Research on Modeling and Effectiveness Evaluation of Space System Based on ABMS

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Abstract. Aiming at the effectiveness evaluation requirements of the space information system, this paper analyzes the difficulties in the modeling and effectiveness evaluation of the space system. A composable and reusable model framework for the space information system and an agent behavior modeling method oriented towards multi-domain connectivity, information processing, and resource management and control are established. A modeling, simulation, and effectiveness evaluation method based on ABMS (Agent Based Modeling and Simulation) for the space cyber information system is proposed. Eventually, the effectiveness of this technology is verified through typical application cases, thereby providing a quantitative analysis tool for system design and evaluation in relevant fields.

Keywords: Space information system; Model framework; ABMS; Resource management and control; Effectiveness evaluation

1 Introduction

The space-based information and communication system consists of various types of satellites such as remote sensing, transmission, communication, and navigation satellites, as well as constellations, ground stations, operation control centers, and inter-satellite and satellite-ground links. Remote sensing satellites include electronic, optical, and SAR types of satellites, while communication satellites include both geostationary and low Earth orbit communication satellites. These different types of satellites can form constellations or operate autonomously through inter-satellite links or independently through ground scheduling, each playing different roles in the system. With the scenario of detecting sea surface targets as a hypothetical background, this paper experimentally analyzes the impact of the resource architecture, operational strategies, and equipment capabilities of the space-based information and communication system on sea surface detection, identifies key influencing factors, and provides suggestions and basis for the construction of the space-based information and communication system [1]. This system plays an important role in multiple fields, especially in the detection, communication, and navigation of sea surface targets, where its complexity and multi-domain nature pose many challenges to its effectiveness evaluation [2].

Currently, the modeling methods for the space-based information and communication system mainly include system dynamics, network flow models, Petri nets, etc. These methods can describe the static and dynamic characteristics of the system to a certain extent, but they have limitations when dealing with complex scenarios involving multiple domains, tasks, and resources. System dynamics is mainly used to describe the macroscopic behavior of the system, but it is difficult to accurately simulate the microscopic behavior [3]; network flow models are mainly used to describe the flow of information in the network, but they struggle to handle complex interactions across multiple domains [4]; Petri net methods are mainly used to describe the concurrent behavior of the system, but they are not well-suited for handling large-scale complex systems [5]; qualitative evaluation methods mainly rely on expert experience and historical data, making it difficult to accurately describe the dynamic changes of the system [6]; quantitative evaluation methods can provide more accurate assessment results, but traditional simulation methods often fall short in terms of computational efficiency and accuracy when dealing with large-scale, high-complexity space-based information and communication systems [7]. Therefore, a new method is needed to overcome these limitations.

2 Composable Model Framework for Space-Based Information and Communication Systems

In the design process of the system model framework, it is necessary to start from the operational concepts and behaviors of the system, abstract operational entity models based on the performance indicators, effectiveness indicators, and interaction relationships of the system hierarchy at the physical domain, information domain, cognitive domain, and organizational domain. This ensures the generality of abstraction and modeling in these domains. This allows analysts to flexibly and agilely combine and adjust models from the system level for different system analysis problems, while also ensuring the simplicity and ease of use of system analysis [6][7][8].

The physical domain is the physical space where conflicts between hostile parties occur, containing all objective elements involved in combat processes. The essence of physical domain elements is their objective reality. The information domain is the information space where conflicts between hostile parties occur, containing all combat elements related to battlefield situation information, as well as the creation, management, and sharing of information. The cognitive domain is the thinking space of combat personnel, containing their perceptions, understandings, and shared situational awareness and decision-making based on this. The social domain is the space where human social behaviors are implemented, consisting of elements related to human social behavior.

Based on this, a hierarchical structure composed of agent models required for analysis of the space-based information and communication system is presented. Among them, operational users include combat forces executing tasks, which in turn command different combat units under various combat formations, and these combat units are composed of various combat platforms, personnel, and facilities. These combat entities constitute a multi-level inclusion relationship, communication relationship, command relationship, and maintenance relationship.

