Hindawi
Journal of Sensors
Volume 2022, Article ID 2888846, 12 pages
https://doi.org/10.1155/2022/2888846

Research Article

Tradeoff Optimization Technology of Effectiveness-Cost for Satellite-Based on CAIV Method

Zhiwei Chen[1] **Jian Jiao**[2] **Xinlin De**[3] **and Dongming Fan**[2,4]

[1]*Unmanned System Research Institute, Northwestern Polytechnical University, Xi'an 710109, China*
[2]*School of Reliability and Systems Engineering, Beihang University, Beijing 100191, China*
[3]*Beijing Institute of Structure & Environment Engineering, Beijing 100076, China*
[4]*School of Transportation Science and Engineering, Beihang University, Beijing, China*

Correspondence should be addressed to Jian Jiao; jiaojian@buaa.edu.cn

Received 10 November 2021; Accepted 10 January 2022; Published 29 January 2022

Academic Editor: Haidong Shao

The tradeoff of effectiveness and cost is a vital problem for complex industrial systems, mainly applied in the weapons and aviation fields. As a typical complex industrial system, the effectiveness-cost tradeoff of the satellites becomes challenging and interesting. This paper takes a remote sensing satellite as a research object, and an integrated approach to assess and optimize its effectiveness and cost is proposed. The characteristic parameters are selected according to an analysis of its structure and mission. Furthermore, the effectiveness evaluation model is established based on the Availability-Dependability-Capability (ADC) model, and the cost parameter model is developed using historical data and regression analysis. According to the Cost as Independent Variable (CAIV) method, the objective function of the satellite effectiveness-cost with the effectiveness-cost tradeoff space is established. The objective function is solved and optimized using a genetic algorithm to achieve a more efficient and economical satellite design scheme.

1. Introduction

The ability to complete missions efficiently by making the most of available resources, i.e., the ability to make a tradeoff between cost and effectiveness, has become a focus in complex industrial systems. There is a great deal of effectiveness study in industrial fields such as military, machinery manufacturing, and civil aviation [1–6], and many classical effectiveness evaluation methods have been proposed, such as the Weapons System Effectiveness Industry Advisory Committee (WSEIAC) model [7], the index method [8], and the system effectiveness analysis (SEA) [3]. However, due to significant differences between the working environment and mission characteristics, applying these methods directly in satellites for effectiveness evaluation is challenging and interesting. In studies about satellite effectiveness, Elhady [9] considered that effective measures usually depend on system performance, availability, reliability, and product quality. The effectiveness of the satellite was calculated semi-quantitatively in the literature [10–12]. These studies made some improvements in effectiveness evaluation, but they mainly focused on the functions and structure of satellites rather than the mission process. Based on system state transformations that occur throughout missions, De et al. [13] refined the effectiveness definition of remote sensing satellites and assessed the effectiveness of different satellite states, but the analysis was relatively simple.

With increasing demands for satellite applications, the cost of satellites has also become a significant problem. Currently, different cost estimation models commonly used for spacecraft include the Unmanned Space Vehicle Cost Model (USCM) [14], the NASA/Air Force Cost Model (NAFCOM) [15], and the Small Satellite Cost Model (SSCM) [16], most of which are based on satellite mass and other performance factors [17]. Furthermore, the Performance-Based Cost Model (PBCM) [18] and KAU Earth Observation Satellite Cost Model (KEOSCM) [19] are proposed to improve the existing models. While cost estimation studies of spacecraft are conducive to reducing the cost of satellites, cost reduction cannot sacrifice system effectiveness, which means that a rational balance between effectiveness and cost is needed.

The US military proposed the CAIV methodology in the 1990s to resolve the contradiction between the shortage of military expenditure and the expansion of demand [20]. This methodology defines cost as an input variable and emphasizes the tradeoff between effectiveness and cost. At present, some scholars have applied the CAIV methodology to the military field [21–23]. The CAIV methodology is used to support the tradeoff of the environmental exploration satellite system, and a tradeoff model of the performance and cost is established in [24]. Apgar discussed [25] the different initiatives to control space mission costs, including CAIV. In this paper, the system effectiveness and cost model are established by analyzing a remote sensing satellite as an object. Then, we optimize the satellite design by analyzing the tradeoff between effectiveness and cost (based on the CAIV methodology) and ensure that the design meets performance requirements at an affordable cost. Although we present this effectiveness-cost modeling and tradeoff analysis methodology for remote sensing satellites, this method can be applied to other space products with minor modifications.

The following sections of the paper are organized as follows. Section 2 mainly analyzes the structure and mission characteristics of a satellite and selects characteristic parameters. Section 3, combined with the mission process of the remote sensing satellite, establishes the evaluation model of effectiveness and cost of the remote sensing satellite, respectively. Section 4 proposes the tradeoff model based on the CAIV method, as well as the effectiveness assessment and cost estimation models established in Section 3, and uses a genetic algorithm to optimize the effectiveness-cost model in the tradeoff space, and finally arrives at the remote sensing satellite design solution with the optimal effectiveness-cost ratio. Finally, the discussion and conclusion are summarized in Section 5.

2. Structure and Mission of Remote Sensing Satellite

2.1. Structure and Characteristics of Satellite. According to its essential functions, the structure of the satellite, specifically a microwave imaging observation satellite, can be divided into payloads and satellite platforms. The specific composition is shown in Figure 1.

2.1.1. Payloads. The payloads of microwave imaging observation satellites mainly include various remote imaging sensors for earth observation, which is the core part of the satellite.

2.1.2. Satellite Platform. Satellite platforms can be divided into different subsystems, including structures-and-mechanisms, thermal control, power, control, propulsion, tracking, telemetry and command (TT&C), data management, and data transmission, which provide support, control, command, and management services.

Limited by the size of the carrier, the materials and instruments used in a satellite must satisfy the requirements of negligible mass, small volume, and low power consumption. Additionally, remote sensing satellites have other working, and technical characteristics, including long life and high reliability, a high degree of automation, and a technology-intensive design, and must suit particular environmental conditions.

(1) Special environmental conditions. A remote sensing satellite is subjected to severe shocks such as overload, vibration, and noise during launch and operates in a space environment with microgravity, intense radiation, and ultralow temperatures

(2) Long life and high reliability. A remote sensing satellite needs to work continuously in orbit for several years, during which it is almost impossible to perform replenishment, maintenance, repair, or replacement. Therefore, long life and high reliability are essential characteristics for a satellite

(3) The high degree of automation. The control of remote sensing satellites is mainly accomplished through the ground station and the TT&C subsystem. As satellite function improves, the degree of automation increases and the ability for autonomous control

(4) Technology-intensive. A satellite is a technology-intensive system, and satellite platforms and payloads apply specific theories, different materials, and equipment, involving many fields of science and technique

2.2. Capability and Mission Analysis of Satellite. To quickly obtain detailed information about a target, a remote sensing satellite needs to adjust its attitude in a short time after receiving control information from the ground station. Moreover, it should also change the angle of the remote sensor rapidly according to user's needs to observe the target quickly and efficiently. When the satellite reaches the predetermined area, target's electromagnetic wave radiated and reflected can be collected and preprocessed by the sensors to realize continuous imaging. The quality of the image will directly affect subsequent decision-making. After obtaining target information, the satellite needs to transmit the information to the ground station for reprocessing in a short time to ensure the timeliness of the information. Hence, a high capability of information processing and transmission is demanded.

