r}\dot{\varphi}}{r} + \lambda \frac{\mu}{r^3} \cos^2 \beta \sin \beta \quad (7b)$$

The spacecraft coplanar state vector can be defined as $\mathbf{x}_{2D} = [r \ \varphi \ \dot{r} \ \dot{\varphi}]^T$ where $\dot{r} = v_r$ is the radial velocity and $\dot{\varphi} = \omega_\varphi$ is the azimuth angular velocity. Thus, the 2D equations of motion for a solar sail can be integrated using first-order system given by:

$$\dot{r} = v_r \quad (8a)$$

$$\dot{\varphi} = \omega_\varphi \quad (8b)$$

$$\dot{v}_r = r\omega_\varphi^2 + \frac{\mu}{r^2} (\lambda \cos^3 \beta - 1) \quad (8c)$$

$$\dot{\omega}_\varphi = -\frac{2v_r\omega_\varphi}{r} + \lambda \frac{\mu}{r^3} \cos^2 \beta \sin \beta \quad (8d)$$

3. Trajectory optimization problem

In this section, the optimization framework is established where the optimization problem is formulated with its constraints and performance index.

3.1. Performance index and constraints

The optimization problem can be defined as finding an optimal steering strategy that is generated from control vectors that was mapped with inputs that compromise of both spacecraft and environment states via neural network (NN). Evolution Algorithm (EA) will evaluate the complete trajectory to train the population to produce

better individuals that consists of the NN parameters and launch parameters to generates better rates of optimality of the solution. For a minimal time trajectory optimization, the flight time for a body rendezvous mission can be defined as

$$T = t_{flight} = t_f - t_0 \quad (9)$$

For a body rendezvous mission, the terminal states of the spacecraft must satisfy the constraints which can be expressed as the Euclidean relative distance between the spacecraft and the target planet Δr_f and the Euclidean relative velocity of the spacecraft and the target planet Δv_f which are given by

$$\Delta r_f = \|\mathbf{r}_T(t_f) - \mathbf{r}_{sc}(t_f)\| \quad (10)$$

$$\Delta v_f = \|\mathbf{v}_T(t_f) - \mathbf{v}_{sc}(t_f)\| \quad (11)$$

The terminal constraints Δr_f and Δv_f for coplanar formulation are evaluated using 2D position and velocity vectors derived from $\mathbf{x}_{2D} = [r \ \varphi \ v_r \ \omega_\varphi]^T$. The objective function for a solar sail body rendezvous transfer time optimization problem will consist of flight time T , final relative distance to target planet Δr_f and final relative velocity to target planet Δv_f [20] such that

$$J = J(T, \Delta r_f, \Delta v_f) \quad (12)$$

To guide the evolutionary process in the search space, the maximum allowable flight time can be defined as T_{max} where during the fitness evaluation, T will be in the domain of $0 < T \leq T_{max}$. This will ensure that a shorter flight time will produces a higher J_T . The primary fitness function with respect to time can be defined as

$$J_T = 1000 \cdot \left(1 - \frac{T}{T_{max}}\right) \quad (13)$$

Normalization of the terminal constraints in the fitness function can enhance the shape of the search space for EA. By introducing the maximum allowable distance error $\Delta r_{f,max}$ and maximum allowable velocity error $\Delta v_{f,max}$, the terminal constrains can be transformed into normalized sub-fitness measures of ΔR_f and ΔV_f which are defined as

$$\Delta R_f = \frac{\Delta r_f}{\Delta r_{f,max}} \quad \text{and} \quad \Delta V_f = \frac{\Delta v_f}{\Delta v_{f,max}} \quad (14)$$

The sub fitness terms can be used as constraint indicators, which are defined as $J_r = \log(1/\Delta R_f)$ and $J_v = \log(1/\Delta V_f)$. These functions performed as indicators for the inclusion of J_T within the total fitness function. The conditional time fitness, $J_T^* = J_T$ only when both conditions of $J_r \geq 0$ and $J_v \geq 0$ are satisfied. J_T^* will set to zero if the sub fitness assignment is not achieved during search process. This will lead the algorithm to improve terminal conditions first to achieve rendezvous and then it proceed to boost time fitness only when both constraints are achieved.

