Research Article

Fuel-Efficient on-Orbit Service Vehicle Allocation Based on an Improved Discrete Particle Swarm Optimization Algorithm

Wu Jian, Liu Qingguo , Liu Xinxue, and Li Yaxiong

Xi'an High-tech Institute, Xi'an 710025, China

Correspondence should be addressed to Liu Qingguo; teamalpha@163.com

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Given the limited fuel capacity of an on-orbit service vehicle (OSV), proper OSV allocation to satellites during each service mission is critical for economic fuel consumption. This allocation problem can be formulated as an optimization problem with many continuous and discrete design variables of wide domains. This problem can be effectively handled through the proposed approach that combines the tabu search with the discrete particle swarm optimization algorithm (DPSO-TS). First of all, Pontryagin's minimum principle and genetic algorithm (GA) are exploited to find the most fuel-efficient transfer trajectory. This fuel efficiency maximization can then serve as the performance index of the OSV allocation optimization model problem. In particular, the maximization of the minimum residual fuel over individual OSVs is proposed as a performance index for OSV allocation optimization. The optimization problem is numerically solved through the proposed DPSO-TS algorithm. Finally, the simulation results demonstrate that the DPSO-TS algorithm has a higher accuracy compared to the DPSO, the DPSO-PDM and the DPSO-CSA algorithms in the premise that these four algorithms have the basically same computational time. The DPSO-TS algorithm can effectively solve the OSV allocation optimization problem.

1. Introduction

As humans explore space deeper, more and more diverse satellites are deployed into space. On-orbit service of satellites is a type of space operations performed by astronauts, robots, or both to extend the lives of satellites and improve their abilities to perform various tasks [1]. On-orbit service vehicles (OSV) are particularly useful as an effective tool to extend lives of satellites. These vehicles perform several tasks including on-orbit assembly, maintenance, and logistic support [2]. Many important problems of the OSV are investigated in the existing literature. The study of transfer trajectory is the basic work of allocation of OSVs. Direct methods [3–5], indirect methods [6, 7], and hybrid methods [8, 9] are used to study the optimization of transfer trajectories of different types of space vehicles. The hybrid methods, one of which is adopted in this paper to optimize the transfer trajectories, combine the advantages of the direct and indirect methods.

In general, multiple satellites need to be maintained in one service mission. The allocation of OSVs to satellites is an important problem that has the characteristics of a general resource allocation problem. However, the OSV allocation problem is distinguished by two aspects: (a) there are many optimization variables with a wide search scope for each, and (b) the optimization variables are of both the continuous and discrete types. Allocation optimization problem is a complex combinatorial optimization problem and known to be an NP hard, and discrete particle swarm optimization (DPSO) is a commonly used algorithm to solve allocation optimization problems. The traditional DPSO algorithm [10–12] is easy to be trapped in the local optimum, and hence some improved DPSO algorithms are studied. Inertia weight of DPSO is used to balance the global and local search capacity, and then the way of designing the adjustment strategy of inertia weight to solve the problem of falling into local optimum is widely studied. Li et al. [13] propose DPSO-PDM algorithm by the hybridizing adjustment strategy based on new particle

diversity and adaptive mutation strategy, which effectively solves the problem of complex network community detection. Xin et al. [14] propose an improved DPSO algorithm by designing the linearly decreasing inertia weight, which effectively solves the problem of scheduling MIMO radar tasks. Nagra et al. [15] propose an improved a hybrid self-inertia weight adaptive PSO algorithm. The methods mentioned above improve the performance of DPSO algorithm by adjusting the inertia weight. There are some methods combining DPSO with other algorithms to improve the performance of DPSO algorithm. Wang et al. [16] propose SA-DPSO algorithm which combines the DPSO algorithm and simulated annealing algorithm. Vairam et al. [17] propose CHIDPSO algorithm by combining DPSO algorithm and cyber swarm algorithm, which improves the local search capacity of DPSO algorithm. Vasudevan and Sinha [18] proposed a hybrid optimization algorithm by combining GA and PSO. Shayeghi et al. [19] improve the mutation of DPSO based on similarity algorithm for optimization of transmission lines loading. Qi [20] proposes an improved DPSO algorithm by combining the iterated local search. Yang and Xu [21] propose DPSO-MFO algorithm, which is able to provide excellent performances as a nature-inspired heuristic algorithm. The methods mentioned above improve the performance of DPSO by enhancing the exploration and exploitation abilities, but the balance of exploration and exploitation is not controlled. Too much exploitation makes the algorithm converge quickly often to a local optimum, and too much exploration slows down the convergence of the procedure although it increases the probability of finding the global or near-optimum solution of the optimization problem.

The tabu search (TS) algorithm is a hill-climbing algorithm, which is simple and easy to implement [22–24]. In order to keep the balance of exploration and exploitation abilities, we introduce TS algorithm into DPSO algorithm to improve the performance of DPSO algorithm. The proposed method keeps the balance of exploration and exploitation abilities by controlling the inertia weight and the length of the tabu table. The background of this paper is that multiple satellites need to be maintained in one service mission. As fuel is extremely important for OSVs, the fuel-efficient problem becomes the focus of allocation optimization problem. This paper is organized as follows. First, we establish in Section 2 an optimization model for the minimum duration transfer trajectory by using a hybrid method. Then, we propose in Section 3 an algorithm that combines DPSO algorithm with TS algorithm. This DPSO-TS algorithm is used for solving the OSV allocation optimization problem. Finally, in Section 4, we carry on several simulations to demonstrate the superiority of the DPSO-TS algorithm over DPSO algorithm and some, and the results demonstrated have higher convergence accuracy than DPSO algorithm and two relevant representative algorithms including DPSO-PDM algorithm and CHIDPSO algorithm.