According to the application and mission process of a remote sensing satellite, three main functional characteristics of the satellite can be concluded: the high-speed attitude maneuvering capability, the high-resolution imaging capability, and the ability to transmit large bandwidth information. In order to quantitatively measure satellite capabilities, these three functions or capabilities can be divided based on the composition of the satellite and described using design parameters so that they can be evaluated using the

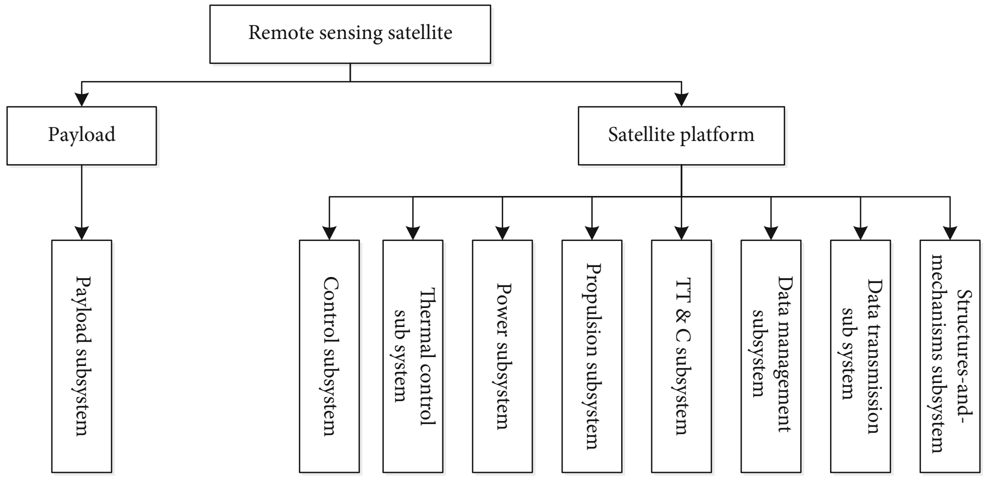

Figure 1: The composition of remote sensing satellite.

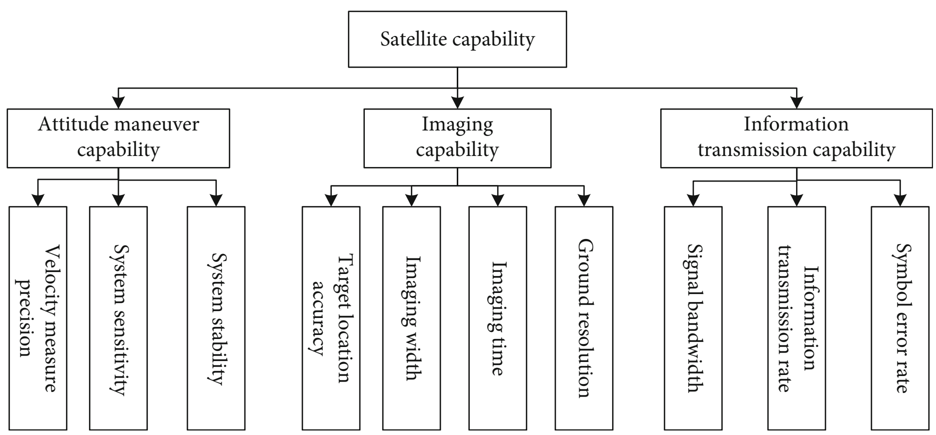

Figure 2: Capability indicators of remote sensing satellite.

performance of the satellite. After discussing with aerospace experts, some representative parameters are chosen as capability indicators to measure system capacity according to the function and structure of the satellite. For example, the imaging capability is measured by target location accuracy, imaging width, imaging time, and ground resolution. The specific composition is shown in Figure 2.

Among these three capabilities, high-resolution imaging is the central capability that is fundamental in determining the whole satellite's capability. At the same time, the attitude maneuvering and information transmission capabilities support the capability of the satellite platform from the perspective of satellite design and operation, reflecting the capability of coordinating and matching with imaging capability.

Based on the analysis of the structural characteristics and central capabilities of remote sensing satellites, we can safely conclude that the subsystems influencing the capability of satellites are payloads, control, propulsion, and data transmission subsystems; the subsystems that indirectly impact the capability are structures-and-mechanisms, thermal control, power, TT & C, and data management subsystems. Therefore, the satellite structure is moderately simplified. The indirect impact subsystems are collectively called auxiliary subsystems; furthermore, the reliability of the structures-and-mechanisms subsystem is regarded as one. Its impact on the capability of the satellite could be ignored because it adopts margin design based on safety factors. The logical relationships between the structure and the mission capability of remote sensing satellites are shown in Figure 3.

The state changes of each subsystem will affect different capability indicators, that will in turn affect the overall capability of the satellite. The arrows between the elements in Figure 3 indicate their relationships of influence. For example, the payload subsystem impacts all the capability indicators of the imaging capability and has a specific influence on the information transmission capability of the satellite. The auxiliary subsystem does not directly affect the capability index in the mission process, but it plays a fundamental role in supporting the remote sensing satellite and indirectly impacts all the capability indicators.

The propulsion, control, payload, data transmission, and auxiliary subsystems are represented by N_1, N_2, N_3, N_4, N_5, respectively, and each subsystem has two states: normal (N) and fault ($\bar{N}$). Therefore, there are 32 possible system states of the satellite. However, according to the actual operation of the satellite and the practical significance of these states, when