For the body rendezvous transfer time minimization, two fitness functions can be considered:

$$J_1(T, \Delta r_f, \Delta v_f) = J_T^* + \frac{1}{\sqrt{\Delta R_f^2 + \Delta V_f^2}} \quad (15)$$

$$J_2(T, \Delta r_f, \Delta v_f) = J_T^* + \frac{1}{\sqrt{2 \cdot \max(\Delta R_f, \Delta V_f)^2}} \quad (16)$$

The convergence behavior of the algorithm can be fundamentally based on the fitness criteria where J_1 evaluates both constraints as a whole while J_2 offers single improvement to a poorer constraint. The selection of the fitness criteria depends on the mission type. This modular technique is an advantage of evolution algorithm as it is able to adapt to different scenarios by reshaping the fitness selection. During the search process, J_2 can be considered first before J_1 , this helps the algorithm to approach to a feasible region before improving the constraints as a whole in J_1 .

3.2. Evolving neural network optimization method

In this study, the solar sail steering strategy is generated using an evolving neural network (ENN). The simpler coplanar body rendezvous generates the steering strategy using only the ENN, which is represented by the green and blue loops in figure below. In this framework, the genomes ξ which consist of the neural network (NN) parameter vectors π and the launch parameter vectors p are iteratively evolved by an evolution algorithm (EA) over successive generations to find a near global optimal trajectory. One candidate will carry a network steering strategy with its associated launch conditions. A set of genomes will be grouped as a population that will undergo iterative evolution process that includes initialization, evaluation, selection, crossover, mutation and reproduction. Each of the genomes will go through the neural network trajectory integrator to generate steering strategy to be later evaluated. Based on the parameter set encoded in each genome, the steering strategy is then generated by the NN through propagation over predefined segments. At each time step, the NN will be fed the spacecraft states x_{SC} and target states x_T which are used to generate the spacecraft control vector U . The NN will map these inputs to generate a vector of outputs which will be translated into steering vectors $U_{2D} = [\beta]$. The newly integrated spacecraft states will be fed back to the NN to generate the next steering vectors for the next segment. This process is repeated until the predefined integration segments completed or terminal constraints are satisfied. Once final constraints achieved, the integration loop ends and final states and flight time will be evaluated through defined fitness function $J = J(T, \Delta r_f, \Delta v_f)$. EA will evaluate the genomes and evolve them through the EA loop to produce much fitter individuals in the population enabling the search to converge towards individuals that able to perform best steering with respect to the mission requirements such as rendezvous. This process is repeated over successive generations until the predefined maximum number of generations or the specified convergence limit is reached. Final global search solution can be achieved in the coplanar case as the surviving best genome represents the final best solution.

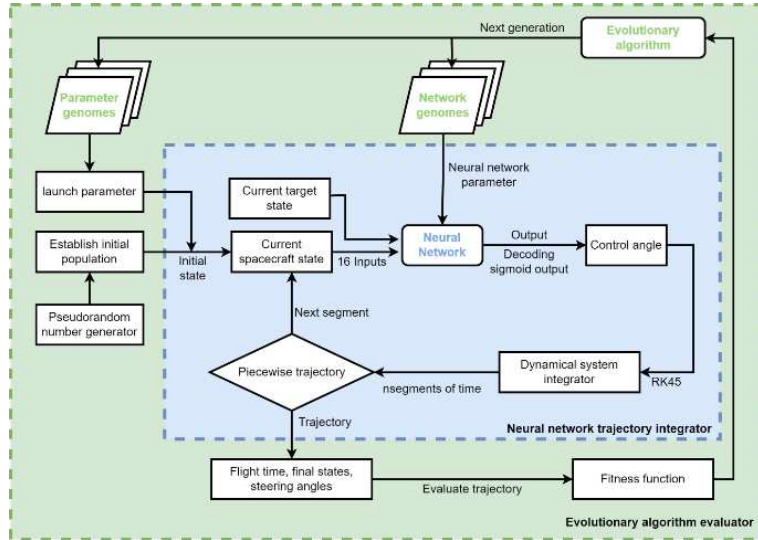


Fig. 2. Trajectory optimization using ENN

4. Coplanar mars rendezvous demonstrator

This section presents several coplanar Earth-Mars body rendezvous cases with different solar sail spacecraft performances and simulation parameters. The influence on transfer time will be examined based on different spacecraft performance of $a_c = 1.0, 0.5$ and 0.1 mm/s^2 . All transfers are under terminal constraints of $\Delta r \leq 500,000 \text{ km}$ and $\Delta v \leq 0.5 \text{ km/s}$. Multiple initial numbers of integration points are also presented for the $a_c = 0.1 \text{ mm/s}^2$ case.