In order to make the paper readable, the nomenclature of variables is shown in Table 1 before the optimization models are established.

2. Transfer Trajectory Optimization Based on a Hybrid Method

In this section, we provide the differential equations of motion of an OSV in an Earth-centred inertial (ECI) coordinate system. Then, an optimization model of the OSV transfer trajectory is established.

2.1. OSV Equations of Motion. The differential equations of motion [25] are

$$\begin{cases} \dot{\mathbf{r}} = \mathbf{v}, \\ \dot{\mathbf{v}} = -\frac{\mu}{|\mathbf{r}|^3} \mathbf{r} + \frac{F}{m} \mathbf{a}, \\ \dot{m} = \frac{-F}{(g_0 I_{sp})}, \end{cases} \quad (1)$$

where $\mathbf{r}$ is the position vector, $\mathbf{v}$ is the velocity vector, F is the thrust, m is the OSV mass, I_{sp} is the specific impulse of the engine, and $\mathbf{a} = [\alpha_x, \alpha_y, \alpha_z]^T$ is the unit vector of in the thrust direction.

2.2. Transfer Trajectory Optimization. Assuming that the maneuvering time of each OSV is known or has been already determined, an optimization model for the transfer trajectory between each pair of an OSV and a satellite is established based on a hybrid method, which exploits Pontryagin's minimum principle [26, 27] and genetic algorithm (GA) [28]. The more fuel one OSV has retained, the longer it can stay in the orbit and the more satellites it can serve. Therefore, the mass of the remaining fuel can be taken as the optimization index to be maximized, namely,

$$\max J = m(t_f), \quad (2)$$

where t_f is the terminal time of each transfer trajectory and m is a function of the change in the OSV fuel mass.

Based on the OSV equations of motion in formula (1), the Hamilton function can be derived as

$$H = \lambda_r \mathbf{v} + \lambda_v - \left(\frac{\mu}{|\mathbf{r}|^3} \mathbf{r} + \frac{F}{m} \mathbf{a} \right) - \lambda_m \frac{F}{g_0 I_{sp}}, \quad (3)$$

where λ_r and λ_v are the adjoint variables of the state variables and λ_m is the adjoint variable of the OSV mass m .

According to Pontryagin's minimum principle, the optimal thrust direction $\mathbf{a}^*$ is obtained by solving $\|\mathbf{a}\| = 1$ and $\partial H / \partial \mathbf{a} = 0$. Then, the optimal thrust direction is

$$\mathbf{a}^* = \frac{\lambda_v}{\|\lambda_v\|}. \quad (4)$$

The partial derivatives of the Hamiltonian with respect to the adjoint variables are thus obtained. Consequently, the adjoint variables can be shown to satisfy the following differential equations:

TABLE 1: Nomenclature of variables.

Variable	Explanation
$\mathbf{r}$	Position vector
$\mathbf{v}$	Velocity vector
F	Thrust
m	OSV mass
I_{sp}	Specific impulse
α	Thrust direction
t_f	Terminal time of transfer trajectory
λ_r	Adjoint variables of position vector
λ_v	Adjoint variables of velocity vector
λ_m	Adjoint variable of the OSV mass
α^*	Optimal thrust direction
$F_{\max}$	Maximum of thrust
t_{off}^1	Switching-off time of the 1 st thrust segment
t_{on}^2	Switching-on time of the 2 nd thrust segment
t_{off}^2	Switching-off time of the 2 nd thrust segment
β	Design parameters of transfer trajectory
P_T	Population size of GA
P_c	Crossover probability of GA
P_m	Mutation probability of GA
N_t	Maximum iterations of GA
N	Count of OSVs
M	Count of satellites
O	Denotation of OSV
S	Denotation of satellites
$\mathbf{X}$	Allocation matrix
t_m	Maneuvering time
m_{remain}^k	Remaining fuel mass of O_k after maintaining
M_B	Population size of DPSO
K	Number of satellites needed to be maintained
T_D	Maximum iterations of DPSO
ω	Inertia weight
c_1	Cognitive coefficient
c_2	Social coefficient
h	Iteration counter
δ	Time step
$t_{\max}$	Mission duration
P_i^h	Individual fitness extreme
P^h	Global fitness extreme
P^g	Global fitness extreme
l_T	Length of the tabu table
M_T	Size of the candidate set
T_T	Maximum iterations of TS
Openlist	Candidate set
Tabulist	Tabu table

$$\begin{cases} \dot{\lambda}_r = \frac{\mu}{|\mathbf{r}|^3} \lambda_v - \frac{3\mu \cdot \lambda_v}{|\mathbf{r}|^5} \mathbf{r}, \\ \dot{\lambda}_v = -\lambda_r, \\ \dot{\lambda}_m = -\frac{F}{m^2} \|\lambda_v\|. \end{cases} \quad (5)$$

Initial boundary conditions are

$$\begin{cases} \mathbf{r}(t_0) = \mathbf{r}_0, \\ \mathbf{v}(t_0) = \mathbf{v}_0, \\ m(t_0) = m_0, \end{cases} \quad (6)$$

and the terminal boundary constraints are

$$\begin{cases} \mathbf{r}(t_f) = \mathbf{r}_f, \\ \mathbf{v}(t_f) = \mathbf{v}_f. \end{cases} \quad (7)$$

The optimal control under finite-thrust conditions is the switching mode of the engine strategy (bang-bang control). In this paper, the adopted switching mode is the on-off-on mode of the engine working sequence, and the switching moments are taken as the optimization variables. In the switching-on segment, the thrust is set to $F_{\max}$. In the switching-off segment, the thrust is set to zero.