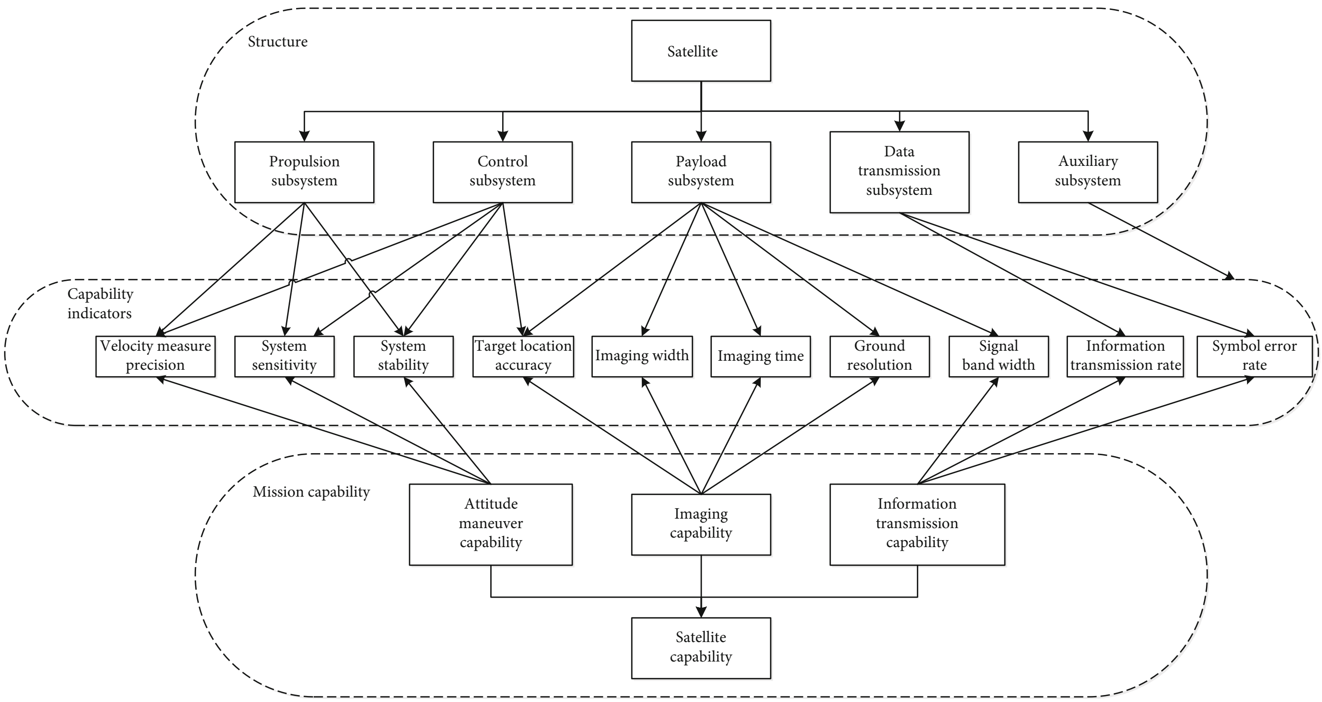

Figure 3: The logical relationship between the structure and mission capability of the satellite.

Table 1: The meanings of remote sensing satellite states.

State number	System state	Capability situation
1	$N_1N_2N_3N_4N_5$	Satellite capabilities are standard, and remote sensing missions can be carried out.
2	$\bar{N}_1N_2N_3N_4N_5$	Attitude maneuver capability is impaired, and satellite capabilities are slightly reduced.
3	$N_1\bar{N}_2N_3N_4N_5$	Capabilities of attitude maneuver and imaging are impaired, and satellite capabilities are slightly reduced.
4	$N_1N_2\bar{N}_3N_4N_5$	Capabilities of information transmission and imaging are impaired, and satellite capabilities are significantly reduced.
5	$N_1N_2N_3\bar{N}_4N_5$	Information transmission capabilities are impaired, and satellite capabilities are slightly reduced.
6	$\bar{N}_1\bar{N}_2N_3N_4N_5$	Capabilities of attitude maneuver and imaging are impaired, and satellite capabilities are significantly reduced.
7	$\bar{N}_1N_2\bar{N}_3N_4N_5$	Three capabilities are impaired, and satellite capabilities are critically reduced.
8	$\bar{N}_1N_2N_3\bar{N}_4N_5$	Capabilities of attitude maneuver and information transmission are impaired, and satellite capabilities are significantly reduced.
9	$N_1\bar{N}_2\bar{N}_3N_4N_5$	Three capabilities are impaired, and satellite capabilities are critically reduced.
10	$N_1\bar{N}_2N_3\bar{N}_4N_5$	Three capabilities are impaired, and satellite capabilities are critically reduced.
11	$N_1N_2\bar{N}_3\bar{N}_4N_5$	Capabilities of information transmission and imaging are critically impaired, and satellite capabilities are reduced.
12	Error	Satellite capabilities are lost, and remote sensing missions cannot be carried out.

the auxiliary subsystem fails or the fault number of other subsystems is greater than or equal to three (≥3), it can be regarded that the remote sensing satellite has lost its essential capability and cannot continue to perform the mission. The states in which the satellite cannot continue to perform its mission are classified as ERROR states, and thus, the number of system states of the satellite is simplified to 12. The specific meanings of each state are shown in Table 1.

3. Modeling of Effectiveness and Cost for Remote Sensing Satellite

3.1. Effectiveness Model for Remote Sensing Satellite. Effectiveness is a widely applied concept, so it should be precisely defined before analysis. The most common understanding of effectiveness is the real-world ability of a specific system to accomplish a specific mission. Based on the above discussion about capability and mission characteristics, the definition of the effectiveness of a remote sensing satellite can be summarized as *the ability to carry out mission-specific remote sensing continuously within a designated area and a specified period of time, where the collected information should meet a specific requirement.*

In this paper, the effectiveness of the satellite is calculated using the ADC model [7]. The ADC model was proposed by WSEIAC, in which system effectiveness is regarded as a measure of the degree to which a system can meet a set of mission requirements and is the comprehensive embodiment of system availability (A), dependability (D), and capability (C). By combining the *ADC* model with probability theory, the effectiveness of remote sensing satellite can be expressed as:

$$E = A\bullet D\bullet C_a, \tag{1}$$

where A is an availability vector, representing the probabilities of the satellite in different states when it begins its mission. D is a dependability matrix representing the transition probability between different system states during the mission. C_a is a capability vector, representing the inherent capability of the satellite under different states. The detailed expression of A, D, and $C_a$will be discussed in the following sections.

3.1.1. Availability of Remote Sensing Satellite. The availability of remote sensing satellites is represented by a row vector A, that is, $A = [A_1, A_2 \cdots A_i \cdots A_n]$, where A_i is the probability that the satellite is in the state i at the beginning of the mission, n is the total number of satellite states, and $\sum_{i=1}^{n} A_i = 1$. Since the analyzed satellite is a single satellite and there is no backup, only repairable faults are considered, and nonrepairable faults will result in mission failure. Using a_1, a_2, a_3, a_4, a_5 represents the probabilities, respectively, that five subsystems (shown in Figure 3) can operate normally, and let MTBF and MTTR represent the average time between fault and the average repair time of these subsystems, respectively; thus,

$$a_i = \frac{\mathrm{MTBF}_i}{(\mathrm{MTBF}_i + \mathrm{MTTR}_i)}. \tag{2}$$

And the probabilities that the subsystems cannot operate normally at the beginning are

$$\bar{a}_i = 1 - a_i. \tag{3}$$

There are twelve states in remote sensing satellites (shown in Table 1). The probability that the satellite is in a particular state at the beginning of the mission is the product of the state probabilities of five subsystems, for example, $A_1 = a_1 a_2 a_3 a_4 a_5$. So, the availability vector is:

$$A = [A_1 \quad A_2 \quad A_3 \quad A_4 \quad A_5 \quad A_6 \quad A_7 \quad A_8 \quad A_9 \quad A_{10} \quad A_{11} \quad A_{12}]. \tag{4}$$

