Simulation and Evaluation of a Space Station Operational Plan
Considering Launch Delay of Cargo Vehicles*

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Efficient operation is important to make full use of the capabilities of China’s space station. Determining the stochastic impacts of emergencies on the operational scenario of the space station is critical for successful implementation. However, few studies have assessed the uncertainties in the operational processes of the space station. To fill this gap, discrete event simulation (DES) is used to develop an evaluation method for the contingent operational plan of a space station. First, DES is used to develop a model framework of the space station operations, and the launch delay of cargo vehicles is introduced into the integrated simulation procedure. Second, the precision of the results and the computational efficiency are improved using the variance reduction technique. The corresponding effect on the number of simulation trials is confirmed using four constraints and three measurable metrics. Finally, the proposed method is applied to a two-year space station operational plan. The results show that maintaining a short interval between the launch date of the cargo vehicles and the start of the launch windows can decrease prolonged duration after a launch delay. A statistical analysis can be used to determine a safe interval between the dates of the events and vehicle launch.

Key Words: Space Station, Operational Plan, Variance Reduction, Discrete Event Simulation, Space Transportation

1. Introduction

Since 1971, when the former Soviet Union successfully launched the first space station, “Salyut”, the major space powers in the world have launched and assembled 10 space stations, including the “Mir” space station and the International Space Station (ISS).1,2) As a base for long-term on-orbit living and working, and an important guarantee for deep-space exploration, space station operation involves logistics missions; namely, visits by cargo vehicles and manned vehicles, and a variety of complex on-orbit missions. The different operational missions are coupled with each other, and the logistics missions are executed to enable resource resupply and crew rotation. Therefore, the diverse operational missions within a certain time should be scheduled, optimized and simulated to improve the stability of space station operation.

China is scheduled to begin the construction of its own space station in 2020 and intends to complete and operate the manned station by 2022. China will then become one of the few countries that have mastered the technology of long-duration manned space flight.3–5) From an engineering perspective, some scholars have investigated models of space station operational mission planning,6) decision-making for space station logistics strategies,7) multi-objective optimization of space station short-term mission planning,8) and overall mission planning for space station long-term operation.9) Although these approaches enable valid formulations for planning space station operational missions, the uncertainties of the missions are not considered. Therefore, a robust planning approach for on-board missions10) and a space logistics mission planning optimization framework11) have been developed incorporating uncertainties in devices and launch delays as perturbations. However, these methods have not been able to successfully predict the performance of a mission scheme in the presence of uncertainties.

To compensate for this shortcoming, discrete event simulation (DES) is utilized here to quantify the effects of uncertainties in the operational process by incorporating randomness into simulation models. DES can simulate events occurring at discrete time points with high computational efficiency, and therefore has been used increasingly in system analysis and decision support during the last few decades.12–16)

The simulation and evaluation of a space station operational plan are mainly aimed at validating the feasibility of the plan and analyzing the plan’s performance on the basis of a more realistic simulation model. Major space countries have developed operational systems such as the International Planning Software System (IPS),17) Operations Preparation and Planning System (OPPS),18) SpaceNet,19–21) and Manifest Assessment Simulation Tool (MAST).22–25) However, the simulation models described in Saint,17) Zoechinger et al.,18) Lee et al.,19) Grogan et al.20) and Ho et al.21) do not consider probabilistic events during the operational process, and cannot perform uncertainty analyses for space station operation. For example, MAST mainly focuses on the modeling of the launch processes of space shuttles and does not consider operational progress.

For this study, a DES approach is developed to evaluate a space station operational plan using stochastic analyses together with a launch delay of a cargo vehicle. Generally, delays might occur due to uncertainties, such as inclement
weather, damaged goods, and infrastructure problems, and may threaten the safe operation of the space station. Hence, it is necessary to consider the occurrence patterns of vehicle launch delays and their possible impacts. The new approach provides an effective simulation method for mission designers to predict the potential risks of space station operations and can aid the selection of the most satisfactory plan by analyzing the different operational strategies.

First, the model framework of the space station operational scenario is established based on the characteristics of the station operational process, in which the objects consist of the events, materials and astronauts. The characteristics of the objects are abstracted to describe the system state of the space station operational scenario. Then, stochastic models of the cargo vehicle’s launch delay, including the occurrence patterns and impacts, are considered in the simulation process. A simulation policy of dual time scales combining the event-scheduling approach and clock-advance method is developed to drive the simulation. Furthermore, based on the variance reduction technique and Monte Carlo simulation, a more precise and efficient simulation experimental method is utilized to determine the stochastic impacts of the launch delay. Finally, four constraints and three measurable metrics are defined to quantify the impacts of the stochastic aspects.

This study establishes the DES model for logistics missions and on-orbit missions for a space station operational scenario. The feasibility and performance of the operational plan are quantitatively evaluated based on the associated constraints and metrics. In addition, the variance reduction technique is applied to optimize the simulation experiment to save computing time and resources. Warning outputs and statistics of simulation results can help mission designers adjust their plans to be more reasonable.