Combat entities facing the space-based information and communication system need to represent not only the composition of the physical domain but also the behaviors of the information domain and cognitive domain in the system. Therefore, it is necessary to determine a reasonable operational entity structure to support the model representation of combat entities. The components in the operational entity model mainly include physical domain components, information domain components, and cognitive domain components [9].

Physical Domain Components: Physical domain components include satellites, ground stations, operation control centers, etc. These components, most of which are equipment objects, provide flight, movement, detection, communication, and combat capabilities for the entity model, representing the inherent capabilities of the combat entity.

Information Domain Components: Information domain components need to represent the situational information perceived by the operational entity. This situational information includes threats from the enemy, friendly combat entities, as well as combat actions and tactical coordination information that need to be executed. For this purpose, the information domain components in the operational entity model mainly include local target lists, broadcast variables, and local command lists.

Cognitive Domain Components: Cognitive domain components are the core components that control the behavior of the agent model, reflecting the decision-making behavior of the operational entity model. Analysts can reflect the differences in combat behavior under different combat scenarios through the decision-making behavior model of the cognitive domain, as well as examine how information superiority in system operations is transformed into decision-making superiority and ultimately into combat superiority.

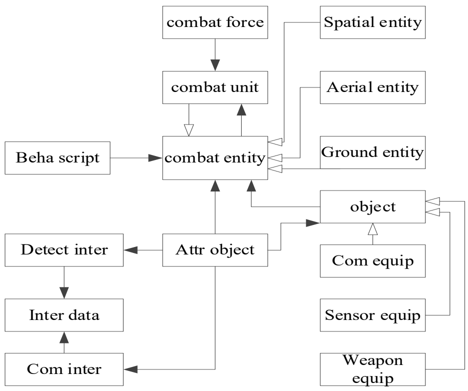


Fig. 1. Composable Model Framework for the Space-Based Information and Communication System.

The model framework for the space-based information and communication system is shown in Figure 1.

The components and data in the figure represent only the components that users need to define and use when developing simulation applications for the space-based system. In the model framework of the space-based information and communication system, combat forces include combat units that can be commanded. combat units are derived from combat entity objects, so combat entities can represent combat units composed of multiple combat entities, as well as individual combat entities.

Based on the above framework design, the model structure for each entity of the space-based information and communication system is shown in the following figure 2:

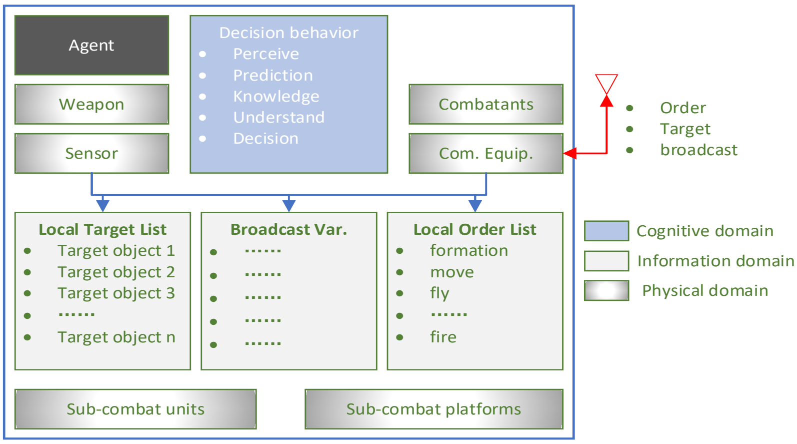


Fig. 2. Composition of the Entity Model for the Space-Based Information and Communication System.

The above abstract models all contain the physical domain, information domain, and cognitive domain.