3.1.2. Dependability of Remote Sensing Satellite. The dependability matrix (D) of the remote sensing satellite is an n-order-matrix, that is, $D = [d_{ij}]_{n\times n}$, where $d_{ij}(i, j = 1, 2, \cdots, n)$ represents the probabilities of transitions from initial state i to state j during the mission. Therefore, the state changes of the satellite can be expressed mathematically as a stochastic process, $\{X(t), t \geq 0\}$, where t is time. In the stochastic process, the probability of the satellite transferring from one state to another is only related to the present state so that the process can be transformed into continuous-time Markov chains. The mathematical expression of continuous Markov chains is:

$$P\{X(t+u) = j | X(u) = i\} = p_{ij}(u, t). \tag{5}$$

It represents the probability that the system is in state i at time u and is transferred to state j after time interval t. According to the historical data of similar satellites, it can be assumed that the reliability of the subsystems is subject to exponential distribution, so the probability of state transition is independent of the time u. Therefore, $p_{ij}(u, t)$ can be written as $p_{ij}(t)$.

In the state transition process, we assume that two or more faults cannot cooccur in the satellite [13], and the satellite state does not change within an operation time of Δt($\Delta t \longrightarrow 0$) after a state transition. This assumption is also in line with the actual situation and can significantly reduce the computational complexity. Then, the transition probability $p_{ij}(t)$ satisfies regularity condition:

$$\lim_{t\longrightarrow 0} p_{ij}(t) = \begin{cases} 1, i = j, \\ 0, i \neq j. \end{cases} \tag{6}$$

For any fixed $i, j \in I$, $p_{ij}(t)$is a consistent, continuous function of t and has the following limits:

$$\begin{cases} \lim_{\Delta t\longrightarrow 0} \dfrac{p_{ij}(\Delta t) - 1}{\Delta t} = q_{ij}, i = j, \\ \lim_{\Delta t\longrightarrow 0} \dfrac{p_{ij}(\Delta t)}{\Delta t} = q_{ij}, i \neq j, \end{cases} \tag{7}$$

where q_{ij} is called transfer intensity of a homogeneous Markov process. The transfer intensity of homogeneous Markov chains of continuous-time can form a matrix shown below:

$$Q = \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1n} \\ q_{21} & q_{22} & \cdots & q_{2n} \\ \cdots & \cdots & q_{ij} & \cdots \\ q_{n1} & q_{n2} & \cdots & q_{nn} \end{bmatrix}. \tag{8}$$

From the matrix Q, the equation can be deduced to evaluate the transition probability for any time interval t, which can be expressed by the Kolmogorov forward:

$$\frac{dp_{ij}(t)}{dt} = \sum_{k} p_{ik}(t) q_{kj}, \tag{9}$$

where the initial conditions are $p_{ij}(0) = \begin{cases} 1, i = j \\ 0, i \neq j \end{cases}$, and $P(t)$ can be written in matrix form:

$$P(t) = \frac{d}{dt} P(t) Q^{-1}. \tag{10}$$

The transfer intensity matrix Q can be obtained based on the fault rates of the satellite subsystems, and then, the state transition probability matrix $P(t)$ after a time interval t, i.e., the dependability matrix D, of the satellite can be calculated. According to the definition of satellite effectiveness, the remote sensing mission of the satellite is a continuous process, so the mission will fail once the satellite fails. Therefore, the dependability matrix D is an upper triangle matrix without considering the maintenance of the satellite during the mission.

Due to space constraints, only the fourth row of matrix D is used as an example, where $\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5$ represent the propulsion, control, payloads, data transmission, and auxiliary subsystems' failure rates. In the same way, other elements in matrix D can be deduced.

$$\begin{aligned}
&D_{4,1} = D_{4,2} = D_{4,3} = D_{4,5} = D_{4,6} = D_{4,8} = D_{4,10} = 0, \\
&D_{4,4} = e^{-t(\lambda_1+\lambda_2+\lambda_4+\lambda_5)}, \\
&D_{4,7} = e^{-t(\lambda_2+\lambda_4+\lambda_5)} - e^{-t(\lambda_1+\lambda_2+\lambda_4+\lambda_5)}, \\
&D_{4,9} = e^{-t(\lambda_1+\lambda_4+\lambda_5)} - e^{-t(\lambda_1+\lambda_2+\lambda_4+\lambda_5)}, \\
&D_{4,11} = e^{-t(\lambda_1+\lambda_2+\lambda_5)} - e^{-t(\lambda_1+\lambda_2+\lambda_4+\lambda_5)}, \\
&D_{4,12} = 2e^{-t(\lambda_1+\lambda_2+\lambda_4+\lambda_5)} - e^{-t(\lambda_1+\lambda_2+\lambda_5)} - e^{-t(\lambda_1+\lambda_4+\lambda_5)} \\
&\qquad - e^{-t(\lambda_2+\lambda_4+\lambda_5)} + 1.
\end{aligned} \tag{11}$$

3.1.3. Capability of Remote Sensing Satellite. The column vector C_a represents the capability of remote sensing satellites, $C_a^T = [C_{a1}, C_{a2} \cdots C_{ak} \cdots C_{an}]$, where C_{a1} implies the perfect performance state and C_{an} implies the worst state. Therefore, when calculating the capability of remote sensing satellites, C_{a1} should be calculated first, and the remaining capability values can be evaluated by comparing them with C_{a1}. It is obvious that the capability indicators shown in Figure 2 cannot be directly calculated, so they should first be normalized and transformed into a unified quantitative style. The design range of the indicator P_i can be divided into subranges, and the evaluation value $u(P_i)$ can be determined according to the normalization function. Equation (12) is an example of a normalization function, in which the design range of the indicator P_i is divided into five subranges, and different evaluation values $u(P_i)$ are assigned using the functions, where 10 represents the best performance, and 0 represents the worst.

$$u(P_i) = \begin{cases} 0, \wedge P_i \leq p_1, \\ 10 \times \dfrac{P_i - p_1}{p_2 - p_1}, \wedge p_1 < P_i < p_2, \\ 10, \wedge p_2 \leq P_i \leq p_3, \\ 10 \times \left(1 - \dfrac{P_i - p_3}{p_4 - p_3}\right), \wedge p_3 < P_i < p_4, \\ 0, \wedge P_i \geq p_5. \end{cases} \tag{12}$$

For capability indicators that are difficult to evaluate using a linear function in Equation (12), the piecewise interval evaluation method can be adopted. According to the data variation range of specific capability indicators, the dividing point and number of capability evaluation intervals are determined, and the corresponding capability evaluation value $u(P_i)$ is given. Taking the symbol error rate as an example, the lower rate corresponds to a better capability evaluation value. The capability evaluation interval of this indicator has five ranges, namely $[0, 10^{-8}]$, $[10^{-8}, 10^{-7}]$, $[10^{-7}, 10^{-6}]$, $[10^{-6}, 10^{-5}]$, and $[10^{-5}, \infty]$, and the corresponding evaluation value is 10, 8, 6, 4, and 0, respectively.