2. Space Station Operation Model Analysis

2.1. Space station operational analysis

The cargo vehicles in the operational phase of a space station supply materials periodically, such as spare parts for maintenance, utilization materials, instruments, propellant, and crew provisions. The duration between two neighboring visits of cargo vehicles is defined as one operational cycle, and the whole operational period can be divided into several cycles, as illustrated in Fig. 1.

Two major categories of missions, namely, on-orbit missions and logistics missions, are contained in every operational cycle. On-orbit missions are executed aboard the station and include crew activities, experiments and maintenance operations, all of which consume three main categories of materials: crew provisions, experiment instruments, and operation equipment.

Logistics missions are divided into visits of manned vehicles and cargo vehicles. The crew rotation period is strictly constrained due to physiological and psychological health issues. Moreover, on-board materials should be stored in limited amounts to support normal operation and missions. Therefore, logistics missions need to be planned in order to fulfill crew rotation and resupply materials through manned vehicles and cargo vehicles, respectively. The planning method for obtaining the nominal scheme refers to Zhu. Notably, launch delays may occur due to uncertainties and can affect subsequent missions and even the entire plan.

2.2. Space station operational model framework

A space station operational scenario comprises two parts: events and the system state, both of which focus on the utilization of on-board materials. Thus, the operation simulation studied in this paper is actually a logistics simulation, and the following four hypotheses are proposed before establishing and simulating the operational model.

Hypothesis 1. The station systems retain their states between discrete points in time, and changes in state are triggered only by events, irrespective of environment.

Hypothesis 2. The completion of missions is related only to the satisfaction of the required resource.

Hypothesis 3. The interactions of the systems utilize resources, irrespective of communication.
Hypothesis 4. The simulation time interval is given in days, with the minimum step of one (1) day.

According to the characteristics of the operational process, the model comprises three main layers: the task scheduling layer, astronaut execution layer and station system layer, which constitute the model framework. The task scheduling layer prioritizes the events and distributes them to other layers. This layer also arranges temporary missions to provide necessary assistance for emergencies. The astronaut execution layer performs the events and consumes on-board materials. Finally, the station system layer contains specific systems, such as vehicles, life support systems and thermal control systems, and the systems' states are changed by the operations of maintenance, crew activity and experiments.

These layers are linked together with the event chain, and the number of events differs in each chain. When an operational plan of 2–5 years is uploaded to the operational model from Earth, the task scheduling layer can partition it into operational cycles and send the events of the present cycle to the astronaut execution layer. Then, the crew performs the daily events in the station system layer and change the systems' states.

The model framework is abstracted to comprise five simulation entities: the control center, crew, station system, resource distribution center and vehicles. The relationships among them are depicted in Fig. 2. The control center receives the operational plan and other instructions from the input port of the model and commands the crew and vehicles to execute the missions. The completion of the missions is also output by this center. The resource distribution center manages the consumption and supply of the on-board materials and outputs the utilization and stored amount of materials. Moreover, the crew operates the station system to perform the events and provides feedback on the fulfillment status. The vehicles arrange the resource resupply and crew rotation under the concern of launch delay probabilities, which helps evaluate the influence of a delay in resource supplies on on-orbit missions.

3. Simulation Model

3.1. Scenario objects models

To facilitate the modeling and simulation of the operational plan, the classes of both the events and system state are abstracted using the object-oriented methodology.

The characteristics of the events are abstracted into basic, required characteristics and constraint characteristics, as presented in Eq. (1):

\[
\text{Event} = \{\text{ID, Name, Priority, EventType, StartTime, EndTime, Man-hour, Power, Communication, Probability, Delayday, RelatedEventNum, EVAYN, EVATimes, EVASkillAsk, MaterialList, RubbishList, AstronautList}\}
\]

(1)

where ID is the identification number of the event to distinguish it from other events; Name describes the meaning of the event; Priority expresses the importance of the event to the system; EventType denotes the consumption type; StartTime and EndTime represent the times when the event occurs and ends, respectively; Man-hour, Power and Communication are the required working hours of the astronauts, the power and the communication bandwidth, respectively; Probability means the delay probability of the event; Delayday is the mean value of the exponential distribution for the delay duration after a cargo vehicle launch delay occurs; RelatedEventNum denotes the ID of the triggered events; EVAYN, EVATimes and EVASkillAsk represent the attributes of extravehicular activity, including the judgement of occurrence, required number and skills of the astronauts, respectively; MaterialList gives the list of resupplied or consumed materials; RubbishList provides a list of the generated waste; and AstronautList is the list of astronauts required to complete the mission.

