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Autonomous multi-target rendezvous mission planning using artificial intelligence

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Abstract
Active debris removal has been a hot topic of the space security. Multi-target rendezvous mission is an efficient and economical way for space debris removal. An autonomous mission planning approach based on the back propagation neural network and the genetic algorithm is proposed in this paper. A trained neural network is utilized to obtain the approximations of the optimal trajectory parameters. The rendezvous sequence and accurate transfer trajectory is solved using the genetic algorithm. The simulation results show that the proposed method exhibits favourable in the efficiency and precision.

1. Introduction

The large and growing number of space debris seriously threatens the safety of spacecraft, and has attracted widespread attention. This threat is even worse for some special orbits, such as Sun-synchronous orbit (SSO) that is a common type of orbit for remote sensing satellites. Thus, Active debris removal (ADR) has become a hot topic of space technology in recent years [1-5]. Multi-target rendezvous mission is widely recognized because of the high efficient and economical. Many scholars and researchers have conducted research on related issues [6-8]. The mission planning is one of the focus, which involves the selection and ordering of targets, as well as the transfer trajectory optimization.

Multi-rendezvous mission planning is a considerable challenge to trajectory design and optimization. It is a variant of the well known traveling salesman problem (TSP) with a time-varying cost function, which is an typical example of the NP-hard problem in combinatorial optimization. A large number of enumeration algorithm and their improvements are unilized to solve this combinatorial optimization problem. In previous literatures, Multi-rendezvous mission planning is generally partitioned into two subproblems, the target sequence optimization and the transfer trajectory optimization, to reduce optimization difficulty and complexity. Cerf used a branch and bound algorithm that is an explicit enumeration of all possible sequences to obtain the rendezvous sequence [9]. Although some simplification strategies are also defined to limit the search space, it is still unacceptable to the increase of calculation burden with the candidate growth. The branch and bound algorithm is suitable for sequence issues and can obtain the global optimal solution at the cost of calculation time. Therefore, to improve the algorithm efficiency, various pruning techniques are extensive applied in the famous Global Trajectory Optimization Competition (GTOC) and China Trajectory Optimization Competition (CTOC) [10-14]. Zhao adopted the branch and bound algorithm with greedy strategy to search the debris sequence and won the championship of the CTOC-8 [11]. Pruning with local performance index has extremely applicability to the sequence search problems. JPL constructed a local performance index function based on flight time, propellant consumption and weighting factors to prune the poor branches in GTOC-5, which help them won the competition [13]. In addition, pruning approach based parameter constraints is also a general strategy in branch and bound algorithm. Tsinghua university and national university of defense technology used this approach to solve the trajectory of visiting a maximum of asteroids in GTOC-5 [12, 14].

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The local performance index and parameter constraints can effectively reduce the solution space and improve computational efficiency. However, These formulas and parameters depend on professional experience and intuition.
Heuristic algorithm is a type of optimization method that has outstanding global optimization capabilities. It has been explored as an alternative to solve combinatorial problems in multi-rendezvous mission analysis. Compared with the traversal search of the branch and bound, Heuristic utilize stochastic individual and population evolutionary theory of natural selection to perform optimization operations, which avoids the computational burden trap resulting from the problem scale. Izzo designed chromosomes with encoding asteroid sequences and used GA for the identification of good asteroid sequences in GTOC-5 [15]. Ant Colony Optimization (ACO) is another heuristic approach that is applied to solve the multi-rendezvous problem. Stuart incorporated ACO and multi-agent coordination method and successfully obtained a debris mitigation tour scheme [16].
It is a very challenging works to directly solve the multi-rendezvous trajectory that is an complex combinatorial optimization problem. In the existing methods, both traversal methods and Heuristic algorithms, An encounter sequence is first obtained, and then the exact trajectory is solved [10]. Because of the coupling of sequence and trajectory optimization, a simplified approximation model is usually employed to estimate the transfer trajectory during the sequence optimization to improve computational efficiency. In traditional mathods, the approximation models are generally built based two-body dynamics, lambert solutions, or empirical formulas. The applicability and accuracy of the obtained models are unreliable when dealing with problems in different situations.
In this paper, An autonomous multi-rendezvous mission planning approach using back propagation (BP) neural network and GA is proposed to perform the ADR mission scheme. Firstly, a trained BP neural network is utilized to substitute the traditional approximation model. The computing efficiency of network is not affected by the dynamics and accuracy requirements. Furturemore, this method can be reused in a variety of situations as long as the trained network is obtained. Then, GA is employed to obtain the optiminal rendezvous sequence and transfer trajectory. Finally, a ADR mission is performed to verify the feasibility of the proposed method.
The rest of this paper is organized as follows: Section 2 intuoduces the multi-rendezvous problem for the ADR of sun-synchronous orbit. In Section 3, the methodology of optimal multi-rendezvous trajectory design for ADR mission is formulated. A three-impulse transfer strategy and the structure of BP neural network is brief. The simulation and results are shown and analysed in Section 4, and the conclusions are summarized in Section 5.