Then, the AHP [26] is introduced to determine the weight of the capability indicators so that the capability of the satellite can be assessed quantitatively. A hierarchical structure model is established according to the structure of capability indicators in Figure 2, and values of pairwise contrast are scored by discussing with experts in the aerospace industry in order to construct judgment matrices. Then, the order of importance and consistency test is performed on the indicators of the same level to get the weight w_i of each indicator in the hierarchical model. Using the weights and the evaluation values $u(P_i)$, the capability of the satellite to accomplish the mission in a normal state can be calculated, i.e., $C_{a1} = \sum w_i \bullet u(P_i)$.

According to the definition of different satellite states (shown in Table 1), the capability of satellites in other states can be regarded as a reduction of capability in normal states because the state of the satellite subsystems impacts the capability indicators. An influence coefficient of capability indicators (ρ) is introduced to represent the extent to which the satellite subsystems impact each capability indicator under different conditions, where $\rho = 0$ means that the subsystem failure does not influence the capability indicator, while $\rho = 1$ means that the subsystem fault has a decisive influence. Thus, the reduction of the capability indicator is shown in the following equation:

$$\begin{cases} u(P_i)' = \left(1 - \sum \rho\right) \bullet u(P_i), \left(\sum \rho \leq 1\right), \\ u(P_i)' = 0, \left(\sum \rho > 1\right), \end{cases} \tag{13}$$

where $u(P_i)$ is the evaluation value of capability indicator in the normal state and $u(P_i)'$ is the reduction value. Thus, the capabilities of the satellite in other states are $C_{ak} = \sum w_i \bullet u(P_i)'$.

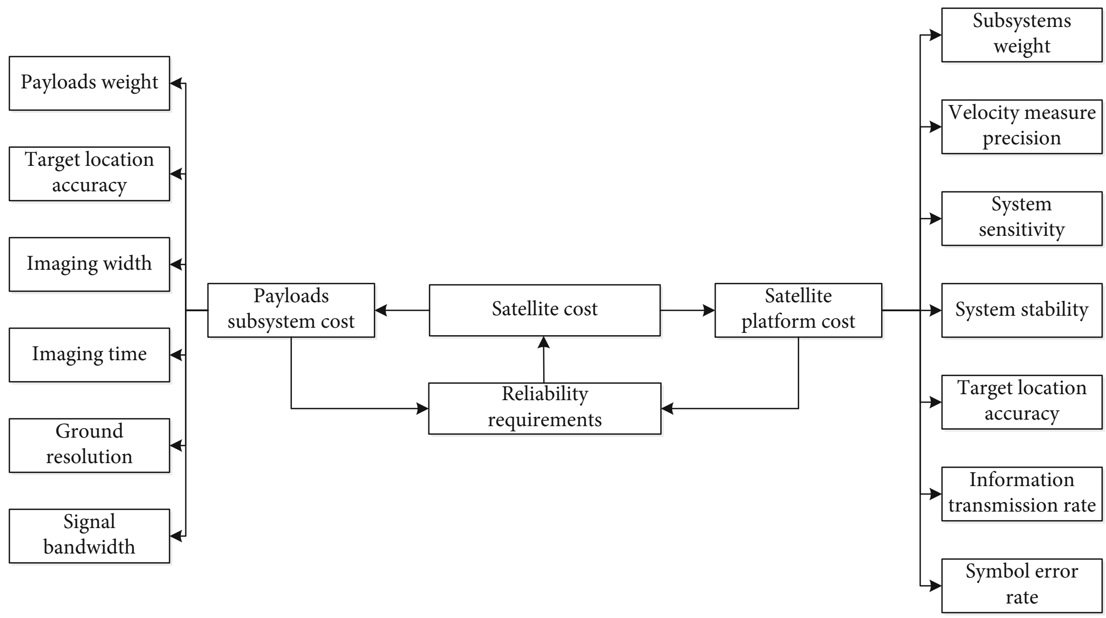

Figure 4: The cost relationship structure for a remote sensing satellite.

3.2. Cost Model for Remote Sensing Satellite. The cost of research and development can be quickly and efficiently estimated based on the design parameters, which is usually called parameter cost estimation [27]. Similarly, the cost of remote sensing satellites is evaluated based on the analysis of system composition. The functional relationship between each subsystem cost and design parameters is established based on the physical characteristics, design parameters, and cost data from similar historical data. This study only considered the cost associated with satellite design, development, and test.

3.2.1. Establish the Cost Relationship Structure for Remote Sensing Satellite. The cost relationship between the structure and mission capability of the satellite is shown in Figure 4. The cost of the satellite consists of the payload subsystem and satellite platform subsystems, i.e.,

$$C_o = \sum_i C_{oi}, \tag{14}$$

where C_{oi} is the cost of each subsystem of the satellite. The cost is affected by many factors, such as weight, capability indicators, and reliability requirements. The specific impacts and cost models for each subsystem are discussed below.

3.2.2. Cost Models of Satellite Subsystems. According to the USCM, which is widely used for cost estimation of satellites [14], the cost model of the satellite subsystem is:

$$C_{oi} = a_i X^{b_i}, \tag{15}$$

where C_{oi} is the cost of the satellite subsystem, X is the weight of subsystem, and a_i and b_i are correction coefficients. Based on the cost relationship structure of the remote sensing satellite, the original USCM is amended, and different capability indicators are introduced as correction variables so that the cost models of different subsystems can be obtained. The correction coefficients in the models can be calculated using regression analysis on historical data.

(1) The Cost Model of the Propulsion Subsystem

$$C_{o1} = A_1 \bullet X^{a_1} \bullet P_1^{b_1} \bullet P_2^{c_1} \bullet P_3^{d_1} \bullet P_4^{f_1}, \tag{16}$$

where C_{o1} is the cost of the propulsion subsystem, X is the total weight of the propulsion subsystem, P_1 is the velocity measure precision, P_2 is the system sensitivity, P_3 is the system stability, P_4 is the reliability requirement, and A_1, a_1, b_1, c_1, d_1, and f_1 are the correction coefficients.

(2) The Cost Model ofthe Data Transmission Subsystem

$$C_{o2} = A_2 \bullet X^{a_2} \bullet P_5^{b_2} \bullet P_6^{c_2} \bullet P_4^{f_2}, \tag{17}$$

where C_{o2} is the cost of the data transmission subsystem, X is the total weight of the data transmission subsystem, P_5 is the information transmission rate, P_6 is the symbol error rate, P_4 is the reliability requirement, and A_2, a_2, b_2, c_2, d_2, and f_2 are the correction coefficients.

