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Solar Sail Interplanetary Transfer: Part II- Hybrid Layered Evolving Neural Network Based Global Optimization

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Abstract Solar Sailing is a sustainable approach to deep space travel which allows for a higher payload ratio due to the unique space vehicle performance which provides a renewable propulsion system powered by solar radiation pressure from the Sun. Formulating an optimal trajectory with a minimal transfer time while maintaining mission constraints presents significant analytical and computational burdens as it requires solving a complex optimal control theory problem. Conventional methods for solving this optimization problem often led to significant challenges as they generally rely on an initial guess that must be close to the global optimum. Instead, this study develops a method of using an evolving neural network optimization technique that combines artificial neural network (ANN) and evolutionary algorithm (EA) for finding an optimal sailcraft steering. This method enables a broader search domain than the conventional optimal control techniques, resulting trajectories that are nearer to the global optima solutions. In addition, this study showcases the capability of solar sail in performing an example interplanetary trajectory transfer up to 7% – 18.956 % improvement in flight time compared with established and published benchmarks.

1. Introduction

Increased research attention has been given to solar sailing as recent advancements through interplanetary missions demonstrated its capability to perform as a propellant free propulsion driven solely by the solar radiation pressure [1], [2], [3]. The promising characteristics of solar sail which include the delivery of large velocity increment and flexible mission profiles provide a viable and sustainable alternative for a high energy demand mission without reliance on complex gravity assist manoeuvres [2], [4], [5]. The idea of solar sailing still remains challenging due to the complexity often trajectory optimization problems that often involve high nonlinearity, nonconvexity and sensitivity to selection of initial guesses or costates. This problem formulation often suffers from poor convergence and makes the solutions difficult to obtain [2], [5], [6], [7], [8]. Traditional trajectory optimization approaches suffer from severe computational and operational limitations that restrict their practical applicability [2], [5], [6], [7]. For instance, the indirect method applies Pontryagin's minimum principle that requires solving the two-point boundary value problem that is quite complex to solve as the convergence is very sensitive to its initial guesses [6], [8], [9]. This problem is particularly challenging in multi-revolution transfers of a low-thrust propulsion system like a solar sail [2], [4]. In comparison, the direct method can be described as a much more robust conventional approach that transforms the optimal control problems into a large nonlinear programming problem. Nevertheless, it is computationally intensive and lacks assurance of a global solution [5], [6]. To overcome these fundamental limitations, adaptation of machine learning and artificial intelligence in solving trajectory optimization problems offers a promising alternative framework [9], [10]. Machine learning techniques such as artificial neural networks presents instantaneous dynamical predictions based on extensively learned datasets that are suitable to be extended for online implementation [5], [8], [9]. While the approximation capabilities of a neural network is a powerful tool, pairing them with an evolutionary algorithm will improve the solver ability with the global search functionality [5], [6]. While the globally searched neural network architecture via an evolution algorithm assisted the learning process to solve the optimal control problem, the broad search space that typically leads to suboptimal solutions is traded off with a significant computational cost which is a common limitation of evolutionary metaheuristic approaches. This motivates the research exploration of alternative configurations involving structural modification within the evolution neural network approaches that enable easier convergence to a unique solution that potentially can be expanded modularly to similar optimization problems.

2. 3D Simulation model

This section presents the numerical formulations of the simulation model that includes the resulting forces, sail orientation and the orbital dynamics used in the interplanetary transfer demonstration.

2.1. Solar sail force and orientation model

The force experienced by an ideal sail is caused by the solar radiation pressure (SRP) which generates $\mathbf{F}_{SRP}$ on the perfectly reflecting solar sail surface. At a solar distance r , the solar radiation pressure can be expressed as $P = P_0(r_0/r)^2$ [11]. At the reference of solar distance $r_0 = 1 AU$, the solar radiation flux $S_0 = 1368 \text{ Wm}^{-2}$ and $P_0 = S_0/c = 4.563 \mu\text{Nm}^{-2}$ lead to $P = 4.563(r_0/r)^2 \mu\text{Nm}^{-2}$. $\mathbf{F}_{SRP}$ acts along the sail normal vector $\mathbf{n}$ which is perpendicular to the sail plane. Both the sail normal vector $\mathbf{n}$ and the sail tangential vector $\mathbf{t}$ together define the sail cone angle β and clock angle α [12] as illustrated in Fig. 1. The solar radiation pressure force acting on the solar sail is defined as:

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

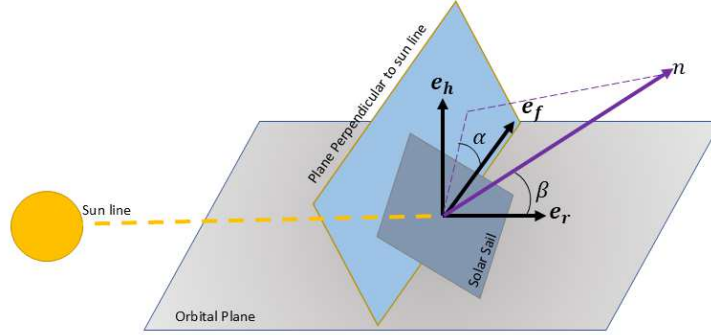


Fig. 1. Definition of cone angle β and clock angle α .

Characteristic acceleration a_c can be defined as $a_c = 2P_0A/m$ and the lightness number λ is defined as $\lambda = a_c/(\mu/r_0^2)$.

2.2. 3D orbital dynamics and steering

The 3D solar sail interplanetary trajectory analysis conducted for this framework is based on the following assumptions:

- i. The solar sail is modelled as an ideal sail with deformation neglected.
- ii. The solar sail spacecraft is only affected by gravitational attraction and SRP forces.
- iii. The Sun is modelled as a point mass and as the sole source of solar radiation.
- iv. The attitude changes of the spacecraft are assumed to occur instantaneously.

In this study, the sail motion is modeled as heliocentric motion in the heliocentric ecliptic spherical reference frame. The equations of motion for a solar sail are derived from the gravitational and SRP acceleration components [4], defined as

$$\ddot{\mathbf{r}} = \mathbf{a}_g + \mathbf{a}_{SRP} = \mathbf{F}_g/m + \mathbf{F}_{SRP}/m \quad (2)$$

Substituting $\mathbf{F}_{SRP}$ into Eq. 2 yields

$$\ddot{\mathbf{r}} = -\frac{\mu}{r^2} \mathbf{e}_r + \lambda \frac{\mu}{r^2} \cos^2 \beta \mathbf{n} \quad (3)$$

Resolving the equations along the unit vectors of the heliocentric ecliptic spherical reference frame leads to the following 3D equations of motion that use 2 control variables, the cone angle β and clock angle α which form the steering vector $\mathbf{U}_{3D} = [\alpha, \beta]^T$, given by:

$$\ddot{r} = r\dot{\theta}^2 + r\dot{\theta}^2 \cos^2(\theta) + \lambda \frac{\mu}{r^2} u_1 - \frac{\mu}{r^2}. \quad (4a)$$

$$\ddot{\phi} = -2\frac{\dot{r}}{r}\dot{\phi} + 2\dot{\phi}\dot{\theta} \tan(\theta) + \lambda \frac{\mu}{r^2} \frac{1}{r \cos(\theta)} u_2, \quad (4b)$$

$$\ddot{\theta} = -2\frac{\dot{r}}{r}\dot{\theta} - 2\dot{\phi}^2 \sin(\theta) \cos(\theta) + \lambda \frac{\mu}{r^2} \frac{1}{r} u_3. \quad (4c)$$

The state vector can be defined as $\mathbf{x}_{3D} = [r \ \phi \ \theta \ \dot{r} \ \dot{\phi} \ \dot{\theta}]^T$. The dimensionless control functions u_1, u_2

and u_3 defined in terms of the steering angles α and β with the rotational angle $\zeta = \text{atan2}(\dot{\theta}, \phi \cos \theta)$ are given as

$$\begin{bmatrix} u_1(\beta) \\ u_2(\alpha + \zeta, \beta) \\ u_3(\alpha + \zeta, \beta) \end{bmatrix} = \begin{bmatrix} \cos^3(\beta) \\ \cos(\alpha + \zeta) \sin(\beta) \cos^2(\beta) \\ \sin(\alpha + \zeta) \sin(\beta) \cos^2(\beta) \end{bmatrix} \quad (5)$$

3. Trajectory optimization problem

This section presents the optimization method used in this study. The section will provide the performance index and constraints and gives an overview of the hybrid optimization algorithm used.