4.1. Coplanar body rendezvous, Mars, $a_c = 1.0 \text{ mm/s}^2$

The results will present how ENN solves the body rendezvous problem. The spacecraft must not only be in the correct orbit but also ne in close proximity to the target body in terms of relative distance and velocity. This allows for analysis of practical mission applications. Steering strategy can be defined as $S: \{(x_{SC}, x_T)\} \mapsto u$. The fitness function will be $J = J(T, \Delta r_f, \Delta v_f)$ and the integration dynamics is set according to Eqs. 8a, 8b and 8c. Simulation parameters for the ENN can be set as follows:

Table 1

Coplanar Earth-Mars body rendezvous simulation parameters using ENN, $a_c = 1.0 \text{ mm/s}^2$.

Parameters	Values
Characteristic acceleration, a_c	1.0 mm/s^2
Maximum allowable flight time, T_{max}	450 days
Initial number of data points, N	25
Maximum relative distance, $\Delta r_{f,max}$	500,000 km
Maximum relative velocity, $\Delta v_{f,max}$	0.5 km/s
Target body	Mars
Launch date	10/07/2020

The 2D body rendezvous transfer to Mars trajectory and steering strategy are shown below:

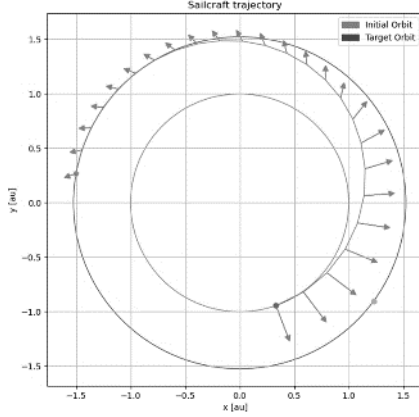


Fig. 3. Trajectory with acceleration vectors of coplanar Earth-Mars body rendezvous using ENN, $a_c = 1.0 \text{ mm/s}^2$

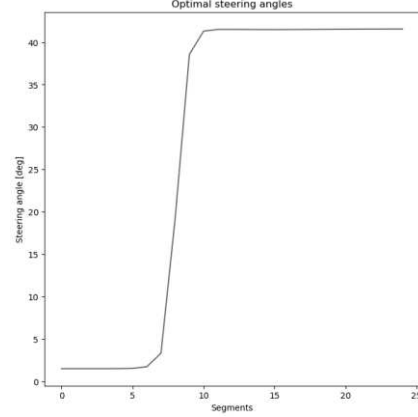


Fig. 4. Steering angles of coplanar Earth-Mars body rendezvous using ENN, $a_c = 1.0 \text{ mm/s}^2$

The 2D body rendezvous transfer to Mars performance can be summarized as follows:

Table 2

Coplanar Earth-Mars body rendezvous simulation results using ENN, $a_c = 1.0 \text{ mm/s}^2$

$a_c \text{ [mm/s}^2\text{]}$	$t_{flight} \text{ [days]}$	N_f	$\Delta r_f \text{ [km]}$	$\Delta v_f \text{ [km/s]}$
1.0	393.60	24	425,404.62	0.44

4.2. Coplanar body rendezvous, Mars, $a_c = 0.5 \text{ mm/s}^2$

Solving low thrust interplanetary problem can be challenging especially when sailcraft performance parameter increased. Solving an Earth-Mars rendezvous problem may be straightforward for $a_c = 1.0 \text{ mm/s}^2$ but lowering the characteristic acceleration requires more computation and a better learning strategy for the neural network as the solution space gets bigger and narrower to find an optimal solution. When solving Earth-Mars case with $a_c = 0.5 \text{ mm/s}^2$ and lower, it is discovered that the neural network learns better when given a range of transfer dates as different transfer date will give different initial spacecraft and target conditions. For some conditions, a solar sail might “catch” the target planet better when change in true anomaly, θ is at a certain value. The Mars orbits around the Sun with a period of $P_{sid} = 687$ days and the relative position between Earth-Mars repeats with a sidereal period of $P_{syd} = 780$ days. The variation of $\Delta\theta_i$ which is the angle initial angle difference between spacecraft and target along its sidereal period, whereby for an Earth-Mars transfer, the best launch condition for a very low thrust propulsion system is not necessarily achieved when $\Delta\theta_i$ is minimum like an impulse transfer but rather require a short buffer to let the solar sail to decelerate. In fact, we can vary the launch date parameter for ENN to generate genome that can choose the best $\Delta\theta$ with respect to minimize $J(T, \Delta r_f, \Delta v_f)$.