(3) Cost Model ofPayload Subsystem

$$C_{o3} = A_3 \bullet X^{a_3} \bullet P_7^{b_3} \bullet P_8^{c_3} \bullet P_9^{d_3} \bullet P_{10}{}^{e_3} \bullet P_{11}{}^{g_3} \bullet P_4^{f_3}, \tag{18}$$

where C_{o3} is the cost of the payload subsystem, X is the total weight of the payload subsystem, P_7 is the target location accuracy, P_8 is the imaging width, P_9 is the imaging time, P_{10} is the ground resolution, P_{11} is the signal bandwidth, P_4 is the reliability requirement, and $A_3, a_3, b_3, c_3, d_3, e_3, f_3$, and g_3 are the correction coefficients.

Table 2: The reliability of subsystems.

Subsystem	1	2	3	4	5	6	7	8
Propulsion subsystem	0.9859	0.9859	0.988	0.988	0.988	0.988	0.988	0.985
Control subsystem	0.9033	0.9253	0.9338	0.9338	0.925	0.921	0.92	0.944
Payloads subsystem	0.902	0.8300	0.9266	0.926	0.901	0.895	0.808	0.8965
Data transmission subsystem	0.9495	0.9171	0.9675	0.9675	0.977	0.966	0.976	0.847
Auxiliary subsystem	0.9189	0.8914	0.8868	0.8868	0.9307	0.8791	0.9448	0.8846

Table 3: The weight of subsystems (kg).

Subsystem	1	2	3	4	5	6	7	8
Propulsion subsystem	96	111	103	103	75	45.5	55	175
Control subsystem	191	220.2	234	234	183	170.77	172	330
Payloads subsystem	606	729.8	798	750	475	940	392	742
Data transmission subsystem	136	175.2	190	190	72	63.3	125	227
Auxiliary subsystem	895	964	971	971	907	793.09	534	1162

Table 4: The cost of subsystems (RMB).

Subsystem	1	2	3	4	5	6	7	8
Propulsion subsystem	2018	2384	2517	2517	1829	1578	1528	3112
Control subsystem	1786	2251	2862	2862	1151	1011	1001	4207
Payloads subsystem	4884	3956	6497	6021	3264	6449	1687	5453
Data transmission subsystem	2247	2240	3130	3130	1223	1288	2484	2834
Auxiliary subsystem	14013	13244	13256	13256	15308	11128	10898	13404

(4) The Cost Model of the Control Subsystem

$$C_{o4} = A_4 \bullet X^{a_4} \bullet P_1^{b_4} \bullet P_2^{c_4} \bullet P_3^{d_4} \bullet P_7^{e_4} \bullet P_4^{f_4}, \tag{19}$$

where C_{o4} is the cost of the control subsystem, X is the total weight of the control subsystem, P_1 is the velocity measure precision, P_2 is the system sensitivity, P_3 is the system stability, P_7 is the target location accuracy, P_4 is the reliability requirement, and A_4, a_4, b_4, c_4, d_4, e_4, and f_4 are the correction coefficients.

(5) The Cost Model of the Auxiliary Subsystem

$$C_{o5} = A_5 \bullet X^{a_5} \bullet P_4^{f_5}, \tag{20}$$

where C_{o5} is the cost of the auxiliary subsystem, X is the total weight of the auxiliary subsystem, P_4 is the reliability requirement, and A_5, a_5, and f_5 are the correction coefficients.

By collecting and preprocessing the historical data of remote sensing satellites, the design parameters and cost of each subsystem of similar satellites can be estimated. Since there are price fluctuations throughout different years, all costs of historical satellites will be converted to the price in 2016 to maintain a uniform measurement of the fitted data. The detailed data can be found in Tables 2–6. Nonlinear multivariate regression analysis is performed to evaluate the parameters in the above cost models. The Levenberg-Marquardt algorithm [28] is chosen to ensure the stability of the model and reduce the number of calculations and fitting errors of the correction coefficients.

Nonlinear models are complex compared to other models, and it is difficult to obtain their regression parameters. Marquard introduced the damping factor based on the Gauss-Newton method and proposed the Marquardt algorithm. The method has a high fitting efficiency and low error for nonlinear model fitting. It inherits the global optimization-seeking feature of the original algorithm and speeds up the convergence speed. The basic principle of the Marquardt method is to calculate the sum of squares of residuals through continuous data iteration, which is used to evaluate whether the fitted parameters achieve the best fitting effect. When the sum of squares of the residuals reaches a minimum value, the iterative process ends, and the resulting regression parameters are the final results of the cost curve fitting, which leads to the cost estimation model for each subsystem.

The cost models for each subsystem are listed in Table 7.

4. Tradeoff Optimization between Effectiveness and Cost of Remote Sensing Satellite

4.1. The Methodology of Cost as an Independent Variable (CAIV). The US military proposes the CAIV methodology to solve the contradiction between the limitation of system resources and the unlimited expansion of demand. The two most fundamental characteristics in the CAIV

Table 5: The capability indicators of satellites.

Capability indicator	1	2	3	4	5	6	7	8
Velocity measure precision (m/s)	4	2	1.8	1.8	6	6	6	1
System sensitivity (°)	5	5	6	6	4	4	4	8
System stability (°/s)	0.55	0.5	0.6	0.6	0.4	0.35	0.35	0.6
Target location accuracy (m)	35	40	30	30	40	30	40	35
Imaging width (km)	25	25	28	25	18	28	18	30
Imaging time (h)	2	1.8	2.5	2	1.5	2.5	1	2.5
Ground resolution (m)	3	3	4	4.5	10	2	10	4
Signal bandwidth (mhz)	600	600	580	580	550	500	500	600
Information transmission rate (Gbps)	15	14	16	16	15	13	13	17
Symbol error rate	10^{-7}	10^{-7}	10^{-8}	10^{-8}	10^{-6}	10^{-6}	10^{-6}	10^{-8}

Table 6: The value range of satellite capability indicators.

Velocity measure precision (m/s)	System sensitivity (°)	System stability (°/s)	Target location accuracy (m)	Imaging width (km)
0.5-10	4-8	0.35-0.7	30-50	10-30
Imaging time (h)	Ground resolution (m)	Signal bandwidth (mhz)	Information transmission rate (Gbps)	Symbol error rate
0.5-3.5	0.5-20	100-600	5-20	$1*10^{-8}$-$1*10^{-5}$

methodology are that it takes cost as an input variable rather than an output variable and emphasizes the optimization of the tradeoff between cost and effectiveness. In the process of tradeoff and optimization, cost, like other input indicators, is managed and controlled as a constraint by imposing upper and lower limits. Therefore, when determining the cost range, we should not set a particular target arbitrarily but conduct a series of cost and effectiveness analyses to comprehensively understand what cost changes can improve the effectiveness and which parameters can effectively control cost.