3.1. Performance Index and 3D terminal constraints

In this study, the optimization problem comprises of finding an optimal trajectory via a steering strategy that produced by the outputs of the neural network (NN) which is mapped from the inputs of spacecraft and environment states. The evolution algorithm (EA) will evaluate the final completed trajectory to improve the NN parameters to produce a better solution. We can evaluate the trajectory with the flight time of the transfer which is given as

$$T = t_{flight} = t_f - t_0 \quad (6)$$

To perform a body rendezvous, a set of terminal constraints needs to be defined. The final states of the spacecraft need to satisfy the final relative distance relative to target planet Δr_f and final relative velocity relative to the target planet Δv_f . These constraints are expressed as

$$\Delta r_f = \|\mathbf{r}_T(t_f) - \mathbf{r}_{sc}(t_f)\| \quad (7)$$

$$\Delta v_f = \|\mathbf{v}_T(t_f) - \mathbf{v}_{sc}(t_f)\| \quad (8)$$

In the 3D formulation, the constraints are evaluated using the position and velocity vectors derived from the 3D state vector given by

$$\mathbf{x}_{3D} = [r \quad \phi \quad \theta \quad \dot{r} \quad \dot{\phi} \quad \dot{\theta}]^T \quad (9)$$

The objective function for a time minimum solar sail body rendezvous optimization problem will consist of the time and the terminal constraints [13]. This objective function can be defined as

$$J = J(T, \Delta r_f, \Delta v_f) \quad (10)$$

The maximum allowable flight time can be defined as T_{max} where during the fitness evaluation, the flight time T will be in the domain of $0 < T \leq T_{max}$. A shorter time will produce a higher fitness according to the expression:

$$J_T = 1000 \cdot \left(1 - \frac{T}{T_{max}}\right) \quad (11)$$

Normalization of the terminal constraints can help in the search process of the EA. The maximum allowable distance error $\Delta r_{f,max}$ and maximum allowable velocity error $\Delta v_{f,max}$ can be introduced to give the normalized terminal constraints as

$$\Delta R_f = \frac{\Delta r_f}{\Delta r_{f,max}} \quad \text{and} \quad \Delta V_f = \frac{\Delta v_f}{\Delta v_{f,max}} \quad (12)$$

The constraint indicators are defined as $J_r = \log(1/\Delta R_f)$ and $J_v = \log(1/\Delta V_f)$. These indicators are used to determine the inclusion of the conditional time fitness J_T^* which is defined as

$$J_T^* = \begin{cases} J_T, & J_r \geq 0 \text{ and } J_v \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

Two fitness functions can be considered for the body rendezvous transfer time minimization in this study:

$$J_1(T, \Delta r_f, \Delta v_f) = J_T^* + \frac{1}{\sqrt{\Delta R_f^2 + \Delta V_f^2}} \quad (14)$$

$$J_2(T, \Delta r_f, \Delta v_f) = J_T^* + \frac{1}{\sqrt{2 \cdot \max(\Delta R_f, \Delta V_f)^2}} \quad (15)$$

The selection of the fitness criteria depends on the mission type and the search stage. This modular technique is an advantage for the evolution algorithm as it is able to adapt to different scenarios. J_1 offers evaluation as a whole while J_2 improves one constraint at a time.

3.2 Neural network as a steering strategy generator

Using a Neural Network (NN) framework, the 3D solvers employ a feed-forward Artificial Neural Network (ANN) to produce a steering strategy. A parameterized network function can be established to define the ANN network structure as follows:

$$N_\pi: \mathcal{X} \subseteq R^{n_i} \mapsto \mathcal{Y} \subseteq (0,1)^{n_o} \quad (16)$$

The function N_π represents the ANN which maps an input vector from the input space $\mathcal{X}$ to an output vector in the output space $\mathcal{Y}$ of the system where n_i and n_o represents the numbers of input and output neurons which set the dimensions of $\mathcal{X}$ and $\mathcal{Y}$. The ANN for a given network structure behaves depending on the neural network parameters π which includes the weights of the neurons and the biases which define the network function.

Conventional ANN is trained by comparing the generated output with the desired output. By calculating the difference, the network can be improved based on the resulting error. By tuning the values of the neural network parameters π , the goal of the framework is to minimize the output error and gain the best performing network function, which in this case leads to a better steering strategy.