For the GA-based hybrid method, the orbital optimization problem is converted into an optimization problem with parameters, including the initial values of the adjoint variables, the switching-off time t_{off}^1 of the first thrust segment, the switching-on time t_{on}^2 of the second thrust segment, and the switching-off time t_{off}^2 of the second thrust segment. For maximizing the mass of the remaining OSV fuel under the given constraints, seventeen parameters $\beta = [\lambda^1(t_0), \lambda^2(t_0), t_{\text{off}}^1, t_{\text{on}}^2, t_{\text{off}}^2]$ are taken as optimization variables. The solution of this optimization problem using genetic algorithm is carried out as follows:

Step 1: the design parameters $\beta = [\lambda^1(t_0), \lambda^2(t_0), t_{\text{off}}^1, t_{\text{on}}^2, t_{\text{off}}^2]$ are encoded. Thirty chromosomes are generated randomly to form the initial population. The population size P_T , the crossover probability P_c , the mutation probability P_m , and the maximum number of iterations N_t are set.

Step 2: for each chromosome, the equations are solved to get the optimal thrust direction under the conditions (6) and (7). Then, the equations of motion (1) are solved to obtain the transfer trajectory. The fitness values of all chromosomes in the current generation are computed based on the fitness function in formula (2).

Step 3: for the next generation, chromosomes are selected using the roulette-wheel selection method. Some genes on two different chromosomes reciprocally cross according to the crossover probability and mutate according to the mutation probability. The execution of the selection, crossover, and mutation operations produces the next generation population.

Step 4: steps 2 and 3 are repeated until the GA fitness function values go below $\varepsilon = 10^{-6}$ or the maximum number of iterations N is reached.

The hybrid method results in the OSV transfer trajectory with the maximum mass of the remaining fuel at a given maneuvering moment.

3. OSV Allocation Optimization Based on the DPSO-TS Algorithm

The OSV allocation optimization problem can be solved through the DPSO algorithm. The inertia weight ω is an important parameter of the DPSO algorithm. The larger the inertia weight ω is, the stronger the global search capability is. TS algorithm is a hill-climbing algorithm with good local

search performance, and it improves the efficiency of DPSO algorithm by exploiting the neighborhood of the results obtained by DPSO algorithm. In order to keep the balance between exploration and exploitation in DPSO-TS algorithm, we set the inertia weight ω to a larger value to get strong exploration ability. We propose to use TS algorithm in each iteration of DPSO algorithm to improve local search capacity on conditions that the exploitation ability is limited by setting the appropriate length of the tabu table.

3.1. Mathematical Optimization Model. Assume there are N OSVs denoted by $O = (O_1, O_2, \dots, O_N)$, and M satellites denoted by $S = (S_1, S_2, \dots, S_M)$. Each OSV serves at most a satellite in one mission, and each satellite can be served at most once. The allocation matrix $\mathbf{X}$ can be written as

$$x_{ij}(t_m) = \begin{cases} 1, & O_i \text{ serving } S_j \text{ with manoeuvring time } t_m, \\ 0, & O_i \text{ not serving } S_j \text{ with manoeuvring time } t_m, \end{cases} \quad (8)$$

where $i = 1, 2, \dots, N$, $j = 1, 2, \dots, M$ and t_m is manoeuvring time. $\mathbf{X}$ includes the allocation plan of OSVs and their manoeuvring times. The mathematical model of OSV allocation problem can be written as

$$\max f(\mathbf{X}) = \max\{\min[m_{\text{remain}}^1(\mathbf{X}), m_{\text{remain}}^2(\mathbf{X}), \dots, m_{\text{remain}}^s(\mathbf{X})], (s \leq N)$$

$$\text{s.t.} \begin{cases} \sum_{j=1}^M x_{ij}(t_m) \leq 1, & \forall i = 1, 2, \dots, N \\ 0 < \sum_{i=1}^N x_{ij}(t_m) \leq 1, & \forall j = 1, 2, \dots, M \\ m_{\text{remain}}^k \geq m_{\text{keep}}, & \forall k = 1, 2, \dots, N, \end{cases} \quad (9)$$

where m_{remain}^k is the remaining fuel mass of the k^{th} OSV after maintaining, and m_{keep} is the mass of the fuel used to keep the orbit. The inner min operator $\min[m_{\text{remain}}^1(\mathbf{X}), m_{\text{remain}}^2(\mathbf{X}), \dots, m_{\text{remain}}^s(\mathbf{X})]$ returns the minimum mass of the remaining fuel among individual OSVs used to maintain satellites according to $\mathbf{X}$. The outer max operator $\max\{\min[m_{\text{remain}}^1(\mathbf{X}), m_{\text{remain}}^2(\mathbf{X}), \dots, m_{\text{remain}}^s(\mathbf{X})]\}$ searches for the allocation plan $\mathbf{X}$ that maximizes the minimum mass value. The optimization index reflects the overall service capability of OSVs.

3.2. Optimization Problem Solution Based on the DPSO-TS Algorithm. The OSV allocation optimization problem can be solved using the proposed DPSO-TS algorithm. Details of the DPSO-TS algorithm are given for two parts: the implementation steps of DPSO-TS algorithm and DPSO algorithm and some steps and strategies of DPSO-TS algorithm.

3.2.1. The Implementation Steps of DPSO-TS Algorithm. The implementation steps of DPSO-TS algorithm are

Step 1: set the DPSO-TS parameters including the population size M_B of the particle swarm, the OSV

count N , the number of satellites K need to be maintained, the maximum number of iterations T_D , the inertia weight ω , the cognitive coefficient c_1 , the social coefficient c_2 , and the iteration counter $h=1$. Select a certain time step δ to discretize the mission duration t_{max} .

Step 2: initialize the OSV particle swarm population. Set parameter values for each particle including an OSV serial number and a randomly generated maneuvering moment. For computational efficiency, maneuvering moments and OSV numbers of OSVs are separately used for the DPSO update by formula (12). The fitness function values $f(Ps_i)$ of all particles are calculated, and the individual fitness extreme P_i^h and the global fitness extreme P_g^h are recorded.