Table 3

Coplanar Earth-Mars body rendezvous simulation parameters using ENN, $a_c = 0.5 \text{ mm/s}^2$

Parameters	Values
Characteristic acceleration, a_c	0.5 mm/s^2
Maximum allowable flight time, T_{max}	600 days

Initial number of data points, N	100
Maximum relative distance, $\Delta r_{f,max}$	500,000 km
Maximum relative velocity, $\Delta v_{f,max}$	0.5 km/s
Target body	Mars
Launch date	[01/02/2020, 01/08/2020]

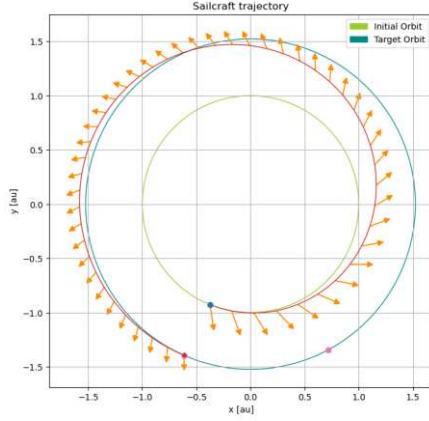


Fig. 5. Trajectory with acceleration vectors of coplanar Earth-Mars body rendezvous using ENN, $a_c = 0.5 \text{ mm/s}^2$

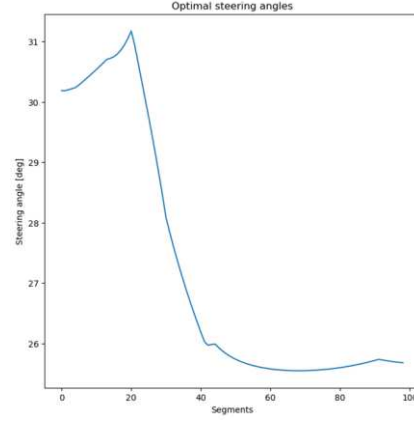


Fig. 6. Steering angles of coplanar Earth-Mars body rendezvous using ENN, $a_c = 0.5 \text{ mm/s}^2$

The 2D body rendezvous transfer to Mars performance can be summarized as follows:

Table 4

Coplanar Earth-Mars body rendezvous simulation results using ENN, $a_c = 0.5 \text{ mm/s}^2$

$a_c \text{ [mm/s}^2\text{]}$	$t_{flight} \text{ [days]}$	N_f	$\Delta r_f \text{ [km]}$	$\Delta v_f \text{ [km/s]}$	Launch date
0.5	588.00	98	461,216.90	0.45	31/05/20

4.3. Coplanar Body rendezvous, Mars, $a_c = 0.1 \text{ mm/s}^2$

In previous simulations, the solver can easily find a solution with minimal data points such as 25 for $a_c = 1.0 \text{ mm/s}^2$ and 100 for $a_c = 0.5 \text{ mm/s}^2$. However, as we simulate the body rendezvous problem for a high performance spacecraft such as $a_c = 0.1 \text{ mm/s}^2$, the low thrust trajectory optimization problem shows significant difficulty in finding optimal results. In addition of extremely narrowed and highly constrained solution to be found for a body rendezvous problem, the solver also requires to further minimize time with respect to $J = J(T, \Delta r_f, \Delta v_f)$. Selection of data points is very important as the solver works by as the sub-fitness constraints achieves, the integration will stop. If Δr_f and Δv_f skips between the data points, the solution missed the opportunity to learn that this set of near global solutions. We can vary the integration data points of Mars as follows:

Table 5

Coplanar Earth-Mars body rendezvous simulation parameters using ENN, $a_c = 0.1 \text{ mm/s}^2$