However, when solving optimal control problems, the exact steering output is not known, making this training method not practical as it requires a known output. This problem can be formulated as a reinforcement learning (RL) approach where an action is taken by a learning agent through interaction with the environment in different situations. This can be considered as delayed reinforcement learning problem since the steering strategy can be only be evaluated after a complete trajectory is obtained, in this case via the fitness calculated from the final states. In this setup, ANN represents the learning agent while the current situation is represented the spacecraft states $\mathbf{x}_{SC}$ and target states $\mathbf{x}_T$. The action is the spacecraft control vector $\mathbf{U}$ which defines the steering strategy S as:

$$S: \{(\mathbf{x}_{SC}, \mathbf{x}_T)\} \mapsto \mathbf{U} \quad (17)$$

At each time step, a neuron output with a value ranging from 0 to 1 is generated, which can be translated into control angles. The modular design of the framework depends on the mission requirements. When considering a simple orbit transfer, the NN may only requires inputs from the spacecraft states $\mathbf{x}_{SC}$. For a body rendezvous that is applied in this study, both the 2D and 3D case require the spacecraft states $\mathbf{x}_{SC}$ and target states $\mathbf{x}_T$ to generate the control vectors. For the coplanar case, the ANN will generate single control vector $\mathbf{U}_{2D} = [\beta]$ while for the 3D case, the ANN will generate a control vector of $\mathbf{U}_{3D} = [\alpha, \beta]^T$. The number of inputs and outputs depends on the mission requirements, as feeding the NN with relevant state inputs would help in generate better steering outputs. For a 3D rendezvous it can be more computationally demanding as it requires 24 input neurons, $n_i = 24$ with $n_o = 2$. The inputs can be derived from the current spacecraft $\mathbf{x}_{SC}$ and target states $\mathbf{x}_T$ expressed in different coordinate systems. For coplanar rendezvous, the number of inputs can be lower with $n_i = 13$ and $n_o = 1$ because some of the target state variables do not change in a circular target orbit.

The best network parameters can be found via Evolutionary Algorithm (EA) where the ANN parameter π is encoded into a genome ξ which represents the original network function N_π . One advantage of using an EA is the adaptability, whereby the genomes can be modified to include additional variable to support the search process. Additional launch parameter $\mathbf{p}$ can be encoded in the genome, resulting it to $\xi = (\pi, \mathbf{p})$. The launch parameter $\mathbf{p}$ includes launch conditions and launch date that allow the candidate genome to represent a network steering strategy with its own associated initial conditions which together generate a candidate trajectory.

3.3. Hybrid evolving neural network optimization framework

In this study, the solar sail steering strategy is generated using an evolving neural network (ENN) paired with a local optimizer. The 3D steering strategy is generated using both blue and green block in the ENN loop but is further refined using a local optimizer represented by the orange loop. The neural network (NN) parameter vectors π and the launch parameter vectors $\mathbf{p}$ will produce a single genome ξ which will generate a near global optimal trajectory through successive evolution generations using an evolution algorithm (EA). A genome would consist of a set of network steering strategies paired with their launch conditions. A group of genomes will form a population that undergoes evolutionary processes such as initialization, evaluation, selection, crossover, mutation and reproduction, and will go through the neural network trajectory integrator each time to generate the steering angles before being evaluated. The spacecraft control vector $\mathbf{U}$ will be generated by the NN through propagation over predefined segments by feeding the spacecraft states $\mathbf{x}_{SC}$ and target states $\mathbf{x}_T$ into the NN based on the

parameters encoded in each of the individual genome. The 3D steering vector that is generated by the NN will be in the form of $\mathbf{U}_{3D} = [\alpha, \beta]^T$. The next steering vector for the next segment will be generated after the integrated spacecraft states are looped back to the NN and this process will be repeated until the terminal constraints are satisfied or the number of integration data points is reached. A single solution will be evaluated by the EA using the fitness function $J = J(T, \Delta r_f, \Delta v_f)$ once the integration process ends. This process will be iteratively repeated to evolve the genome ξ to become a better fit individuals in the population which leads to an individual that gives the best solution so far. This convergence process is performed under maximum number of generations or convergence limits. The surviving genome represents the best final solution before refinement in the next stage. For the 3D formulation, the best genome obtained from the ENN will be used to initialize a local optimizer, in this case the Covariance Matrix Adaptation Evolution Strategy (CMA-ES). CMA-ES establishes the best genome as an initial mean with an initial step size to perform a local search around the best solution. This local solver updates the covariance matrix and step size over successive iterations using the same fitness criteria. This refinement allows improvement in both terminal constraints and main objective for the more complex 3D body rendezvous which enables the algorithm to converge to a much refined and fitter solution.