2. Problem description

Sun-synchronous orbit (SSO) is a significant space resource, which is the ideal orbit for remote sensing satellites. Debris from scrapped remote sensing satellites has long been concentrated on nearly SSO, and seriously threatens the safety of spacecraft running on SSO. Therefore, a problem of ADR mission planning on typical SSOs is considered in this paper. The range of orbital elements of the typical SSOs is shown in Table 1. The orbits of debris to remove are quasi-circular.

Table 1: The range of orbital elements of the typical SSOs

Elements	**Range**
Altitude /km	600 ~ 1000
Eccentricity	0 ~ 0.01
Inclination /deg	96 ~ 100

During the ADR mission, the mission spacecraft is launched to the initial orbit that is near the target debris area, and the subsequent work is done autonomously by the spacecraft. In this paper, it is the process of debris rendezvous rather than the clearing techniques is focused. Hence, it is assumed that the debris is removed as the spacecraft rendezvous them. The spacecraft with an autonomous mission planning system will select target debris from a number of candidates and plan rendezvous sequences and transfer trajectories.

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3. Statement of methodology

3.1 Three-impulse transfer strategy

The debris to remove is scattered on the SSOs with different orbital altitudes and planes. It is fuel-intensive to directly adjust the orbital plane. An economical way is to alter the orbital plane with J_2 perturbation, but the time of flight will become very long due to the small difference in orbital altitude. For Balancing fuel consumption and time cost, a three-impulse strategy is proposed in this paper.
For each debris rendezvous mission, the transfer trajectory is divided into two stages: the waiting stage and the rendezvous stage, as shown in Figure 1. Firstly, the spacecraft applies an impulse maneuver to transfer to the waiting orbit. The spacecraft will stay on the waiting orbit for a while to reduce the difference of orbital plane using J_2 perturbation. When the waiting orbit coplanar with the target orbit or the upper limit of the dwell time is reached, a Bi-impulse transfer is performed to rendezvous taget debris, which is called the transfer stage in this paper.