Step 3: the particle positions are updated by formula (12). The fitness function values $f(Ps_i)$ of all particles are calculated. The individual fitness extreme P_i^h and the global fitness extreme P_g^h are updated.

Step 4: the parameters of TS algorithm are set including the length l_T of the tabu table, the size M_T of the candidate set, and the maximum number of iterations T_T .

Step 5: set the initial solution $P_T = P_g^h$ and the optimal solution $P_{T\text{best}} = P_g^h$ of the TS algorithm.

Step 6: according to the centrality and diversity search strategies, generate the neighborhood of the current solution, and select N_T particles from the neighborhood as the candidate set $\text{Openlist}(Y)$.

Step 7: according to the fitness function value $f(Y_i)$, judge whether the amnesty criterion is met. If so, the corresponding candidate solution Y_i will be placed in the tabu table $\text{Tabulist}(Y)$ and the solution in the tabu table will be released. Otherwise, keep the tabu table intact.

Step 8: check whether the TS terminal conditions are satisfied. If so, output $P_g^h = P_{T\text{best}}$. Otherwise, go to Step 6.

Step 9: increase the iteration number, $h = h + 1$. Check whether the DPSO termination conditions are satisfied. If so, output P_g^h . Otherwise, go to Step 3.

The flow chart of DPSO-TS algorithm is shown in Figure 1.

3.2.2. Some Steps and Strategies of DPSO-TS Algorithm

(1) *Coding of Particles.* Particles of the OSV allocation problem are encoded in a decimal system where each particle has a length of $2 \times N$. Each particle is encoded as shown in Figure 2, where $O_1, \dots, O_N$ are N OSVs, and $t_1, \dots, t_N$ are the corresponding maneuvering moments. The value of O_i indicates the number of satellites served by the i^{th} OSV. This value belongs to the set $(0, 1, 2, \dots, M)$, where 0 means no satellite is served. We set the duration of the mission to $[0, t_{\text{max}}]$. If $O_i = 0$, set $\{t_i = -1\}$.

FIGURE 1: Flow chart of DPSO-TS.

FIGURE 2: Coding of a particle in the OSV allocation problem.

(2) *Calculation of the Fitness Function.* Objective function (9) is taken as the fitness function for the particles

$$\max f(Ps_i) = \max \left\{ \min \left[m_{\text{remain}}^1(Ps_i), m_{\text{remain}}^1(Ps_i), \dots, m_{\text{remain}}^s(Ps_i) \right] \right\}, \quad (s \leq N), \quad (10)$$

where Ps_i is the i^{th} particle.

(3) *Particle Position and Velocity Update.* The position of a particle is determined by the particle velocity, the individual fitness extreme, and the global fitness extreme [29]. The particle position and velocity in a PSO algorithm are updated as

$$\begin{cases} v_i^{h+1} = \omega \cdot v_i^h + c_1 \cdot r_1 \cdot (P_i^h - x_i^h) + c_2 \cdot r_2 \cdot (P_g^h - x_i^h), \\ x_i^{h+1} = x_i^h + v_i^{h+1}, \end{cases} \quad (11)$$

where P_i^h is the individual fitness extreme of the i^{th} particle in the h^{th} iteration; P_g^h is the global fitness extreme in the h^{th} iteration; x_i^h is the fitness function value of the i^{th} particle in the h^{th} iteration; x_i^{h+1} is the fitness function value of the i^{th} particle in the $(h+1)^{\text{th}}$ iteration; v_i^h is the particle velocity value of the i^{th} particle in the h^{th} iteration; v_i^{h+1} is the particle velocity value of the i^{th} particle in the $(h+1)^{\text{th}}$ iteration; ω is the inertia weight which reflects the extent to which a particle keeps the current velocity; c_1 is the cognitive coefficient, which measures how far a particle gets close to the individual fitness extreme; c_2 is the social coefficient, which measures how far a particle gets close to the global fitness extreme; and both r_1 and r_2 are random numbers in the interval $[0, 1]$.

On the basis of the PSO, we propose the following DPSO update rules for the particle position and velocity:

$$Ps_i^{h+1} = c_2 \otimes F_3 \{ c_1 \otimes F_2 [\omega \otimes F_1(Ps_i^h), P_i^h], P_g^h \}, \quad (12)$$

where Ps_i^h and Ps_i^{h+1} are the fitness function values of the i^{th} particle in the h^{th} and $(h+1)^{\text{th}}$ iterations, respectively. Formula (12) includes three formulas which are written as formulas (13)–(15).

$$\Psi_i^h = \omega \otimes F_1(Ps_i^h) = \begin{cases} F_1(Ps_i^h), & \text{rand} < \omega, \\ Ps_i^h, & \text{rand} \geq \omega, \end{cases} \quad (13)$$

$$\Phi_i^h = c_1 \otimes F_2(\Psi_i^h, P_i^h) = \begin{cases} F_2(\Psi_i^h, P_i^h), & \text{rand} < c_1, \\ \Psi_i^h, & \text{rand} \geq c_1, \end{cases} \quad (14)$$

$$Ps_i^{h+1} = c_2 \otimes F_3(\Phi_i^h, P_g^h) = \begin{cases} F_3(\Phi_i^h, P_g^h), & \text{rand} < c_2, \\ \Phi_i^h, & \text{rand} \geq c_2. \end{cases} \quad (15)$$

In formula (13), Ψ_i^h is the value of the i^{th} particle in the h^{th} iteration and is obtained via the product $\omega \otimes F_1(Ps_i^h)$. The function rand generates a random number from a uniform distribution on $[0, 1]$. If $\text{rand} < \omega$, the function

$F_1(Ps_i^h)$ is computed leading to the random generation of two integers a and b , from the set $(0, 1, 2, \dots, M)$, and hence the interchange of the values of the i^{th} particle at positions a and b . If $\text{rand} \geq \omega$, the output is Ps_i^h which means that the coding values of the i^{th} particle are kept unchanged.