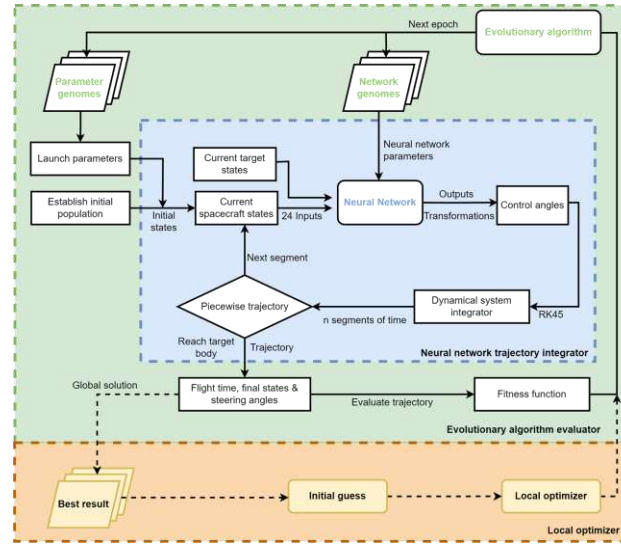


Fig. 2. Hybrid evolution neural network algorithm flow chart.

5. 3D Earth-Mars rendezvous demonstration

The proposed hybrid evolution neural network solver capability is demonstrated in this section through an interplanetary body rendezvous mission using a solar sail. The problem is formulated as a minimum-time Mars body rendezvous with a specified solar sail performance with terminal target constraints. The simulation parameters are defined in Table 1:

Table 1

3D Earth-Mars body rendezvous simulation parameters using hybrid ENN, $a_c = 1.0 \text{ mm/s}^2$

Parameter	Values
Target body	Mars
Characteristic acceleration, a_c	1.0 mm/s^2
Maximum allowable flight time, T_{max}	450 days
Initial number of data points, N	450
Maximum relative distance to target planet, $\Delta r_{f,max}$	500,000 km
Maximum relative velocity to target planet, $\Delta v_{f,max}$	0.5 km/s
Launch date range	01/07/2020 - 01/08/2020

Based on the simulation parameters summarized in Table 1, the proposed hybrid solver is applied to solve the minimum-time rendezvous problem of the solar sail to Mars. The optimization evolves both launch parameters and neural network parameters while maintaining the specified distance and velocity constraints.

Table 2

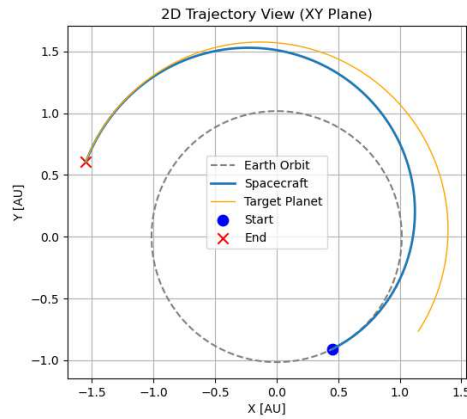
3D Earth-Mars body rendezvous simulation results using hybrid ENN, $a_c = 1.0 \text{ mm/s}^2$

Parameter	Value
Flight time, t_{flight}	364.70 days
Relative distance to target planet, Δr_f	476,002.31 km
Relative velocity to target planet, Δv_f	0.5 km/s
Launch date	19/07/2020

The global solution achieves a minimum transfer time of 364.7 days, representing a reduction from the initial integration time of 450 days and signifying the effective convergence of the evolutionary search toward an optimal solution. This result highlights the capability of the proposed framework to simultaneously optimize both the neural network parameters and launch parameters through learned steering strategies.