In the simulation scenario, the system state is composed of the characteristics of the materials and astronauts, as expressed in Eqs. (2) and (3),

\[
\text{Material} = \{\text{ID, Name, Mass, UpTime, ConsumptionType, Circulate, RubbishProduce, Period, DateInProduced, ExpirationDate, Warning, Safety, AstronautPertinence}\}
\]

(2)
where ID is the identification number of the material; Name describes the meaning of the material; Mass is the on-board mass of the material; UpTime denotes the resupply time; ConsumptionType represents the type of material consumption; Circulate expresses the cyclic utilization rate of the material; RubbishProduce refers to the quality of rubbish produced after using the material; Period means the material usage period; DateInProduced and ExpirationDate describe the production date and expiration date of the material, respectively; Warning and Safety represent the maximum and minimum values of inventory mass, respectively; and AstronautPertinence is the judgement of whether the material is consumed by astronauts.

\[
\text{Astronaut} = \{ID, Name, Type, UpTime, Duration\}, \quad (3)
\]
where ID is the identification number of the astronaut; Name describes the code name of the astronaut; Type denotes the type of the astronaut, such as pilot, commander, engineer or payload specialist; UpTime indicates the time that the astronaut arrives at the station; and Duration is the duration of the astronaut’s residency.

The consumption of the materials consists of two categories: continuous consumption and discrete consumption. Continuous consumption is directly proportional to the number of astronauts and simulation time. The consumption rates are further divided into two types: constant rate and variable rate. The consumption rate for material with constant rates remains the same in each cycle, while that with a variable rate is altered with changes in the environment and triggering of events. Therefore, continuous consumption rates are abstracted as expressed in Eq. (4).

\[
\text{ConsumeRate} = \{ID, Name, Rate, ChangeCondition\}, \quad (4)
\]
where ID is the identification number of the material, Name is the meaning of the material; Rate is the consumption rate of the material, and ChangeCondition denotes the change conditions of the variable rate.

Additionally, discrete consumption is related to the event requirement. Hence, there is no need to set the rate of discrete consumption before the simulation.

### 3.2 Stochastic models

During the simulation, the launch delay of a cargo vehicle is modeled as an accidental event with a small probability \( P(LDCV) \), and a random number generator \( \text{Random()} \) is used to determine whether or not the accidental event occurs. If the generated value is smaller than the set probability, the event occurs, as expressed in Eq. (5),

\[
\text{Random()} \leq P(LDCV), \quad (5)
\]
where \( \text{Random()} \) generates the random number with a [0, 1] uniform distribution.

A prolonged duration \( \Delta d_{c,v} \) is required for preparation for relaunch once a launch delay of the cargo vehicle occurs. \( \Delta d_{c,v} \) is a stochastic value and is modeled by an exponential distribution,\(^{30}\) as expressed in Eq. (6),

\[
\Delta d_{c,v} = \lambda_{c,v} \times \text{RandomExponential}(), \quad (6)
\]
where \( \text{RandomExponential}() \) generates a random number with exponential distribution, the parameter of the exponential distribution is \( \lambda = 1 \), and \( \lambda_{c,v} \) represents the maximum value of the exponential distribution for the prolonged duration for the launch delay of the cargo vehicle. Therefore, the launch time of the delayed cargo vehicle is calculated as presented in Eq. (7):

\[
t'_{c,v} = t_{c,v} + \Delta d_{c,v}. \quad (7)
\]
where \( t'_{c,v} \) is the modified launch time and \( t_{c,v} \) is the nominal launch time. If \( t'_{c,v} \) is not within the range of any launch window, the launch time is set to be the start date of the neighboring launch window.

### 3.3 Integrated simulation procedure

The discrete system simulation principle and the event-scheduling approach can be directly utilized to model the entire system with all events scheduled to occur.\(^{32-34}\) However, that approach is not appropriate for a simulation with continuous consumption of materials if the duration between the two neighboring events is too long. Therefore, a method of dual time scales that combines the event-scheduling approach and clock-advance method is proposed to drive the simulation.

The method arranges two categories of scales on the timeline. One is the scale of the event occurrence time \( t'_{e,v} \), and the other is the scale of constant time step \( t \). As time passes by, the scheduled events occur, their effects on the system are recorded, and the simulation time is advanced to the next time scale until the end time, as depicted in Fig. 3.

The integrated simulation procedure is schematically illustrated in Fig. 4 and elaborated as follows.

- **Initialization of simulation**
  - The initial conditions of the simulation and the random parameters are set, including the on-board masses of materials, the characteristics of the astronauts, the scheme of the on-orbit missions and logistics missions, \( P(LDCV) \) and \( \lambda_{c,v} \), etc. Then, the list of events scheduling all missions is generated.
- **Emergency processing**
  - When a launch delay of the cargo vehicle occurs, the launch time is modified according to Eq. (7).
- **Transition of events**
  - The list of events is divided into three parts: EventVecTobe, EventVecNow, and EventVecDone. EventVecTobe hosts the events that have not occurred, EventVecNow hosts the processing events and EventVecDone hosts the finished events. First, the events satisfying the start-up condition are moved from EventVecTobe to EventVecNow. Then, the events satisfying the completion condition are moved from EventVecNow to EventVecDone.

\[
\begin{align*}
& t_1' \rightarrow t_2' \rightarrow t_2 \rightarrow t_3' \rightarrow t_3 \rightarrow 3t \rightarrow 4t \rightarrow t_5'
\end{align*}
\]

\[ t' \]

Fig. 3. Timeline of dual time scales.
• Event processing
The events of EventVecNow are processed, and their effects on the system are recorded, including the inventory masses of materials, the masses of wastes, the condition of crew rotation, etc. When the end time is reached, measurable metrics are calculated using the recorded data.