In formula (14), Φ_i^h is the value of the i^{th} particle in the h^{th} iteration, and is obtained via the product $c_1 \otimes F_2(\Psi_i^h, P_i^h)$, where P_i^h is the individual fitness extreme position in the h^{th} iteration. If $\text{rand} < c_1$, the function $F_2(\Psi_i^h, P_i^h)$ is computed leading to the random generation of two integers a and b , from the set $(0, 1, 2, \dots, M)$, and hence the interchange of the values of Ψ_i^h and P_i^h at positions a and b . If $\text{rand} \geq c_1$, the output is Ψ_i^h , which means that the coding values of Ψ_i^h are kept unchanged.

In formula (15), P_g^h is the global fitness extreme position in the h^{th} iteration. If $\text{rand} < c_2$, function $F_3(\Phi_i^h, P_g^h)$ is computed leading to the random generation of two integers a and b , from the set $(0, 1, 2, \dots, M)$, and hence the interchange of the values of Φ_i^h and P_g^h at positions a and b . If $\text{rand} \geq c_2$, the output is Φ_i^h which means that the coding values on Φ_i^h are kept unchanged.

(4) *Some Strategies of TS Algorithm.* In this paper, the initial solution of the TS algorithm is the global extremum. P_g in each iteration of the DPSO algorithm. The fitness function is written as in formula (10). TS algorithm includes some strategies: if the solution is superior to the current optimal solution, the optimal solution should be amnesty; tabu tables which are first-in first-out (FIFO) queue are used to prevent repeated search for visited solutions and to avoid falling into local loops; the centralized search strategy refers to strengthening search in the neighborhood of good solutions. A diversity search strategy looks for solutions in unknown or highly unexplored regions.

4. Simulations and Analyses of Results

4.1. *Simulations.* The parking orbit elements of satellites (at 0:00 on July 1, 2009) in need of service are shown in Table 2. The parking orbit elements of the OSVs (at 0:00 on July 1, 2009) are shown in Table 3. The maintaining time for a satellite is an hour, and the on-orbit service mission should be achieved in 24 hours (From 0:00 on July 1, 2009 to 0:00 on July 2, 2009), which means $t_m + t_{\text{tra}}$ (t_{tra} is the duration of OSV and satellite from maneuvering time to rendezvous time) is in $[0, 23 \times 3600 \text{ s}]$. The mass of each OSV is 1000 kg, each OSV carries 600 kg fuel the engine thrust is 490 N, and the gas jet velocity of 3000 m/s. m_{keep} is 100 kg. The population size P_T is 20, the crossover probability P_c is 0.7, the mutation probability P_m is 0.1, and the maximum number of iterations N_t is 30. The population size M_B is 20, maximum

TABLE 2: Parking orbit elements of satellites.

Satellite	A (km)	e	I (°)	α (°)	Ω (°)	f (°)
S_1	9306	0.238550	28.321	224.138	307.927	135.862
S_2	7059	0.000225	98.084	76.815	185.081	283.332
S_3	9237	0.000165	52.006	171.386	350.005	188.701
S_4	7828	0.001219	101.618	87.562	293.441	282.681
S_5	7707	0.054088	99.031	56.562	347.938	308.882
S_6	7554	0.002882	90.045	245.844	85.215	113.968
S_7	8428	0.201645	82.982	262.555	29.901	44.341
S_8	9501	0.213200	28.226	34.607	152.421	325.392
S_9	9401	0.016556	64.822	302.192	337.387	56.304
S_{10}	9939	0.321639	56.917	231.629	218.498	128.371
S_{11}	10687	0.355917	57.022	347.224	317.457	122.776
S_{12}	6903	0.000549	96.390	110.033	325.324	203.070

TABLE 3: Parking orbit elements of OSVs.

OSV	A (km)	e	I (°)	α (°)	Ω (°)	f (°)
O_1	7751	0.000120	32.223	56.232	76.223	255.520
O_2	8400	0.000225	78.002	102.332	253.010	122.243
O_3	8526	0.004120	76.924	154.257	73.020	243.000
O_4	9201	0.370056	55.223	180.922	223.001	95.620
O_5	7002	0.004021	87.235	102.556	330.765	88.598
O_6	8002	0.529030	145.667	156.007	200.321	270.321
O_7	9923	0.052301	120.023	254.124	122.232	55.220
O_8	7125	0.003924	42.084	51.815	255.081	30.200
O_9	8838	0.000249	98.178	69.604	155.872	150.009
O_{10}	9123	0.013793	52.674	109.398	23.270	200.020
O_{11}	7685	0.004693	37.477	52.707	158.017	60.000
O_{12}	9215	0.489300	55.371	128.871	305.501	80.000
O_{13}	7453	0.004218	23.618	77.562	293.441	50.101
O_{14}	9675	0.054089	99.031	56.562	187.938	160.032
O_{15}	6874	0.000555	97.420	104.012	316.284	204.781
O_{16}	7534	0.003002	91.145	239.735	84.325	113.000

number of iterations T_D is 30, the inertia weight ω is 0.8, the cognitive coefficient c_1 is 0.6, and the social coefficient c_2 is 0.6. The length l_T of the tabu table is 2, the size M_T of candidate is 5, and the maximum number of iterations T_T is 8. Time step δ is 1 s, and $I = t_m/\delta$. The simulation performs ten independent experiments. In order to reduce computational time, each trajectory is computed by one independent blade of blade servers.