3 Agent Behavior Modeling Method

The decision-making process of an agent's behavior reflects the complex process of transforming information superiority into decision-making superiority and ultimately into combat superiority under informationized conditions. This process includes a series of processes such as information processing, situational awareness, situation prediction, threat judgment, and decision-making actions. At the same time, this process is also the most variable part of system research, and how to reasonably and effectively support the representation of agent decision-making behavior is a core content of system effectiveness evaluation research. The modeling of agent decision-making behavior is a complex modeling process, and its decision results have the most significant impact on combat outcomes.

To describe decision-making behavior in simulations, several behavior representation methods have been formed, including reactive behavior representation methods, rule-based behavior representation methods, and activity-based behavior combination methods [9].

- **Reactive Behavior Representation Method:** Generally used for simple agent behavior modeling. Reactive decision rules allow agents to interact with other agents and respond to environmental changes, usually associating external stimuli with specific related reactions. Its advantage is that the rules are very simple, but the adaptability is usually very limited or cannot continue to evolve.
- **Rule-Based Behavior Representation Method:** Uses production rules to describe changes in combat entity decision-making behavior. The advantage is that knowledge is easy to represent, and the entire reasoning process only involves matching antecedents and performing consequents, but it cannot reflect the dynamic nature of combat processes over time, and flexibility is not strong, making development more difficult.
- **Activity-Based Behavior Combination Method:** Is a more flexible agent behavior representation method, which can represent the different activities of an agent at different times and under different conditions according to the order of activities executed in the simulation process.

This paper draws on the activity-based behavior combination method, strengthens the process description mode, and proposes a process-based behavior representation method. This method requires that the behavior of combat entities can be described in a serial manner according to processes or threads, and when delays occur in the simulation process, the execution of behaviors can be paused to ensure the causal correctness of the activity execution process in time among different agents. This approach is particularly suitable for the description and modeling of combat activities.

Supported by the process-based activity representation method, the decision-making behavior of each operational entity can be represented as a simulation process. Each entity's decision-making process consists of a series of activities, which can describe the complete process experienced by an operational entity from the start of the activity to the end of the simulation, including several events and activities that occur during this period, as well as the logic and timing relationships between these events and activities. The order of expression of these activities in the process represents the sequence of activity execution, and the execution conditions of activities can be controlled through flexible control statements. Processes are combinations of events and activities, so they can more comprehensively describe the state transition process in combat entity decision-making activities.

4 ABMS-Based Effectiveness Evaluation for Space-Based Information and Communication Systems

4.1 Features of the ABMS Method

Compared with traditional effectiveness simulation evaluation methods, the ABMS-based method can clearly represent the behavior modeling of specific individuals, while many traditional effectiveness simulations average or aggregate the entities in the system, and the corresponding computational models also attempt to simulate only the changes in the aggregated characteristics of these entities. The most important and difficult part of modeling is closely related to the interactions and adaptive behaviors of the entity Agent ensemble.

In terms of model structure, ABMS can represent the internal behavior of each individual. An Agent's behavior may depend on observations of other individuals but does not directly access these individuals' behavioral representations. This natural modularity follows the boundaries between individuals, and the encapsulation in model structure gives ABMS a clear advantage in system experimentation. In an ABMS, each entity has its own Agent or Agents model. An Agent makes decisions based on the information it has obtained or its "perception of the world," and its internal behavior does not need to be directly accessed by the rest of the system, so each Agent model in the system can only make decisions and take actions based on its maintained "perception of the world."

In terms of system representation, the combat process is determined by the discrete decisions of entities, and ABMS can most naturally represent this step-by-step decision-making execution process. The ABMS method is easier to depict the entities in the system. An Agent in an ABMS corresponds one-to-one with the individuals in the modeled system, making it easier for modelers to abstract Agent models and interaction relationships, characterizing the overall system behavior from local Agent behaviors. ABMS also makes it easier to depict the interaction space in the system, allowing for the definition of any topology form of Agent interaction. It is convenient to independently abstract the detection, communication, engagement relationships between entities, and their interactions with the environment.

The evaluation of space-based network information systems belongs to typical system experiments, and using the ABMS method can more effectively construct problem scenarios and carry out effectiveness evaluation experiments.