The environment is defined using DE405 NASA SPICE ephemeris data and the evolutionary process led to an optimal launch date of 19/07/2020. Initially, prior to the local refinement loop, the obtained solution yields terminal errors of Δr_f and Δv_f of 183,956.18 km and 0.5 km/s respectively. As the refinement algorithm highly prioritizes the primary optimization goal J_T , the solver achieves an earlier arrival transfer time of 364.7 days with a compensation in the terminal distance to $\Delta r_f = 476,002.31 \text{ km}$. This behavior is a normal characteristic of layered evolutionary optimization frameworks where the search prioritizes the primary objective once the secondary objectives are satisfied. However, the transfer remains a valid Mars body rendezvous as the final relative distance to target is still within the planet's sphere of influence and the terminal relative velocity also remains low.

A benchmark reference for a minimum transfer time for Mars rendezvous has been established by [14] who approximated the minimum transfer time for a 1.0 mm/s^2 solar sail to Mars to be roughly 400 *days* with a maximum transfer of 450 days. Subsequent studies have demonstrated flight times with their respective solvers and mission requirements with 407.7 days reported by [15], [16]. A coplanar transfer of roughly 429 days was also demonstrated for different cases which was transformed to a 395.9 days 3D Mars rendezvous by [17]. This indicates that the demonstrated transfer performed an 8.825 % improvement from the lower bound approximation and an 18.956 % improvement from the upper bound estimation by [14]. When compared with subsequent studies, the results show a 7 % – 15 % improvement in terms of flight time.

Fig. 3. Ecliptic projection of 3D Earth-Mars body rendezvous trajectory using hybrid ENN, $a_c = 1.0 \text{ mm/s}^2$

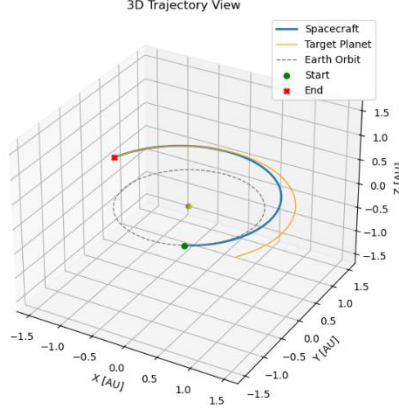


Fig. 4. 3D view of Earth-Mars body rendezvous trajectory using hybrid ENN, $a_c = 1.0 \text{ mm/s}^2$

The optimized solar sail trajectory is illustrated in Fig. 3 and Fig. 4 in both 2D and 3D representations. Through the learned steering strategies, the neural network generated solution yields orbital phasing behavior in which the spacecraft reaches the vicinity of the Mars orbit earlier in the transfer and continuously aligns with the target planet to achieve close proximity for the terminal conditions. This behavior is guided by the sub fitness J_r and J_v , resulting in a smooth low-thrust continuous body rendezvous. For a fast sail with performance of $a_c = 1.0 \text{ mm/s}^2$, the solution yields to a single revolution transfer to Mars. The corresponding steering strategies mapped from the neural network to steer the solar sail are shown in Fig. 5 and Fig. 6 where the control histories exhibit smooth and bounded steering behaviors within the dynamical constraints of a solar sail.

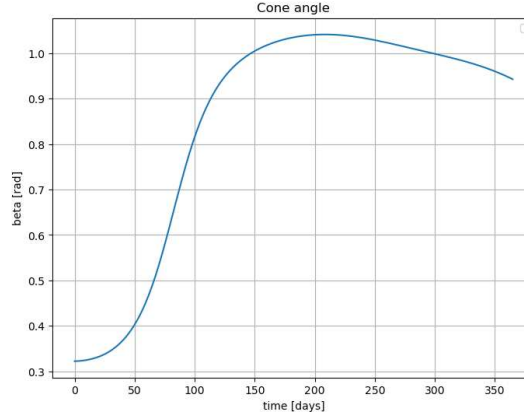


Fig. 5. Sail cone angle of 3D Earth-Mars body rendezvous trajectory using hybrid ENN, $a_c = 1.0 \text{ mm/s}^2$.