We design comparison experiments with DPSO algorithm, DPSO-PDM algorithm, and CHIDPSO algorithm. The parameters of DPSO algorithm are the same as those of DPSO-TS algorithm. The parameters of DPSO algorithm, part of DPSO-PDM algorithm, are the same as those of DPSO-TS algorithm, and the other parameters are the same as those in the article written by Li et al. [13]. The parameters of the DPSO algorithm part of CHIDPSO algorithm are the same as those of DPSO-TS algorithm, and the other parameters are the same as those in the article written by Vairam et al. [17].

4.2. Analyses of Results. Results including allocation plans, computational time, and the mass of the remaining fuel obtained by DPSO-TS algorithm, DPSO algorithm, DPSO-PDM algorithm, and CHIDPSO algorithm in ten

independent experiments are shown in Tables 4–7, separately. The maneuvering time of OSV selected from the integer from the duration of on-orbit service mission is $[0, 23 \times 3600 \text{ s}]$. The maneuvering time I obtained by these four algorithms in different experiments are shown in Tables 4–7, and the best results can be obtained at these maneuvering times. It can be seen from Tables 4–7 that the average mass of the remaining fuel obtained by DPSO-TS algorithm, DPSO algorithm, DPSO-PDM algorithm, and CHIDPSO algorithm is 538.5 kg, 467.8 kg, 488.9 kg, and 508.8 kg; the average mass of the remaining fuel obtained by DPSO-TS algorithm is better than that of the other algorithms. Except the ninth experiment of DPSO-TS algorithm, the mass of the remaining fuel obtained by DPSO-TS algorithm in the other experiments is superior to that obtained by the other algorithms in any experiment; the average computational time obtained by DPSO-TS algorithm, DPSO algorithm, DPSO-PDM algorithm, and CHIDPSO algorithm is 1792.3 s, 1623.2 s, 1769.1 s, and 1797.3 s. The average computational time obtained by DPSO-TS algorithm differs from the shortest average computational time by 169.1 s, which has no effect on the service mission because there is a long preparation time before the mission is executed. The computational time of these four algorithms can be considered basically the same.

TABLE 4: Results of allocation optimization based on DPSO-TS algorithm.

No.	X	S ₁	S ₂	S ₃	S ₄	S ₅	S ₆	S ₇	S ₈	S ₉	S ₁₀	S ₁₁	S ₁₂	t _c (s)	f(X)
1	OSV	O ₄	O ₈	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₄	O ₉	O ₇	O ₁₂	O ₁₅	1801.4	540.3
	I	2301	6415	67	167	2251	449	781	1	299	5233	649	3339		
2	OSV	O ₉	O ₈	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₄	O ₄	O ₇	O ₁₂	O ₁₅	1788.9	537.4
	I	4609	6422	1776	167	2254	2304	222	0	298	5233	1233	3339		
3	OSV	O ₄	O ₈	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₄	O ₉	O ₇	O ₁₂	O ₁₅	1801.4	541.7
	I	5521	6413	67	169	2217	32	781	0	299	5233	24	144		
4	OSV	O ₄	O ₁₅	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₄	O ₉	O ₇	O ₁₂	O ₈	1791.7	539.3
	I	221	6415	69	167	2251	667	781	5	299	4446	640	301		
5	OSV	O ₄	O ₈	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₄	O ₉	O ₇	O ₁₂	O ₁₅	1739.5	540.0
	I	2304	6392	67	167	2251	379	780	0	299	5233	649	3332		
6	OSV	O ₉	O ₈	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₄	O ₄	O ₇	O ₁₂	O ₁₅	1820.9	549.6
	I	4001	6409	378	166	2259	1339	239	15	298	5409	1602	3337		
7	OSV	O ₇	O ₈	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₉	O ₁₄	O ₄	O ₁₂	O ₁₅	1800.9	539.8
	I	5521	6413	25	169	2217	32	699	7	271	5233	755	144		
8	OSV	O ₄	O ₈	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₄	O ₉	O ₇	O ₁₂	O ₁₅	1802.8	538.2
	I	5522	6413	65	168	2216	32	781	2	299	5233	23	142		
9	OSV	O ₄	O ₁₅	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₄	O ₉	O ₇	O ₁₂	O ₅	1772.3	520.4
	I	5522	6413	65	168	2216	32	781	2	299	5233	23	142		
10	OSV	O ₄	O ₈	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₄	O ₉	O ₇	O ₁₂	O ₁₅	1803.6	538.2
	I	5524	6202	12	168	2109	32	789	0	297	5233	22	144		

TABLE 5: Results of allocation optimization based on DPSO algorithm.