To define the value range for each parameter and cost, the CAIV methodology also proposed the concept of the *tradeoff optimization space*. The tradeoff optimization space can be defined using cost and effectiveness and regarded as a set of all feasible alternatives, and each element in it represents a feasible alternative. For the cost of a satellite, it is necessary to determine the upper limit of C_{omax} within the economically affordable range, and the lower limit C_{omin}, if necessary, it also needs to be determined. On the other hand, we need to determine the ranges of the design parameters used to measure effectiveness. For design parameters, we need to know the constraints of equipment capabilities and the level of the existing technology. Take a certain indicator P_i for example, if the lowest value that can meet the mission requirement is P_i^L, and the highest value that can be achieved under the current technical level is P_i^U, then the value range of the indicator is$P_i^L \le P_i \le P_i^U$. Of course, for some indicators, a smaller value is better than a larger value so that the range will be $P_i^U \le P_i \le P_i^L$.

4.2. Building and Solving the Tradeoff Optimization Model of Satellite. The designers of remote sensing satellites need to select the best design scheme among all alternatives in the established tradeoff optimization space. There are many evaluation criteria for measuring the effectiveness and cost of a design scheme. This paper takes the effectiveness-cost ratio as the criteria, and the tradeoff optimization space is taken as the constraint condition. The tradeoff optimization model of a remote sensing satellite is established as follows:

$$\begin{cases} \max K = E/C_o, \\ \text{s.t.} E = F(P_1, \cdots, P_n), \\ C_o = \varphi(P_1, \cdots, P_n), \\ E \ge 6, \\ 10000 \le C_o \le 30000, \\ P_i^L \le P_i \le P_i^U, i = 1, \cdots, n, \end{cases} \tag{21}$$

where K represents the value of the effectiveness-cost ratio, and the larger the value, the better the satellite design scheme. $E = F(P_1, \cdots, P_n)$ is the effectiveness evaluation model of satellite, which can be calculated based on Equations (1)–(13). According to design's requirements, satellite's effectiveness after running for 10,000 hours must be higher than 6. $C_o = \varphi(P_1, \cdots, P_n)$ is the satellite cost model, which can be calculated using Equations (14)–(20). According to the design requirements, the total cost of remote sensing satellite is estimated to be between 100 million and 300 million (RMB). $P_1, \cdots, P_n$ represent all kinds of parameters of the satellite, and their ranges can be estimated according to the mission requirements.

The tradeoff optimization model can be transformed into an extremum problem of the function with multiple constraints. To avoid the problem of a locally optimal solution in the solving process, a generalized genetic algorithm

Table 7: Cost models for subsystems.

Subsystem	Cost model
Propulsion subsystem	$C_{o1} = 832.3837X^{0.3167} \bullet P_1^{-0.1751} \bullet P_2^{c0.0200} \bullet P_3^{0.0530} \bullet P_4^{22.0525}$
Data transmission subsystem	$C_{o2} = 2.0764X^{1.2182} \bullet P_5^{0.3836} \bullet P_6^{-0.0007} \bullet P_4^{2.6665}$
Payload subsystem	$C_{o3} = 2.5742X^{0.7652} \bullet P_7^{-0.0032} \bullet P_8^{0.0569} \bullet P_9^{0.0236} \bullet P_{10}^{-0.1204} \bullet P_{11}^{0.4727} \bullet P_4^{4.2080}$
Control subsystem	$C_{o4} = 392.1322X^{0.4898} \bullet P_1^{-0.3508} \bullet P_2^{0.0587} \bullet P_3^{0.8144} \bullet P_7^{-0.0464} \bullet P_4^{0.1023}$
Auxiliary subsystem	$C_{o5} = 282.4148X^{0.6225} \bullet P_4^{3.8215}$

Table 8: The value of the capability indicators.

Velocity measure precision (m/s)	System sensitivity (°)	System stability (°/s)	Target location accuracy (m)	Imaging width (km)
9.7323	7.8769	0.6765	30.7965	20.0000
Imaging time (h)	Ground resolution (m)	Signal bandwidth (mhz)	Information transmission rate (Gbps)	Symbol error rate
3.4614	8.0000	237.8178	7.8004	5.0592×10^{-6}

Table 9: The weight and reliability requirements of each subsystem.

Parameter	Propulsion subsystem	Control subsystem	Payloads subsystem	Data transmission subsystem	Auxiliary subsystem
Weight (kg)	185	51	571	255	883
Reliability	0.9804	0.9959	0.9683	0.9733	0.8022

[29, 30] is introduced to solve the extreme value of the effectiveness-cost ratio of the model. The core idea of this algorithm is to perform selection, crossover, mutation, and other related operations on a biological population consisting of a certain number of individuals by simulating the evolutionary laws of organisms in nature to find the optimal solution or approximate solution according to the target requirements. On this basis, other scholars have continued to supplement and develop the genetic algorithm to the completeness, and it has become the most widely used optimization algorithm. The basic parameters of the algorithm are set as follows:

(i) The population size is 100

(ii) Mutation probability is 0.01

(iii) Crossover probability is 0.6

After 30 iterations, the optimization results tend to be stable, and the highest value of effectiveness-cost ratio that can be obtained in the tradeoff optimization space is 4.0705×10^{-4}, where the effectiveness value is 6.8421, the cost value is 168 million (RMB). The value of satellite's capability indicators is shown in Table 8, and the weight and reliability requirements of each subsystem are shown in Table 9.

Before performing the tradeoff optimization of effectiveness-cost, the effectiveness of the satellite is 6.7794, and the cost is about 251 million (RMB), meaning the effectiveness-cost ratio is 2.7047×10^{-4}. Compared with the tradeoff design scheme, the effectiveness of the satellite has increased by 0.9249%, the cost of the satellite has reduced by 33%, and the satellite effectiveness-cost ratio has increased significantly. The tradeoff design scheme of the satellite is more practical than the original design based on meeting performance requirements and affordability.

5. Discussion and Conclusion

Based on the idea of the CAIV methodology, this paper proposes a tradeoff optimization method of effectiveness-cost for a remote sensing satellite, in which multiple models are combined synthetically to improve satellite's design scheme. Compared with the other tradeoff optimization methods, the input cost is taken as an independent variable and is considered in the whole tradeoff process in this work. The proposed approach emphasizes that cost is integral to design indicators to ensure that the input cost is within the tolerable limit. Under the premise of meeting the performance requirements of the satellite, the proposed method can find the optimal scheme from the whole feasible design domain, which is different from selecting the design scheme with the highest effectiveness-cost ratio from several alternative design schemes as the decision result. The tradeoff optimization between cost and effectiveness can efficiently yield calculated results close to the actual use situation, which is beneficial to discover unreasonable links and helps improve the design scheme.