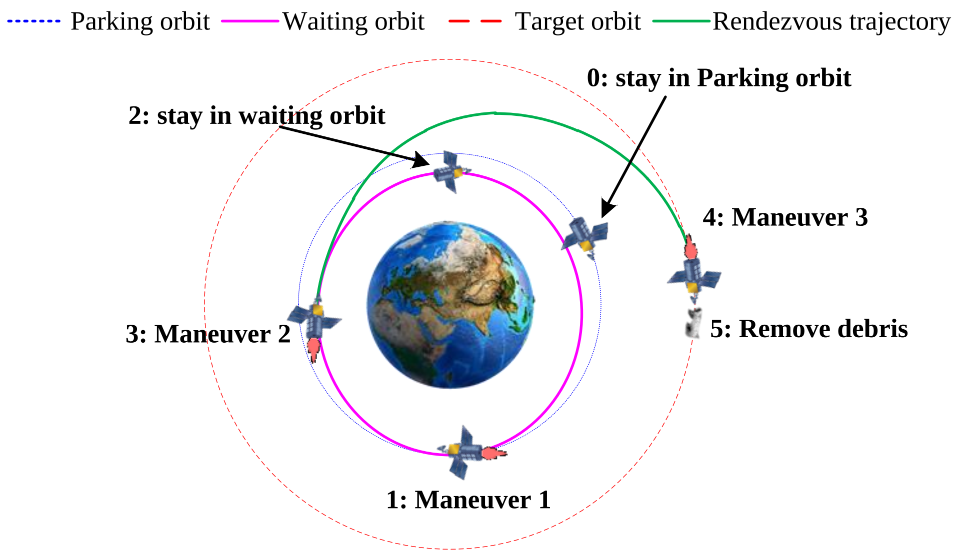

Figure 1: The diagram of the three-impulse transfer strategy

The transfer trajectory of each rendezvous contains waiting leg and rendezvous leg. The waiting leg is from the first maneuver to the second maneuver. The solving of the rendezvous leg is essentially a lambert problem under J_2 perturbation. t_d is the duration from the initial moment to the first maneuver. t_w presents the duration that the spacecraft stay on the waiting orbit. The time of flight from the waiting orbit to the target is referred as t_r. The initial time is set as 0.

$$\begin{cases} (\boldsymbol{V}_{\mathrm{d}},\boldsymbol{V}_{\mathrm{a}})=L(\boldsymbol{r}_{\mathrm{w}},\boldsymbol{r}_{\mathrm{t}},t_{\mathrm{r}}) \\ \Delta\boldsymbol{V}_2=\boldsymbol{V}_{\mathrm{d}}-\boldsymbol{V}_{\mathrm{w}} \\ \Delta\boldsymbol{V}_3=\boldsymbol{V}_{\mathrm{t}}-\boldsymbol{V}_{\mathrm{a}} \end{cases} \tag{1}$$

where $\boldsymbol{r}_{\mathrm{w}}$ and $\boldsymbol{V}_{\mathrm{w}}$ are the position and velocity vectors of the spacecraft at t_w+ t_d. $\boldsymbol{r}_{\mathrm{t}}$ and $\boldsymbol{V}_{\mathrm{t}}$ denote the position and velocity vectors of the debris at t_w+ t_d+ t_r. $\boldsymbol{V}_{\mathrm{d}}$ and $\boldsymbol{V}_{\mathrm{a}}$ are the velocity vector of the spacecraft after the second maneuver and before the third maneuver, respectively. Thence, the object function of each transfer trajectory optimization is defined as follow.

$$J=\sum_{k=1}^{3}\left\|\Delta\boldsymbol{V}_k\right\|=f\left(\Delta\boldsymbol{V}_1,t_{\mathrm{d}},t_{\mathrm{w}},t_{\mathrm{r}}\right) \tag{2}$$

where the first velocity increment $\Delta\boldsymbol{V}_1$ is expressed as $(\Delta V_1,\alpha,\beta)$ in spherical coordinates for convenience.

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The optimal solution can be found using heuristic algorithm such as GA and ACO. Because of the repeated iterations, it is not appropriate to directly put the trajectory optimizer into the sequence optimization. Some approximate formulas that depend on experience are utilized to replace the trajectory optimizer in traditional methods. In this paper, a BP neural network rather than the experience formulas is employed, which has ability to estimate transfer trajectory parameters more accurately. The structure of BP neural network is introduced in the follow section.

3.2 Structure of BP neural network

Artificial neural network (ANN) is a complex network structure formed by a large number of units connected to each other. It can fully approximate to any complex nonlinear relations and is widely used in various fields. BP algorithm is a typical error back propagation algorithm, which was proposed by Rumelhart and Mclleland in 1986 [17]. BP neural network is a multi-layer feedforward neural network. Its main feature is that the signal is forward propagating, and the error is back propagating [18]. As shown in Figure 2, a 3-layers BP neural network is built.