No.	x	S ₁	S ₂	S ₃	S ₄	S ₅	S ₆	S ₇	S ₈	S ₉	S ₁₀	S ₁₁	S ₁₂	t _c (s)	f(X)
1	OSV	O ₇	O ₁₁	O ₆	O ₁₃	O ₁₆	O ₈	O ₃	O ₁₂	O ₉	O ₁₀	O ₁₄	O ₁₅	1622.0	474.2
	I	6600	350	471	337	2535	107	4730	4	335	7774	6629	4209		
2	OSV	O ₇	O ₈	O ₆	O ₁₃	O ₁₆	O ₁₁	O ₃	O ₁₄	O ₉	O ₁₀	O ₁₂	O ₁₅	1607.5	467.3
	I	6630	1323	470	360	2535	24	4735	4701	350	7772	258	4311		
3	OSV	O ₄	O ₁₅	O ₆	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₂	O ₉	O ₇	O ₁₄	O ₈	1610.3	472.8
	I	5501	6009	498	200	2215	33	781	7	299	5405	24	251		
4	OSV	O ₇	O ₁₁	O ₆	O ₁₃	O ₁₆	O ₁₀	O ₃	O ₁₂	O ₉	O ₁₄	O ₂	O ₈	1626.7	478.3
	I	5902	355	400	2099	2435	12	4688	2289	300	5405	18	1455		
5	OSV	O ₄	O ₁₅	O ₆	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₂	O ₉	O ₇	O ₁₄	O ₈	1611.2	470.6
	I	5523	6010	0	1	2420	42	1733	5	249	5422	22	250		
6	OSV	O ₇	O ₈	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₉	O ₁₄	O ₄	O ₁₂	O ₁₅	1629.9	449.4
	I	5322	427	27	469	2015	125	621	4456	378	4236	765	742		
7	OSV	O ₄	O ₁₁	O ₁₀	O ₁₃	O ₁₆	O ₁₅	O ₃	O ₁₂	O ₉	O ₁₄	O ₂	O ₈	1635.5	470.2
	I	4755	327	447	2179	2336	120	4587	67	340	5425	2234	1709		
8	OSV	O ₁₀	O ₁₅	O ₄	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₂	O ₉	O ₇	O ₁₄	O ₈	1638.8	459.3
	I	5090	7426	647	7162	3315	2	4908	3	292	4263	378	140		
9	OSV	O ₄	O ₅	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₆	O ₁₄	O ₉	O ₇	O ₁₂	O ₈	1627.5	468.1
	I	4523	6423	62	1778	4213	310	1741	12	2690	4233	276	242		
10	OSV	O ₄	O ₅	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₂	O ₉	O ₇	O ₁₄	O ₁₅	1622.9	468.0
	I	6734	628	17	1556	6421	422	276	13	449	5345	212	260		

Figures 3–7 show the best, average, and worst fitness value curves obtained by DPSO-TS algorithm, DPSO algorithm, DPSO-PDM algorithm, and CHIDPSO algorithm in the experiments with top 5 optimization results in turn. Figures 3–7 are used to show the changes of results obtained by these four algorithms. No. 6, 3, 1, 5, and 7 experiments of DPSO-TS algorithm are shown in Figures 3–7 in turn. No. 4, 1, 3, 5, and 7 experiments of DPSO algorithm are shown in Figures 3–7 in turn. No. 2, 7, 5, 9, and 8 experiments of DPSO-PDM algorithm are shown in Figures 3–7 in turn. No. 5, 3, 10, 1, and 8 experiments of CHIDPSO algorithm are shown in Figures 3–7 in turn. Figures 8–12 show the

comparison of best fitness value curves obtained by DPSO-TS algorithm, DPSO algorithm, DPSO-PDM algorithm, and CHIDPSO algorithm in the experiments with top 5 optimization results in turn, from which we can see that the DPSO-TS algorithm's fitness value of each iteration is superior to the other algorithms after the eleventh iteration. Figures 8–12 show that the TS algorithm has strong local search capacity.

The simulation results demonstrate that the DPSO-TS algorithm has a higher accuracy compared to the DPSO, the DPSO-PDM, and the DPSO-CSA algorithms and can effectively solve the OSV allocation optimization problem.

TABLE 6: Results of allocation optimization based on DPSO-PDM algorithm.

No.	x	S ₁	S ₂	S ₃	S ₄	S ₅	S ₆	S ₇	S ₈	S ₉	S ₁₀	S ₁₁	S ₁₂	t _c (s)	f(X)
1	OSV	O ₄	O ₁₁	O ₁₀	O ₁₃	O ₁₆	O ₁₅	O ₃	O ₁₂	O ₉	O ₁₄	O ₂	O ₈	1750.5	475.6
	I	4635	127	825	4133	2001	127	2371	60	236	4416	2055	169		
2	OSV	O ₇	O ₈	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₉	O ₁₄	O ₄	O ₁₂	O ₁₅	1789.0	502.4
	I	6754	466	376	169	2167	4125	2621	456	366	4233	65	142		
3	OSV	O ₄	O ₅	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₂	O ₉	O ₇	O ₁₄	O ₁₅	1752.9	481.0
	I	2520	412	79	168	2255	321	780	650	498	5437	6663	4004		
4	OSV	O ₄	O ₈	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₄	O ₉	O ₇	O ₁₂	O ₁₅	1752.4	480.2
	I	2217	6330	162	165	2241	1438	3891	15	245	5204	620	2341		
5	OSV	O ₄	O ₁₅	O ₆	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₂	O ₉	O ₇	O ₁₄	O ₈	1749.5	499.1
	I	2522	160	494	211	1238	4300	6750	334	498	5001	6678	123		
6	OSV	O ₄	O ₈	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₄	O ₉	O ₇	O ₁₂	O ₁₅	1735.6	490.3
	I	5467	3442	678	6637	217	360	4661	15	256	5109	259	341		
7	OSV	O ₄	O ₁₅	O ₁₀	O ₁₂	O ₁₆	O ₁₃	O ₃	O ₉	O ₁₄	O ₇	O ₆	O ₈	1785.9	500.4
	I	5361	412	624	279	327	329	6695	176	10	5408	259	3134		
8	OSV	O ₄	O ₁₅	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₄	O ₉	O ₇	O ₁₂	O ₅	1812.4	492.3
	I	3546	2455	167	163	6721	188	428	0	378	5013	343	667		
9	OSV	O ₄	O ₁₅	O ₆	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₂	O ₉	O ₇	O ₁₄	O ₈	1789.3	495.6
	I	5411	132	600	234	2709	6035	490	29	306	5218	4345	176		
10	OSV	O ₃	O ₆	O ₁₀	O ₁₁	O ₅	O ₁₃	O ₃	O ₁₄	O ₉	O ₇	O ₁₂	O ₈	1773.4	472.4
	I	452	622	152	7065	2036	42	189	236	429	4986	231	744		

TABLE 7: Results of allocation optimization based on CHIDPSO algorithm.