4.2 ABMS Evaluation Method for Space-Based Network Information Systems

Based on the idea of ABMS, designing and developing simulation models for the space-based information and communication system mainly includes five stages: problem description and requirement analysis, discovery and identification of agents, definition of agent interaction relationships and environment, agent behavior representation, and agent model definition. These processes constitute an iterative process of agent modeling and evaluation analysis.

1) Problem Description and Requirement Analysis: This stage mainly determines the problems that need to be solved by agent simulation, establishes the goals and requirements of the simulation research. In this stage, it is necessary to analyze the composition, boundaries, and environment of the system under study; clarify the quantitative indicators used for system analysis and experimentation.

2) Discovery and Identification of Agents: This stage mainly determines the entities and objects that need to be represented in the simulation according to the idea of agent

simulation. ABMS cannot model all entities as agents, but needs to abstract and simplify the system according to the needs of the research problem.

3) Determination of Relationships and Interactions Between Agents: This stage needs to consider the relationships and interactions between agents and other agents as well as the environment based on the discovery and identification of agents. Similarly, these interactions and relationships need to be selected, abstracted, and aggregated according to the needs of problem research.

4) Agent Behavior Representation: This stage mainly uses the process-based behavior representation method to build relevant behavior decision-making models.

5) Agent Model Definition: In this stage, according to the determined agents, agent interaction relationships, and agent behavior representations, the attributes, states, parameters, and behaviors of agents and the environment can be represented through variables, parameters, and algorithms.

ABMS research generally undergoes multiple iterations in these stages. With each iteration, the model becomes more detailed, leading to repeated iterations of these stages. Since multiple iterations are required for each experiment scheme, and there are many uncertain random variables in the combat system, the number of simulations runs for each experimental scheme needs to be controlled within a certain range to ensure that the computational load is manageable. That is, under certain computational accuracy requirements, the number of simulations runs required to achieve the desired accuracy should be determined. This approach allows control over the length of the confidence interval, avoiding conclusions that are not applicable. For this purpose, the following method is proposed for sample size control.

The simulation evaluation for the space-based information and communication system is mainly based on a large number of simulation sample data, and the effectiveness evaluation analysis is carried out based on the following methods:

1) Important influencing factor analysis based on stepwise regression;

2) Importance analysis of influencing factors based on decision trees;

3) Trend analysis of key influencing factors.

The logical relationship between the three types of evaluation analysis methods is shown in Figure 3.

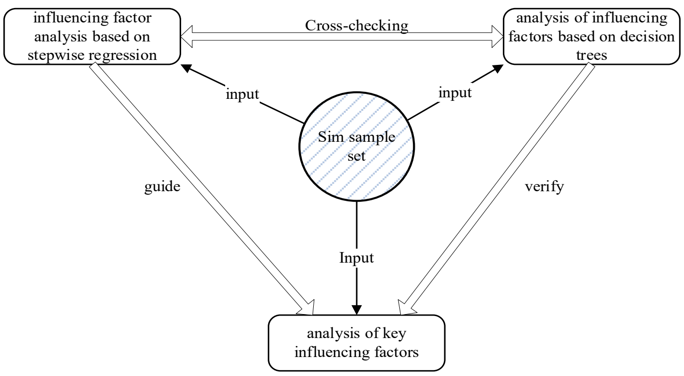


Fig. 3. Logical Relationship Between Evaluation Analysis Methods.