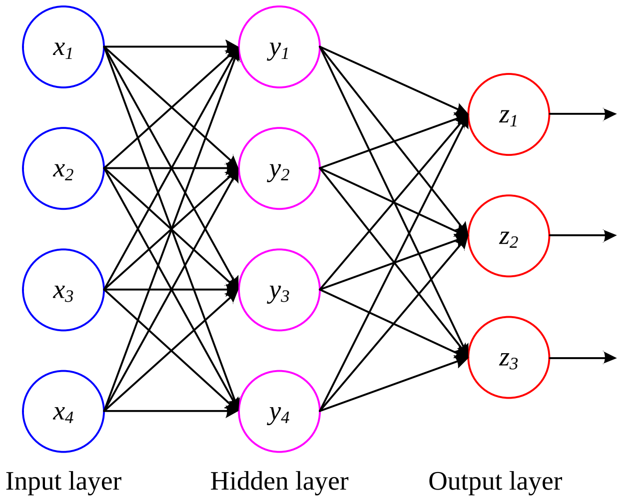

Figure 2: the Structure of BP neural network with 3 layers

The process of BP neural network is mainly divided into two steps. The first is the forward propagation of the signal, from the input layer through the hidden layer, and finally to the output layer. The second step is the back propagation of the error, from the output layer to the input layer in turns. The weight $\boldsymbol{w}$ and offset $\boldsymbol{b}$ between adjacent layers is also adjusted layer by layer from the output layer to the input layer. The output of unit i in layer j is solved as follows

$$y_{ij} = g\left(\boldsymbol{w}_{ij}\boldsymbol{x}_j + b_{ij}\right) \tag{3}$$

where $\boldsymbol{w}_{ij}$ and $\boldsymbol{x}_j$ are the weight and input vector. b_{ij} is the value of the offset. g is the activation function. Purelin, threshold function and sigmoid function are all common activation functions. In theory, when nonlinear and linear activation functions are used together, all nonlinear systems can be approximated. Therefore, the sigmoid function and purelin are respectively selected as the activation function of the hidden layer and output layer in this paper. A 3-layer BP neural network is employed to describe the mapping relationship between the transfer trajectory parameters and the initial states of the spacecraft and the debris.

$$\left(\Delta V, tof\right) = net\left(oe_0, oe_t\right) \tag{4}$$

where oe_0 and oe_t denote the orbital elements of the spacecraft and debris, respectively. ΔV is the total velocity increments and tof is the time of flight.
The target orbits are randomly generated and GA is used to optimize the transfer trajectory between these selected debris. The obtained transfer trajectory is stored as the samples for training. In order to ensure the quality of the sample, every transfer trajectory is calculated three times.

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3.3 Autonomous mission planning approach

With the help of the BP neural network and the three-impulse transfer strategy, an autonomous mission planning approach is proposed in this section. It makes the spacecraft have the ability to select the target debris and design the transfer trajectory. The implementation process of the algorithm is shown in Figure 3.The GA is used to perform the sequence and trajectory optimizations, and the 3-layer BP neural network is applied to estimate the transfer trajectory parameters during sequence optimization.
For the sequence optimization, the object function is defined as

$$J_s = \sum_{k=1}^{5} \Delta V_k = f_s\left(D_1, D_2, D_3, D_4, D_5\right) = \sum_{s=1}^{4} net\left(oe_{D_s}\left(t_s\right), oe_{D_{s+1}}\left(t_s\right)\right) \tag{5}$$

where D_k (k = 1, 2, 3, 4, 5) denotes the number of debris to remove in order. *net* is the trained BP neural network. $oe_{D_s}\left(t_s\right)$ denotes the orbital elements of the debris D_s at t_s.