• Calculation of statistical results
The results of all simulation trials are statistically processed to calculate the corresponding statistical results. Then, the plan is evaluated from the perspectives of constraint satisfaction and statistical results of the measurable metrics.

3.4. Constraints and measurable metrics
In an integrated simulation procedure, feasibility is verified by judging whether or not the considered constraints are satisfied, as expressed in Eqs. (8)–(11).

1) Launch window. The launch time of every cargo vehicle should be within the launch window range.

\[ t_{i,c:v}^j \in \Delta t_j, \quad \begin{cases} i = 1, 2, \ldots, N_{c:v} \\
                j = 1, 2, \ldots, N_{l:w} \end{cases} \]  

where \( t_{i,c:v}^j \) is the launch time of the \( i \)-th cargo vehicle, \( N_{c:v} \) is the total number of cargo vehicles, \( \Delta t_j \) is the launch window range and \( N_{l:w} \) is the total number of launch windows.

2) Minimum time interval of launches. The interval of two neighboring launch missions should be more than 60 days to avoid conflicts with ground infrastructure.

\[ t_{i,c:v}^{j+1} - t_{i,c:v}^j \geq 60, \quad i = 1, 2, \ldots, N_{c:v} - 1 \]  

(9)

3) Maximum time interval of crew rotation. The duration of the crew staying on-board should be less than the upper limit of the rotation period to protect the physiological and psychological health of the astronauts.

\[ t_r \leq t_{c:r}^{\text{Max}}, \]  

(10)

where \( t_r \) is the duration of the crew staying on-board and \( t_{c:r}^{\text{Max}} \) is the maximum value of crew rotation period.

4) Safe operation. The inventory of material must not be less than the minimum quantity, which is based on the requirements for orbital maintenance and the presence of astronauts.

\[ \begin{cases} M_P \geq M_P^{\text{min}} \\
               M_C \geq M_C^{\text{min}} \end{cases} \]  

(11)

where \( M_P \) and \( M_C \) are the actual amounts of the propellant and crew provisions, respectively, and \( M_P^{\text{min}} \) and \( M_C^{\text{min}} \) are the set minimum quantities of the propellant and crew provisions, respectively.
After verifying the feasibility of the operational plan, three measurable metrics are defined to statistically quantify the impact of a launch delay on the nominal scenarios. These metrics are presented in Eqs. (12), (13) and (15).

1) The degree of satisfaction (DS) indicates the degree of satisfaction with which the on-board materials meet the requirement of events, and is defined as the ratio of the sum of each event’s degree of satisfaction of the required materials to the number of events in every cycle, as shown in Eq. (12):

$$DS = \frac{\sum_{j=1}^{N_{Event}} (satisfy_{mat}^j)}{N_{Event}},$$

where $N_{Event}^j$ is the total number of events in the $j$th cycle, and $satisfy_{mat}$ returns as 1 if the required materials of the $j$th event are satisfied and as 0 otherwise.

2) The degree of profitability (DP) is the ratio of the sum of all the experimental priorities to the sum of all the event priorities in each cycle. In the simulation process, the priority of events is categorized into four levels, 1, 2, 3 and 4, where a smaller number corresponds to a more important event. Therefore, the metric is presented in Eq. (13):

$$DP = \frac{\sum_{k=1}^{N_{Experiment}} (satisfy_{mat}^k) \times (5 - Experiment_{priority}^k)}{\sum_{j=1}^{N_{max}} (5 - Event_{priority}^j)},$$

where $N_{Experiment}^k$ is the total number of experiments in the $k$th cycle, $Experiment_{priority}^k$ is the priority of the $k$th experiment, and $Event_{priority}$ is the priority of the $j$th event.

3) The average utilization of cargo vehicles (AUCV) is the variance in the ratio of the upload payload mass to the interval of two neighboring launch missions. The upload payload mass of the cargo vehicle is assumed to be proportional to the interval between two neighboring launches. For each launch, the ratio of these two quantities should be approximately equal to maximize the limited room in the station and minimize the inventory cost. Therefore, redundancy in on-board materials and wasting the loading capabilities of the cargo vehicles are prevented. The metric is calculated using Eq. (15):

$$AUCV = \frac{\sum_{i=1}^{N_{cycle}-1} \left( \frac{M_{Upload}^i}{t_{c:v}^i} - \frac{M_{Upload}^{i+1}}{t_{c:v}^{i+1}} - \tilde{\delta} \right)^2}{N_{cycle} - 1},$$

where $\tilde{\delta}$ is the mean value of the ratio of the upload payload mass to the interval of two neighboring launch missions, and $M_{Upload}^i$ is the upload payload mass of the $i$th cargo vehicle.

4. Simulation Experiment

4.1. Simulation experimental design

In the traditional Monte Carlo method, the higher the required precision, the greater the number of simulation trials should be carried out, which requires more computing time and resources. Therefore, the simulation experiment needs to be designed and optimized to obtain more confident and accurate statistical results within limited simulation times.35-37

Due to the effect of a launch delay, the results of each simulation test are different even with the same initial conditions. Therefore, confidence intervals are used to compress the results to a certain extent. $R_t$ is the result of the $t$th simulation trial, and the sample variance $S^2$ of $N$ independent simulation trials is presented as

$$S^2 = \frac{1}{N-1} \sum_{i=1}^{N} (R_i - \bar{R})^2,$$

where $\bar{R}$ is the grand mean of the samples of $N$ independent simulation trials.