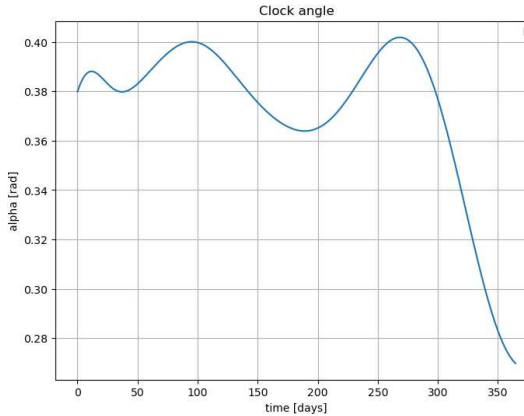


Fig. 6. Sail clock angle of 3D Earth-Mars body rendezvous trajectory using hybrid ENN, $a_c = 1.0 \text{ mm/s}^2$.

The results demonstrate that a solar sail is able to perform a Mars body rendezvous mission using the steering strategy generated by the hybrid evolution neural network solver while maintaining the relative distance and velocity to the target planet within permissible ranges. To further assess the potential practicality of the solar sail

mission, the relationship between the sail performance parameters such as sail size and payload may be examined.

Fig. 7 shows the relationship between characteristic acceleration, sail size and payload mass for a specific sailcraft loading. A solar sail with performance of $a_c = 1.0 \text{ mm/s}^2$ is considered a high performance or fast sail. Theoretically, spacecraft payload masses ranges of 5 kg – 50 kg may be considered for a mission demonstration consideration relative to the vehicle performance.

From Fig. 7, 3 sail size configurations can be identified to design a fast sail to Mars. For the sail side length below 100 m, the allowable theoretical payload mass is limited to around 10 kg. For the sail sizes between 100 m – 200 m, payload masses of 10 kg – 50 kg may be considered. For payload mass greater than 50 kg, a 200 m sail side length requirement is needed. Considering near-term technology perspectives, a solar sail with a side length of 100 m, appears to be realistic which can be translated into roughly 10 kg payload mass which provides the context for Mars rendezvous demonstrations considered in this study.

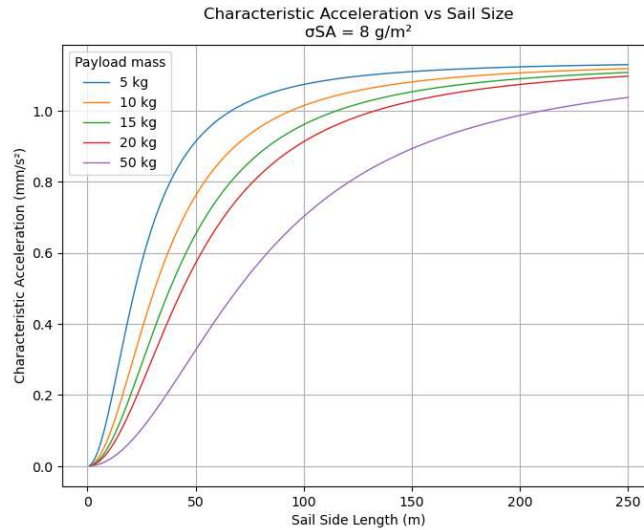


Fig. 7. Sail size relationship

7. Conclusion

This study investigates a minimum-time solar sail body rendezvous problem using a hybrid evolution neural network framework. The proposed approach generates optimal steering strategies via trained neural network and launch parameters, while satisfying the terminal body rendezvous constraints. Further theoretical analysis provides a recommendation for solar sail design requirements based on the optimal solution within this study predefined performance parameters. The proposed algorithm demonstration achieves an interplanetary mission that yields a solar sail with a performance $a_c = 1.0 \text{ mm/s}^2$ performing a body rendezvous in 364.7 days with the final distance relative to the target planet of $\Delta r_f = 476,002.31 \text{ km}$ which lies within the sphere of influence and low velocity relative to the target planet of $\Delta v_f = 0.5 \text{ km/s}$. This demonstration achieves a transfer time that represents around 7 % – 18.956 % improvement compared to existing published benchmarks. In parallel with a demonstration of the algorithm to find a time minimum solution, a theoretical solar sail design requirement is considered based on the obtained performance. For a fast sail, a realistic payload for the vehicle can be considered to be approximately 5 kg to 10 kg can be obtained if the design is limited to 100 m side length. This study demonstrates the capability of the proposed hybrid setup to solve a minimum time mission design problem, generates a solar sail interplanetary trajectory under constraints and presents a theoretical mission profile based on the solution. Further refinement and variations of local optimizers can be tested to improve performance, explore different solar sail mission profiles or even modularized into sets of similar low-thrust trajectory optimization problems.

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