No.	x	S ₁	S ₂	S ₃	S ₄	S ₅	S ₆	S ₇	S ₈	S ₉	S ₁₀	S ₁₁	S ₁₂	t _c (s)	f(X)
1	OSV	O ₁	O ₈	O ₁₀	O ₁₁	O ₁₆	O ₂	O ₃	O ₁₄	O ₆	O ₇	O ₁₂	O ₅	1827.3	511.6
	I	4372	2276	567	5901	253	207	14	15	236	421	3690	1306		
2	OSV	O ₄	O ₁₅	O ₁₀	O ₁₂	O ₁₆	O ₁₃	O ₃	O ₉	O ₁₄	O ₇	O ₆	O ₈	1792.9	506.7
	I	5009	398	521	1277	320	308	650	179	45	5268	250	2971		
3	OSV	O ₂	O ₉	O ₁₀	O ₁₅	O ₁₆	O ₁₃	O ₃	O ₁₄	O ₈	O ₇	O ₁₁	O ₁₂	1779.3	520.3
	I	4538	203	617	7001	3246	319	483	16	99	4205	876	1641		
4	OSV	O ₇	O ₈	O ₁₁	O ₁₂	O ₁₆	O ₁₃	O ₃	O ₉	O ₁₄	O ₄	O ₁₅	O ₁	1833.2	489.3
	I	352	667	2396	4690	392	127	242	4101	326	646	6095	7020		
5	OSV	O ₄	O ₁₅	O ₁₀	O ₁₁	O ₁₆	O ₁₃	O ₃	O ₁₄	O ₉	O ₇	O ₁₂	O ₅	1804.5	520.9
	I	2598	1423	261	460	309	242	428	3356	372	4410	279	461		
6	OSV	O ₂	O ₈	O ₁₀	O ₁₁	O ₁₅	O ₆	O ₃	O ₁₃	O ₄	O ₇	O ₁₂	O ₁₄	1790.3	499.6
	I	3871	100	1278	473	4133	690	431	299	143	428	4638	230		
7	OSV	O ₃	O ₆	O ₁₀	O ₁₁	O ₅	O ₁₃	O ₃	O ₁₄	O ₉	O ₇	O ₁₂	O ₈	1802.0	510.6
	I	4328	3568	142	6011	230	108	48	4376	25	5099	4238	541		
8	OSV	O ₄	O ₆	O ₁₀	O ₁₁	O ₅	O ₁₃	O ₃	O ₁₄	O ₉	O ₇	O ₁₂	O ₈	1739.8	511.5
	I	2407	3699	183	5280	431	324	380	2325	421	5203	6218	1541		
9	OSV	O ₇	O ₁₁	O ₆	O ₁₃	O ₁₆	O ₁₀	O ₃	O ₁₂	O ₉	O ₁₄	O ₂	O ₈	1788.4	499.6
	I	4598	1256	427	3899	2408	19	722	2289	123	6263	701	23		
10	OSV	O ₄	O ₁₂	O ₁₀	O ₁₁	O ₁₆	O ₁	O ₃	O ₅	O ₉	O ₇	O ₁₃	O ₁₄	1815.2	518.3
	I	3911	5235	67	432	2231	370	699	22	491	536	272	4900		

— Best value
 --- Average value
 ... Worst value

(a)

— Best value
 --- Average value
 ... Worst value

(b)

FIGURE 3: Continued.

FIGURE 3: Best, average, and worst fitness value curves in each of the four algorithms' experiment with the first optimization results. (a) DPSO-TS algorithm. (b) DPSO algorithm. (c) DPSO-PDM algorithm. (d) CHIDPSO algorithm.

FIGURE 4: Best, average, and worst fitness value curves in each of the four algorithms' experiment with the second optimization results. (a) DPSO-TS algorithm. (b) DPSO algorithm. (c) DPSO-PDM algorithm. (d) CHIDPSO algorithm.

FIGURE 5: Continued.

FIGURE 5: Best, average, and worst fitness value curves in each of the four algorithms' experiment with the third optimization results. (a) DPSO-TS algorithm. (b) DPSO algorithm. (c) DPSO-PDM algorithm. (d) CHIDPSO algorithm.

FIGURE 6: Best, average, and worst fitness value curves in each of the four algorithms' experiment with the fourth optimization results. (a) DPSO-TS algorithm. (b) DPSO algorithm. (c) DPSO-PDM algorithm. (d) CHIDPSO algorithm.

FIGURE 7: Continued.

FIGURE 7: Best, average, and worst fitness value curves in each of the four algorithms' experiment with the fifth optimization results.

FIGURE 8: Comparison of the best fitness value curves in each of the four algorithms' experiment with the first optimization results.

FIGURE 9: Comparison of the best fitness value curves in each of the four algorithms' experiment with the second optimization results.

FIGURE 10: Comparison of the best value curves in each of the four algorithms' experiment with the third optimization results.

FIGURE 11: Comparison of the best fitness value curves in each of the four algorithms' experiment with the fourth optimization results.

FIGURE 12: Comparison of the best fitness value curves in each of the four algorithms' experiment with the fifth optimization results.

5. Conclusions and Future Research

Fuel-efficient OSV allocation is a basic work to accomplish the on-orbit service mission in the background of deploying a large number of satellites in space in the future. We establish a transfer trajectory optimization model to obtain the mass of remaining fuel, which lays a foundation of allocation model. Then, we propose DPSO-TS algorithm to solve the allocation model, and the simulation results demonstrate that the proposed algorithm is more effective than DPSO algorithm, DPSO-PDM algorithm, and CHIDPSO algorithm. The DPSO-TS algorithm can be applied to other allocation optimization problems.

Although the proposed method has high accuracy, it still has some limitations. Further accelerating the computational time and investigating more algorithms with strong local search capacity in future research would be better.

Data Availability

The simulation data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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