The confidence interval is shown as

$$\bar{R} \pm t_{\alpha/2,N-1} \frac{S}{\sqrt{N}},$$

where $1 - \alpha$ is the confidence level and $t_{\alpha/2,N-1}$ is the value of the $t$-distribution of $(N - 1)$ degrees of freedom.

The precision of the results is determined by $\alpha$ and $N$ in Eq. (17) and could be improved by increasing $N$ at the same confidence level. When $N$ is increased to a certain value $N_{SimMin}$, the precision reaches or exceeds the expectation. Hence, the termination condition of simulation sampling is reached when $N$ equals $N_{SimMin}$ for the required $\alpha$.

The precision of the confidence interval is divided into the absolute precision $\beta$ and relative precision $\gamma$. $\beta$ is the confidence interval radius and $\gamma$ is the ratio of $\beta$ to the absolute value of the point estimate $|\bar{R}(N)|$, as expressed in Eqs. (18) and (19), respectively.

$$\beta = t_{\alpha/2,N-1} \frac{S}{\sqrt{N}},$$

$$\gamma = t_{\alpha/2,N-1} \frac{S}{\sqrt{N}} \left| \frac{\bar{R}(N)}{N} \right|.$$
Therefore, the antithetic variates and batch means method (AV&BMM) is utilized to diminish the error caused by the volatility of \( S^2(n) \), which comprises two steps: antithetic variates simulation and batch means analysis.

1) Antithetic variates simulation

In this situation, the sample result is the mean of the results of two simulation trials. If the probability of the first simulation trial is \([P_1, P_2, P_3, \ldots, P_n]\), then the probability of the second is \([1 - P_1, 1 - P_2, 1 - P_3, \ldots, 1 - P_n]\). The results of \( n \) pairs of simulation trials are \((R_1^{(1)}, R_1^{(2)}), (R_2^{(1)}, R_2^{(2)}), \ldots, (R_n^{(1)}, R_n^{(2)})\), which are independent of each other. \( \tilde{R}_n \) and its variance are calculated in Eqs. (23) and (24), respectively.

\[
R_i = \frac{R_i^{(1)} + R_i^{(2)}}{2}, \quad (i = 1, 2, 3, \ldots, n),
\]

\[
\tilde{R}_n = \frac{1}{n} \sum_{i=1}^{n} R_i,
\]

\[
S^2(\tilde{R}_n) = \frac{1}{n} [S^2(R_i^{(1)}) + S^2(R_i^{(2)}) + 2Cov(R_i^{(1)}, R_i^{(2)})],
\]

where \( Cov(R_i^{(1)}, R_i^{(2)}) \) is the covariance of \( R_i^{(1)} \) and \( R_i^{(2)} \).

In Eq. (24), \( R_i^{(1)} \) is negatively related to \( R_i^{(2)} \) due to the antithetic probabilities of each pair of simulations. Thus, \( S^2(\tilde{R}_n) \) decreases with \( Cov(R_i^{(1)}, R_i^{(2)}) < 0 \), and the precision of the results can be improved.

2) Batch means analysis

In this situation, the results \( R_1, R_2, R_3, \ldots, R_n \) are divided into \( m \) batches, and each batch consists of \( l \) results. The divided results are expressed as follows:

\[
\begin{align*}
R_1, & \quad R_2, \quad \ldots, \quad R_l, \\
R_{l+1}, & \quad R_{l+2}, \quad \ldots, \quad R_{2l}, \\
& \quad \ldots, \\
R_{(m-1)l+1}, & \quad R_{(m-1)l+2}, \quad \ldots, \quad R_{ml}
\end{align*}
\]

\( \tilde{R}_j(l) (j = 1, 2, \ldots, m) \) is the mean of the \( j \)th batch, and \( \tilde{R}_n \) is calculated in Eq. (25):

\[
\tilde{R}(m, l) = \frac{1}{m} \sum_{j=1}^{m} \tilde{R}_j(l) = \tilde{R}_n.
\]

Equation (17) is modified as follows:

\[
\tilde{R}(m, l) \pm t_{\alpha/2, m-1} \frac{S_{\tilde{R}(l)}(m)}{\sqrt{m}}.
\]

The integrated simulation experiment procedure based on AV&BMM is illustrated in Fig. 5 and elaborated as follows.

- **Initialization of the simulation experiment**

The parameters of the simulation experiment are set and include \( m, l, \alpha, \beta_0 \) and \( \gamma_0 \). Moreover, the initial number of simulation trials is \( N_{\text{Initial}} = m \times l \).