Parameters	Values
Characteristic acceleration, a_c	0.1 mm/s^2
Maximum allowable flight time, T_{max}	2500 days
Initial number of data points, N	[25,50,100,500,1000,1500] days
Maximum relative distance, $\Delta r_{f,max}$	500,000 km
Maximum relative velocity, $\Delta v_{f,max}$	0.5 km/s
Target body	Mars
Launch date range	[01/02/2020, 01/08/2020]

Table 6

Coplanar Earth-Mars body rendezvous simulation results with different numbers of initial integration data points using ENN, $a_c = 0.1 \text{ mm/s}^2$

Case	N	$t_{flight} \text{ [days]}$	N_f	$\Delta r_f \text{ [km]}$	$\Delta v_f \text{ [km/s]}$
1	25	2,400.00	24	245,930.77	0.40

2	50	2,450.00	49	186,656.39	0.45
3	100	2,424.24	97	286,955.59	0.41
4	500	2,414.83	483	353,264.46	0.45
5	1000	2,414.91	966	491,010.68	0.41
6	1500	2,436.62	1462	483,916.02	0.28

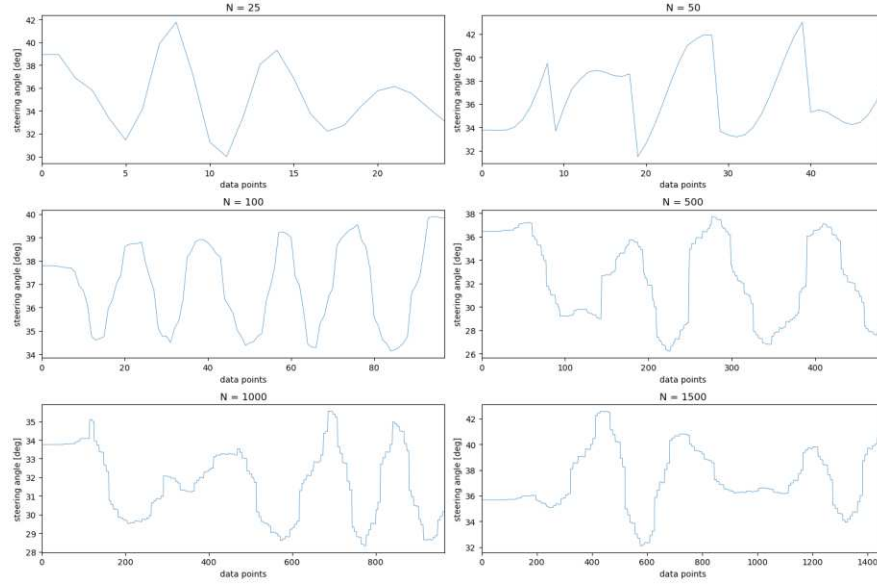


Fig. 7. Steering angles of coplanar Earth-Mars body rendezvous with different numbers of initial integration data points, $a_c = 0.1 \text{ mm/s}^2$

The influence of initial number of integration points, N on solution constraints accuracy becomes apparent when considering the results presented in Table 6. The cold start solutions with different N show trade-offs and variation in error distance relative to target planet, Δr_f and error velocity relative to target planet, Δv_f as the number of initial data points increases. The magnitude of these variations provides critical insight into optimizing computational resources for the solver setup. Starting with $N = 25$, Δr_f is 245,930 km and Δv_f is 0.40 km/s. As N increased to $N = 50$, a substantial improvement trend is observed where Δr_f improved to 186,656 km, representing an improvement of approximately 24% with minimal trade-off in Δv_f from 0.40 km/s to 0.45 km/s. These solutions show a natural global search behavior of the evolutionary algorithm where the algorithm may be able to find a better solution in one terminal constraint but this improvement may be accompanied by trade-offs from in the other constrains while remaining within the constrained solution space. When N is further increased to $N = 1000$ and $N = 1500$ points, no consistent overall improvement can be observed in constraint performance. The best Δv_f performance is obtained at $N = 1500$ with value of 0.28 km/s but burdened with distance trade-off Δr_f of 483,916 km. Although it offers the highest performance of Δv_f , the result shows that increasing N_i does not promise a better solution, where additional integration data points contribute less significantly to constrained performance compared to the initial increase from $N = 25$ to $N = 50$. Such improvement is bounded by a computational trade-off. Higher N values demand more computational resources. While accuracy of the constraints is valuable, it raises the question of efficiency. The ENN offers a unique solution where the gains from increasing N from 500 to 1500 must be weighed against the constraints trade-off and increased computational load, which may not always justify the incremental improvements in accuracy, depending on the objective of the simulation. Ultimately, this analysis highlights the importance of balancing data resolution with solution accuracy. Depending on the demand of the mission itself, for high-precision missions, the variations in constrained accuracy linked with number of integration points can be crucial. However, in scenarios where minor deviations can be tolerated, a lower resolution may offer a more unique solution without compromising mission requirement. ENN offers large solution space exploration where simulation parameters can be adjusted to fit the mission design. An example solution from trajectory case 4 with $N = 500$ can be shown in Fig. 8 and Fig. 9:

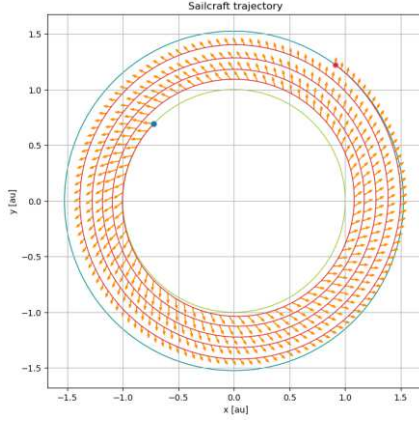


Fig. 8. Trajectory case 4 with acceleration vectors of coplanar Earth-Mars body rendezvous using ENN, $a_c = 0.1 \text{ mm/s}^2$

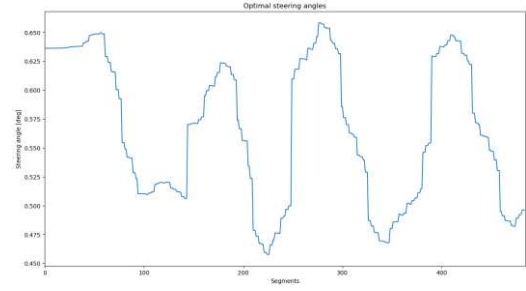


Fig. 9. Steering angles of trajectory case 4 for coplanar Earth-Mars body rendezvous using ENN, $a_c = 0.1 \text{ mm/s}^2$

The 2D body rendezvous transfer to Mars performance can be summarized as follows:

Table 7

Coplanar Earth-Mars body rendezvous trajectory case 4 simulation results using ENN, $a_c = 0.1 \text{ mm/s}^2$

$a_c \text{ [mm/s}^2\text{]}$	$t_{flight} \text{ [days]}$	N_f	$\Delta r_f \text{ [km]}$	$\Delta v_f \text{ [km/s]}$	Launch date
0.1	2,414.83	483	353,264.46	0.45	02/03/20

7. Conclusion

The primary aim of this paper is to assess the capability of a simplified evolution neural network solver and showcase the optimization performance by demonstrating interplanetary transfer trajectories under varying solar sail performance and simulation parameters. This computational framework is developed using an open-sourced python evolution neural network library as the baseline of the template and necessary neural network architecture, evolutionary algorithm evaluation, spacecraft and environmental dynamics which are integrated into the setup. The combined algorithm feeds states of current spacecraft and target states as inputs to the adaptive neural network model with trained parameters to approximate outputs of spacecraft control angles which will be evaluated as a whole trajectory to satisfy the target mission profile. The resulting solution evaluates 3 coplanar transfer cases using varied spacecraft performances. Converging under the same terminal constraints of 500,000 km relative distance to the target and 0.5 km/s relative velocity to the target, the sail achieved the transfer times of 365 days for 1.0 mm/s^2 , 588 days for 0.5 mm/s^2 and 2400 days for 0.1 mm/s^2 . Further testing with different initial numbers of integration points indicates that by increasing the number of initial integration points it can improve the final relative velocity to 0.28 km/s with a terminal relative distance of 483,916 days and an extended flight time of 2436 days. This trend shows the nature of the algorithm adaptive behaviour of the solver which may shift towards a certain constraint satisfaction rather than the overall solution. Increasing the number of initial integration points does not guarantee a better overall objective as one terminal constraint may be improved with deterioration in the other. This study developed a simplified evolution neural network solver that showcases coplanar Earth-Mars transfer trajectories under different solar sail performance and initial integration data point configuration. The modular framework can be extended to support other similar mission profiles in future studies such as transfers to inner planets and near-Earth asteroid missions, which would provide a broader assessment of the developed framework across different mission conditions.

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