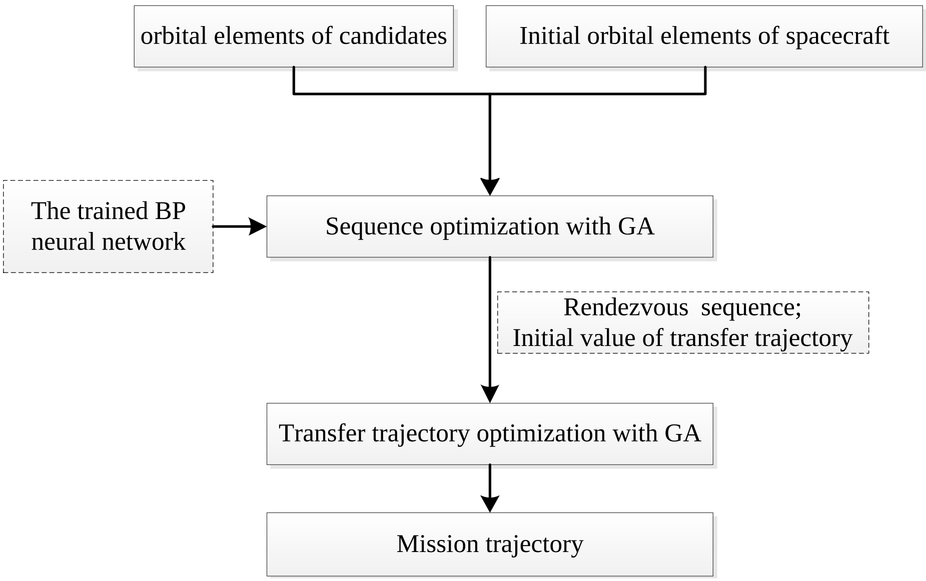

Figure 3: The flow chart of the autonomous mission planning approach

after the rendezvous sequence is obtained, the GA is again applied to optimize the transfer trajectory for each segment according to the order of the rendezvous. The object function is as shown in Eq. (2). The estimated parameters solved from the BP neural network are used as the initial guesses to improve trajectory optimization efficiency. Finally, the whole mission trajectory is solved.

4. Results and discussion

4.1 Sample generation and training

The ADR mission on SSO is taken into consider as an example to verify the feasibility and advantage of the proposed method. Considering the limited fuel of spacecraft, some restrictions on the distribution of candidate orbits are necessary. As shown in Table 1, the candidate target orbits are quasi-circular SSOs, of which the altitudes are from 600 to 1000 km. The range of initial right ascension of ascending node (RAAN) is set from 0 to 30 deg. The rang of argument of periapsis and true anomaly are all from 0 to 360 deg. 100 000 candidate orbits satisfying the constraints are randomly generated, and divided equally into the parking orbit set and the target orbit set. The orbits belong to the parking orbit set and the target orbit set are drawn one by one to form 50 000 samples. GA is used to solve the transfer trajectory from the parking orbit to target orbit for each samples. The range of the variables to optimize is set as shown in the following table.

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Table 2: The range of the variables to optimize for transfer trajectory

Variables	Range
t_d (sec)	[0, 7200]
t_w (day)	[0, 5]
t_r (sec)	[0, 7200]
ΔV_1 (km/sec)	[0, 0.5]
α (deg)	[0, 360)
β (deg)	[-90, 90]

In order to ensure the optimality of the transfer trajectory, each sample is solved three times and the optimal solution is stored. The data structure of the sample is shown in Eq. (6).

$$\mathrm{Sa} = [oe_0, oe_t, \Delta v_1, \Delta v, tof] \tag{6}$$

where oe_0 and oe_t represent the initial orbital elements of the spacecraft and the debris, respectively. Δv_1 is the size of the first velocity increment, and Δv is the size of the total velocity increments. *tof* is the time of flight that is from the initial moment to the moment of rendezvousing debris.

The parameters and structure of BP neural network will affect the training performance and the fitting effect of the final network. A fully-connected BP neural network with three layers is built. The specific parameters are shown in Table 3 and Table 4.

The input is the orbital elements of the spacecraft and the debris. The output is the first and the total velocity increments and the time of flight. Since the values of the parameter vary widely, parameter normalization is necessary. The detailed process of normalization is not repeated here.

Table 3: The structure of the BP neural network

Parameter	Input layer	Hidden Layer	Output layer
Units in each layer	12	200	3
Activation function	--	Sigmoid	Purelin

Table 4: The parameters of the BP neural network

Parameter	Value
Initial learning rate	0.01
Training Optimizer	Gradient Descent
Training epoch	1000

The error of test set for the trained BP neural network is shown in Figure 4. The estimated error of the test data decreases exponentially as the training, and eventually converges to 0.275%. This shows that the trained BP neural network is able to accurately estimate the flight time and fuel consumption of the transfer trajectory for ADR mission.

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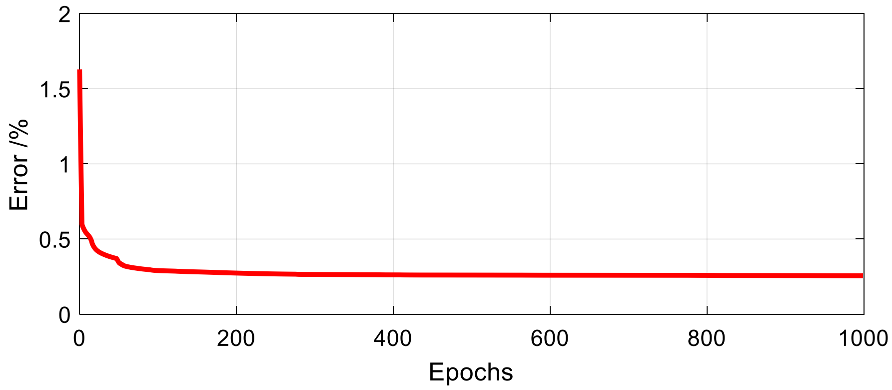