- **Antithetic variates simulation**

When the probabilities of launch delay in the first simulation are \([P_1, P_2, P_3, \ldots, P_n]\), the probabilities in the second

Fig. 5. Integrated simulation experiment procedure based on AV&BMM.
Simulation results are confirmed as \(1 - P_1, 1 - P_2, 1 - P_3, \ldots, 1 - P_n\). Then, when all simulation trials are completed, the results \(R_1, R_2, R_3, \ldots, R_n\) are saved for the next step.

- **Batch means analysis**

\[
\bar{R}(m, l), S_{\bar{R}(m)}(l), \beta_n, \text{ and } \gamma_n \text{ are calculated based on Eqs. (25)-(27) and (18)-(19).}
\]

- **Judgement of simulation termination condition**

When \(\beta_n \leq \beta_0 \) or \(\gamma_n \leq \gamma_0\), the result precision is better than or equal to the expected value. The corresponding termination condition of the simulation is satisfied, and the confidence interval is confirmed as \([\bar{R}(n) - \beta_n, \bar{R}(n) + \beta_n]\).

Otherwise, the number of simulation trials is modified as \(N = (m + 1) \times l\), and the experiment returns to the antithetic variates simulation step.

### 5. Simulation Results

#### 5.1. Case summary

A two-year operational scenario planned by Zhu\(^{31}\) is used to validate the simulation method in this article. The scenario is from January 1, 2023 to January 31, 2025 and is equally divided into four cycles. The crew rotation period is six months, and a crew group consists of three astronauts. The orbit altitude of the space station is 390 km, and an average level of solar activity is assumed. Moreover, in the beginning (January 1, 2023), a manned vehicle and a cargo vehicle are docked with the station, and there are three astronauts residing onboard.

The initial inventory masses of crew provisions and propellant and their nominal consumption rates are listed in Table 1. The consumption rate of the propellant is assumed to be 4 kg/day due to the average level of solar activity.\(^{38}\) Furthermore, other materials are supplied by the first cargo vehicle.

The quantities of man-hours, power and communication to support operations for one day are presented in Table 2 and are similar to those for the ISS plan.\(^{38}\)

The scenario comprises four visits of manned vehicles (MV-I, MV-II, MV-III and MV-IV) and four visits of cargo vehicles (CV-I, CV-II, CV-III and CV-IV). Each manned vehicle can transport three astronauts to the station at one time, and the launch and return dates of the vehicles are listed in Table 3. The launch dates and payload manifests of the cargo vehicles are listed in Table 4, wherein the material wastes are transported when the vehicles return to Earth. Details of the manifests can be found in the study reported by Zhu.\(^{31}\)

The on-orbit missions of the operational plan are partly presented in Table 5; for the details, refer to the study by Zhu.\(^{31}\) Moreover, the statistical amounts of the missions in every cycle are listed in Table 6 according to the three categories and four priorities.

Furthermore, the values of the constraints described in Eqs. (8)–(11) are given in Table 7.

#### 5.2. Determination of the number of simulation trials

In this section, the number of simulation trials is determined before evaluating the operational plan. The probability of cargo vehicle launch delay is set to \(P(LDCV) = 0.5\), and the mean value of the exponential distribution for the delay duration for the launch delay of the cargo vehicle is set as \(\lambda_{LDCV} = 45\) days. Moreover, the initial number of batches and the number of results in each batch are set as \(m = 3\) and \(l = 4\).

AV&BMM and the Monte Carlo method are each utilized to obtain the standard deviation of AUCV, and the compar-

| Materials       | Nitrogen | Oxygen     | Food      | Water     | Clothes | Propellant |
|-----------------|----------|------------|-----------|-----------|---------|------------|
| Initial mass (kg)| 144      | 453.6      | 1080      | 4860      | 885.6   | 720        |
| Consumption rate| 0.8 kg/day| 0.84 kg/person/day | 2 kg/person/day | 9 kg/person/day | 1.64 kg/person/day | 4 kg/day |
| Cyclic utilization rate | 0   | 87%        | 0         | 90%       | 0       | 0          |

| Item                     | Supply | Waste |
|--------------------------|--------|-------|
| Crew provisions (kg)      | 2598   | 2179  |
| Experiment instruments (kg)| 592    | 549   |
| Operation equipment (kg) | 2069   | 733   |

| Item                     | Supply | Waste |
|--------------------------|--------|-------|
| Crew provisions (kg)      | 3235   | 2337  |
| Experiment instruments (kg)| 477    | 647   |
| Operation equipment (kg) | 1207   | 493   |

| Item                     | Supply | Waste |
|--------------------------|--------|-------|
| Crew provisions (kg)      | 2565   | 4139  |
| Experiment instruments (kg)| 429    | 336   |
| Operation equipment (kg) | 1925   | 873   |

### Table 1. Initial inventory mass and consumption rates of crew provisions and propellant.

### Table 2. Daily man-hours, power and communication supply.

| Item                     | Quantity |
|--------------------------|----------|
| Man-hour (h/person)      | 8        |
| Power (kW·h)             | 360      |
| Communication (h)        | 9        |