Compared with the original design and effectiveness-cost ratio, the optimized design scheme is more competitive, as we can see from the case study. However, since the evaluation criteria in the tradeoff optimization model are only related to the effectiveness and cost of the satellite, the results will be affected by the accuracy of the effectiveness and cost models. Therefore, we need to make more precise calculations on the cost and effectiveness of satellites in future research. Additionally, the subjective preference of decision-makers for effectiveness and cost also affects the final satellite design scheme in the actual decision-making process, which is difficult to quantify and should be further discussed.

Data Availability

All of the data used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare no conflict of interest.

Authors' Contributions

Jian Jiao and Zhiwei Chen prepared the conception and the formal description of the proposed solution; they both made the literature review; Dongming Fan analyzed the data; and Zhiwei Chen and Xinlin De implemented the proposed solution and wrote the paper.

References

[1] D. Cave, "Systems effectiveness analysis tool for evaluating guided interceptors," in *32nd Aerospace Sciences Meeting and Exhibit; American Institute of Aeronautics and Astronautics*, Reno, NV, U.S.A, 1994.

[2] W. Guo and X. Shao, "Detection effectiveness of ship-borne radar under interference environment based on ADC model," *Command Control & Simulation*, vol. 3, pp. 47–49, 2014.

[3] H. Shao, H. Jiang, X. Zhang, and M. Niu, "Rolling bearing fault diagnosis using an optimization deep belief network," *Measurement Science and Technology*, vol. 26, no. 11, article 115002, 2015.

[4] W. Bi, F. Gao, and A. Zhang, "A novel weapon system effectiveness assessment method based on the interval-valued evidential reasoning algorithm and the Analytical Hierarchy Process," *IEEE Access*, vol. 9, pp. 53480–53490, 2021.

[5] S. Zhao, S. Song, Q. Qi, and W. Lei, "Cost-efficiency tradeoff is optimized in various cancer types revealed by genome-wide analysis," *Molecular Genetics and Genomics*, vol. 296, no. 2, pp. 369–378, 2021.

[6] L. Washington and A. Levis, "Effectiveness analysis of flexible manufacturing systems," in *Proceedings. 1986 IEEE International Conference on Robotics and Automatio*, pp. 1821–1826, San Francisco, CA, USA, April 1986.

[7] W. F. Stevens, *Weapon System Effectiveness Industry Advisory Committee*, SAE Technical Paper, 1964.

[8] T. N. Dupuy, *Application of the Quantified Judgment Method of Analysis of Historical Combat to Current Force Assessments*, Springer, Boston, MA: Military Strategy and Tactics, 1975.

[9] A. M. Elhady, "Remote sensing satellite system overall effectiveness analysis and modeling," in *2014 IEEE Aerospace Conference*, pp. 1–10, Big Sky, MT, USA, 2014.

[10] L. Tao, "Study of system effectiveness evaluation for optical imaging reconnaissance satellite based on fuzzy theory," in *3rd International Symposium of Space Optical Instruments and Applications*, vol. 192 of Springer Proceedings in Physics, Springer, Cham.

[11] P. Qin, "Effectiveness evaluation for remote sensing satellite application system based on AHP, ADC and gray theory," *Modeling and Simulation*, vol. 6, pp. 218–227, 2017.

[12] H. Chen and Y. Li, "Effectiveness evaluation and evaluating method innovation for weapon system," *Journal of Institute of Command & Technology*, vol. 15, pp. 1–5, 2004.

[13] X. De, J. Jiao, and Y. Zhu, "Modeling and evaluation for effectiveness of remote sensing satellite based on ADC model," in *Proceedings of the 2018 International Conference on Mathematics, Modelling, Simulation and Algorithms ((MMSA 2018)*, Chengdu, China, 2018.

[14] P. Nguyen, L. Lozzi, and W. Galang, *Unmanned Space Vehicle Cost Model*, US Air Force Space and Missile Systems Center (SMC/FMC), California, 2002.

[15] S. Winn and J. Hamcher, *NASA/Air Force Cost Model NAFCOM*, Science Applications International Corporation, 2002.

[16] "Small satellite cost model website," 2018, http://www.aero.org/capabilities/sscm/index.html.

[17] J. R. Wertz, D. F. Everett, and J. J. Puschell, *Space Mission Engineering: the New SMAD; Space Technology Library*, Microcosm Press, El Segundo, 2011.

[18] A. Shao, E. A. Koltz, and J. R. Wertz, "Quantifying the cost reduction potential for earth observation satellites," in *Proceedings of the 12th Reinventing Space Conference*, pp. 199–210, London, UK, 2014.

[19] Y. K. Chang, H. Kim, and J. S. Kang, "Development of reliability-corrected cost model for small earth observation satellites," *Acta Astronautica*, vol. 88, pp. 163–175, 2013.

[20] C. M. A. Kaye, D. R. Graham, and A. L. Gotwald, *Cost as an Independent Variable: Principles and Implementation*, Space and Missile Systems Center Los Angeles Afb Ca, 2000.

[21] Y. T. Tan and B. A. Guo, "Effectiveness-cost analysis & target demonstration method based-on CAIV," *Systems Engineering - Theory & Practice*, vol. 27, pp. 48–53, 2007.

[22] Q. L. Han, X. J. Cheng, and D. Xu, "Mechanical product design cost-effective tradeoff based on CAIV," *Control and Decision*, vol. 29, pp. 1522–1526, 2014.

[23] L. Gu, X. Xi, K. Liu, and S. Wang, "Cost effectiveness model and optimization of weapon system based on cost as an independent variable," in *2016 12th World Congress on Intelligent Control and Automation (WCICA)*, pp. 2455–2459, Guilin, China, 2016.

[24] P. E. Ardanuy, C. F. Schueler, S. W. Miller, K. Jensen, and W. J. Emery, "Use of CAIV techniques to build advanced VIIRS approaches for NPOESS key EDRs," in *Proceedings of the SPIE(2002)*, pp. 142–151, Seattle, United States, 2002.

[25] H. E. Apgar, "Affordable space systems," in *Proceedings of AIAA SPACE 2013 Conference and Exposition*, pp. 1–15, San Diego, United States, 2013.

[26] T. L. Saaty, "How to make a decision: the analytic hierarchy process," *European Journal of Operational Research*, vol. 48, pp. 9–26, 1990.

[27] P. Duverlie and J. M. Castelain, "Cost estimation during design step: parametric method versus case based reasoning method," *The International Journal of Advanced Manufacturing Technology*, vol. 15, pp. 895–906, 1999.

[28] D. W. Marquardt, "An algorithm for least-squares estimation of nonlinear parameters," *Journal of the Society for Industrial and Applied Mathematics*, vol. 11, pp. 431–441, 1963.

[29] C. Dong and X. H. Guo, “A global optimization algorithm based on generalized genetic algorithm,” *Computer Science*, vol. 26, pp. 7–10, 1999.

[30] Z. Chen, T. Zhao, J. Jiao, and F. Ren, “Availability analysis and optimal design of multistate weighted k-out-of-n systems with component performance requirements,” *IEEE Access*, vol. 6, pp. 51547–51555, 2018.