Figure 4: The error of the test set in the training process for the BP neural network

4.2 Autonomous planning of ADR mission

Without loss of generality, the same method is used to randomly generate 20 orbits that satisfy the parameter constraints as the orbits of the candidate debris. The generated orbits of debris is listed in Table 6. The No. 0 is the initial orbital elements of the spacecraft.

Table 5: The initial orbital elements of the spacecraft and the debris

No.	a (km)	e	Inc (deg)	RAAN(deg)	ω (deg)	θ (deg)
0	6878	0	98	15	0	0
1	7429.030	0.007621	98.242	8.717	252.108	84.503
2	7402.401	0.004067	99.302	33.226	272.576	96.397
3	7183.748	0.010440	96.17	8.858	151.428	107.632
4	7245.826	0.003113	96.61	7.579	131.610	1.431
5	7223.908	0.000674	98.03	8.401	216.233	226.455
6	7285.064	0.005946	97.484	22.631	185.771	83.918
7	6918.970	0.003187	97.368	12.98	131.539	56.693
8	7098.502	0.000175	96.274	3.575	87.896	256.21
9	7333.849	0.000875	96.065	12.654	137.88	125.057
10	6889.953	0.00218	99.836	13.803	122.629	175.816
11	7100.981	0.003459	97.279	11.115	313.511	14.615
12	7384.654	0.005947	95.683	12.485	131.395	61.502
13	7203.436	0.005817	97.437	8.108	202.168	158.868
14	7154.921	0.00471	99.094	14.09	13.842	296.436
15	7404.928	0.003	96.235	19.504	202.876	339.953

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16	6809.200	0.007888	95.785	4.095	33.046	93.953
17	7394.388	0.002854	99.030	15.513	263.182	124.246
18	6983.839	0.003931	96.016	20.508	83.685	196.160
19	7371.259	0.000773	98.174	0.523	393.279	85.73
20	7074.251	0.004234	99.927	30.429	85.553	63.858

As mentioned in Section 3.3, the GA is employed to selecte 5 targets and optimize the rendezvous sequence. The object function is given in Eq. (5), and the trained BP neural network in Section 4.1 is used to estimate the velocity increments of each transfer trajectory. The results of simulation is shown in Table 6.

Table 6: The results of the sequence optimization

	Value
Rendezvous sequence	0-14-10-7-9-12
Total velocity increments (km/s)	1.389
Mission duration (day)	11.182
Iterations	134
Computation time (s)	36.458

According to the results of sequence optimization, each transfer trajectory is reoptimized using GA and the object function is same as the Eq. (2). The results are listed in Table 7.

Table 7: The results of the trajectory optimization

	t_d (sec)	**t_w (day)**	**t_r (sec)**	**ΔV (km/s)**
Segment 1	4814	1.583	4584	0.299
Segment 2	22	2.609	3999	0.266
Segment 3	1224	2.276	2739	0.364
Segment 4	2554	1.483	4203	0.352
Segment 5	3947	2.559	5607	0.136

The accurate mission duration and fuel consumption obtained from the trajectory optimization are 10.903 days and 1.418 km/sec, respectively. Compared with the estimated value in Table 6, the estimated error of the trained BP neural network is 0. 279 day and 0. 029 km/sec, which are small and explain the effectiveness of the BP neural network.

5. Conclusion

An autonomous mission planning method based on the BP neural network and the GA is proposed to plan multi-rendezvous mission. a three-impulse strategy is employed for balancing fuel consumption and mission duration. In

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order to improve the efficiency of the sequence optimization, A 3-layer BP neural network is built to estimate the parameters of each transfer trajectory during sequence optimization. The result of numerical simulation confirm the efficacy of the proposed method. The utilization of the BP neural network improves the accuracy and efficiency of sequence planning.

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