### Table 3. Dates of launch and return of manned vehicles.

| Manned vehicle | MV-I | MV-II | MV-III | MV-IV |
|----------------|------|-------|--------|-------|
| Launch date    | 2023/1/1 | 2023/7/1 | 2024/1/1 | 2024/7/1 |
| Return date    | 2023/7/1 | 2024/1/1 | 2024/7/1 | 2025/1/1 |

### Table 4. Dates of launch and return and payload manifests of cargo vehicles.

| Cargo vehicle | CV-I | CV-II | CV-III | CV-IV |
|---------------|------|-------|--------|-------|
| Launch date   | 2023-1-1 | 2023-5-19 | 2024-1-7 | 2024-6-9 |
| Return date   | 2023-5-19 | 2024-1-7 | 2024-6-9 | 2025-1-9 |

| Item                     | Supply | Waste |
|--------------------------|--------|-------|
| Crew provisions (kg)      | 3235   | 2337  |
| Experiment instruments (kg)| 477    | 647   |
| Operation equipment (kg) | 1207   | 493   |

| Item                     | Supply | Waste |
|--------------------------|--------|-------|
| Crew provisions (kg)      | 2565   | 4139  |
| Experiment instruments (kg)| 429    | 336   |
| Operation equipment (kg) | 1925   | 873   |

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Comparison of SAV&BMM and SMC is presented in Fig. 6. For both methods, the occurrence of cargo vehicle launch delay leads to a fluctuation in the standard deviation. SAV&BMM is always less than SMC as the batch number increases, which indicates that AV&BMM can effectively reduce the variance and improve the precision of the simulation results.

The absolute precision $\beta_{AV&BMM}$ at confidence levels of 50%, 80%, 90%, 95%, 98% and 99% are calculated using AV&BMM and presented in Fig. 7. The $\beta_{AV&BMM}$ of each confidence level decreases as the number of batches increases and confidence level decreases, and remains below 0.65 after 26 batches (104 simulation trials). Consequently, $\gamma$ is less than 0.065. Hence, 104 simulation trials can obtain accurate statistics results when $P(LDCV) = 0.5$ and $\lambda_{c,v} = 45$.

Furthermore, to analyze the relationship among $P(LDCV)$, $\lambda_{c,v}$ and $\beta_{AV&BMM}$, three sets of $P(LDCV)$ are designed (i.e., 0.1, 0.3 and 0.5) and four sets of $\lambda_{c,v}$ are tested (i.e., 5, 15, 30 and 40 days). The number of simulation trials is set as 104.

The values of $\beta_{AV&BMM}$ at a confidence level of 99% for different event probabilities and durations are presented in Fig. 8, and other results are provided in detail in Table 8. The results show that, at the same confidence level, $\beta_{AV&BMM}$ increases with both higher event probabilities and longer delay durations. Additionally, during a specific scenario, $\beta_{AV&BMM}$ is higher at a confidence level of 99% than at other confidence levels. Therefore, mission designers can apply $\beta_{AV&BMM}$ at the 99% confidence level to determine the maximal number of simulation trials in AV&BMM.

5.3. Evaluation of operational plan

The tested operational plan is evaluated on the basis of the statistical results of 104 simulation trials. The first aspect of the evaluation is the robustness of the plan, which refers to the average supporting duration of remaining crew provisions and propellant without future supplies. The average values of the supporting duration before the four supplies are shown in Table 9. The average values of the supporting
The durations of the six materials are all more than 114 days, which means that the station has enough time to support the astronauts’ survival and orbital maintenance until the next cargo vehicle arrives. This result also indicates that a cargo vehicle launch delay has been accounted for in the plan, and a redundancy strategy is in place to supply some important materials.

The second aspect is the statistical values of measurable metrics, as presented in Table 10, where the DS is divided into four types to obtain the detailed satisfaction of events in each cycle. In Table 10, the averages of the different DS are all greater than 90%, which demonstrates that most events can be duly completed under the negative impact of a cargo vehicle launch delay. Note that the minimum DS values of the priority 3 events of the first and fourth cycles are less than or equal to 75, which indicates that the plan presents some risk for the arrangement of these events and the supply of these cycles. Therefore, plan designers should develop contingency plans or replan. The corresponding warnings of uncompleted events are listed in Table 12.

Additionally, the utilization of the station is effective since...
The averages of DP are approximately 50 for this tested operational plan.

The third aspect is evaluating the effect of the cargo vehicle launch delays. The nominal launch dates of manned vehicles and cargo vehicles, and the launch windows, are illustrated in Fig. 9. The nominal launch dates of CV-III and CV-IV are close to the end time of the corresponding launch window, and insufficient remaining time can easily cause the modified launch time to exceed the launch window, which will reset the launch time to the start time of the adjacent launch window and produce an additional delay.

The statistics of the prolonged durations for the launch delays are given in Table 11. When $\Delta_{k,e}$ is set to 45, the prolonged durations of CV-I and CV-II are clearly concentrated in the range of $[0, 30]$, and the durations of CV-III and CV-IV mainly appear in the range of $[20, 50]$. That is, the prolonged duration of each vehicle may exceed the launch window, which will increase the delay time. Maintaining the launch time as close as possible to the start time of the launch window (such as CV-I) can effectively reduce the prolonged duration. Therefore, the prolonged duration can be shortened by designing a reasonable interval between the nominal launch date and the end time of the launch window.

For the 104 simulation trials, the warnings of uncompleted events caused by delays of CV-I, CV-II, CV-III and CV-IV are presented in Fig. 10. In the figure, one point represents one event. The event’s priority, occurrence date and number of uncompleted times are all provided in Fig. 10. The statistics are given in detail in Table 12. It can be seen from Fig. 10 and Table 12 that the uncompleted events caused by the delay of CV-I contribute to the largest number of points, and mainly consist of the events of Priority 2 and Priority 3. The main reason for this result is that, during the test planning process, the materials required for events in the first cycle are supplied by the previous cargo vehicle. For example, CV-II carries materials needed in the first month of the third cycle. Even if the launch of the cargo vehicle is delayed, the remaining inventory on the station can support space station operation. Therefore, events in the second, third and fourth cycles are less affected by CV-II, CV-III and CV-IV launch delays. However, the supply for the first cycle can only be carried by CV-I, once event occurrence dates are closer to the launch date of CV-I, and then the required resources are not duly supplied.

![Fig. 9. Windows and dates for vehicle launches.](image)

| Table 10. Statistical values of measurable metrics. |
|---|
| **DS of priority 1 events** |
| Cycle | Maximum | Minimum | Average | Mean square error |
| 1st cycle | 100 | 87.5 | 97.41 | 1.45 |
| 2nd cycle | 100 | 100 | 100 | 0 |
| 3rd cycle | 100 | 100 | 100 | 0 |
| 4th cycle | 100 | 77.27 | 91.78 | 4.53 |
| **DS of priority 2 events** |
| Cycle | Maximum | Minimum | Average | Mean square error |
| 1st cycle | 100 | 77.66 | 93.3 | 2.15 |
| 2nd cycle | 100 | 98.31 | 99.98 | 0.08 |
| 3rd cycle | 100 | 100 | 100 | 0 |
| 4th cycle | 100 | 87.88 | 96.53 | 2.52 |
| **DS of priority 3 events** |
| Cycle | Maximum | Minimum | Average | Mean square error |
| 1st cycle | 100 | 72.9 | 90.8 | 4.06 |
| 2nd cycle | 100 | 95.45 | 99.91 | 0.31 |
| 3rd cycle | 100 | 100 | 100 | 0 |
| 4th cycle | 100 | 75 | 90.06 | 5.54 |
| **DS of all events** |
| Cycle | Maximum | Minimum | Average | Mean square error |
| 1st cycle | 100 | 75.53 | 92.8 | 2.43 |
| 2nd cycle | 100 | 98.08 | 99.98 | 0.1 |
| 3rd cycle | 100 | 100 | 100 | 0 |
| 4th cycle | 100 | 81.68 | 93.63 | 3.68 |
| **DP** |
| Cycle | Maximum | Minimum | Average | Mean square error |
| 1st cycle | 53.35 | 38.45 | 49.16 | 1.63 |
| 2nd cycle | 57.97 | 55.44 | 57.81 | 0.15 |
| 3rd cycle | 51.04 | 51.04 | 51.04 | 0 |
| 4th cycle | 50.93 | 42.86 | 48.27 | 1.64 |
| **AUCV** |
| Maximum | Minimum | Average | Mean square error |
| 21.09 | 6.63 | 11.78 | 1.39 |
when a launch delay occurs. To circumvent this problem, some materials can be transported to the space station in advance. Alternatively, designers can use the warnings in Fig. 10 and Table 12 to adjust events, plan contingency measures, and obtain a safe interval between the event occurrence dates and vehicle launch dates.

6. Conclusions

DES can be a useful method for determining optimal solutions to on-orbit and logistics mission design problems for China’s space station. DES is employed to establish a model framework of space station operations comprising the task scheduling layer, astronaut execution layer and station system layer. The launch delays are considered as contingency events with probabilities in the integrated simulation procedure, where the prolonged durations for preparing the next launch obey exponential distributions. In addition, based on the variance reduction technique and Monte Carlo simulation, AV&BMM is developed to determine the number of simulation trials, which makes the method more effective than traditional Monte Carlo simulation. The constraints of the launch window, minimum time interval of launches, maximum time interval of crew rotation, and safe operation and the metrics of DS, DP and AUCV are defined to verify and evaluate the stochastic impacts of a launch delay. The proposed method is a useful tool for depicting the performance of an operational plan during conceptual design, and three major conclusions are obtained from the demonstration for space station operations:

1) The result precision at a confidence level of 99% is preferred for determining the maximum number of simulation trials in AV&BMM.

2) The shorter the interval between the launch date of the cargo vehicles and the start of the launch windows, the more favourable it is to shorten the prolonged duration after the launch delay.

3) Highly prioritized events should not be arranged near the launch mission of the cargo vehicles, and the resources required for events close to the launch date of the vehicles should be provided by a previous cargo vehicle.

Acknowledgments

This work was partially supported by the National Natural Science Foundation of China (Grant No. 11572345) and the Science Project of the National University of Defense Technology (Grant No. ZK17-03-21).

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