1) Important influencing factor analysis based on stepwise regression mainly uses classical least squares method to fit the significant indicator factors in the simulation of space-based information and communication system effectiveness with survivability, establishing a fitting regression model that reflects the impact relationship between experimental design schemes and combat effects of the space-based system. This is used to analyze the statistical characteristics of simulation results to verify the rationality and effectiveness of the simulation process. On the other hand, it is used to identify the factors that have a significant impact on the capabilities of the space-based information and communication system, but it is not possible to determine the marginal benefit of a specific factor;

2) Importance analysis of influencing factors based on decision trees mainly uses classification and regression tree algorithms to further statistically analyze experimental samples, identifying the ranking of important influencing factors and determining the interval value relationship of the impact of different experimental factors on system capabilities. Compared to 1), the fitting regression model may have certain errors and limitations, and it is difficult to determine the key value of a certain influencing factor, while the analysis based on decision trees can provide factor rankings and specific values, but it cannot give the causal trend of the overall system capability;

3) Trend analysis of key influencing factors is to statistically analyze the change trends between various important influencing factors and assessment indicators such as system capabilities. Since the simulation sample set is the comprehensive impact of all influencing factors and random factors on combat effects under combat confrontation, the trend change between a single influencing factor and the assessment indicators will also contain the impact of other associated factors and will not show a simple linear increase or decrease trend, but the most important factors will show a certain trend.

Among the above three types of analyses, all original inputs are simulation experiment sample sets. Among them, the important influencing factor analysis based on stepwise regression and the importance analysis of influencing factors based on decision trees are mutually corroborative and complementary. The importance analysis of influencing factors based on decision trees is a further quantitative calculation of the important influencing factor analysis based on stepwise regression. The former identifies important factors that are generally a subset of the latter. The important influencing factor analysis based on stepwise regression can give the overall trend between system schemes and combat effects, while the importance analysis of influencing factors based on decision trees can give the key values of important factors; the three types of analyses are interlocked, mutually supportive and verified, ensuring that the experimental results and evaluation analysis are comprehensive, reasonable, and credible, providing scientific method support for subsequent conclusions and recommendations.

4.3 Model Validation

After the development of the relevant models, it is necessary to verify through model testing whether the established models meet the experimental design requirements of the space-based network information system. Model validation is a process that determines whether the computer implementation of the model accurately represents the model developer's conceptual expression and description of the actual system, and from the perspective of the expected application, determines the accuracy of the model in expressing the actual system.

Since the experiment of the space-based network information system belongs to a complex system experiment, it is not possible to obtain data through real experiments, and the model's resolution and abstraction level are relatively high, with not much real data for model confirmation. High-level abstract simulation models need to be supported by technical data from low-level simulation models for model validation. In this experiment, the main method is to use low-level model data to validate high-level models. The basic idea is to use hierarchical simulation experiments to gradually reduce the uncertain space; in different levels of simulation experiments, use models of different resolutions for different problems, reduce unnecessary computational overhead, and ensure the efficiency of simulation validation.

At the same time, for the testing of behavior models in the space-based network information system, it is possible to examine the correctness of the simulation model based on the process display of model operation tracking and visualization. If problems are found in the model testing process, it is necessary to adjust and modify the model's data definition, composition relationships, and behavior models according to the scenario and experimental design for correction.

5 Simulation Experiment and Analysis of the Information and Communication System

5.1 Experimental Design

The space-based information and communication system needs to describe a series of detection activities completed with the support of combat personnel and resources. These activities are mainly used for combat, including data collection, data transmission, data processing, etc. Based on the aforementioned combat business processes, relevant business models are constructed based on the aforementioned methods, taking a certain type of satellite combat business as the combat activity requirements, combining the space-based information and communication system combat process with system simulation, analyzing the impact of space-based information and communication system resources and combat activities on satellite combat activities, and the indicators should cover detection rate, mission completion rate, resource utilization rate, and other combat-related indicators.

Due to the many factors affecting the aforementioned evaluation indicators, it is possible to make choices about related factors based on analysis and evaluation needs, discard obviously unimportant experimental factors based on experience, narrow the experimental exploration space, and improve experimental calculation efficiency. According to the evaluation requirements of the space-based network information system in the task of sea surface target detection, eight factors such as electronic satellite detection accuracy, detailed survey task planning time, optical satellite maximum side swing angle, optical satellite projection radius, detailed survey planning strategy, launch task planning time, and launch preparation time are identified as experimental factors, and the impact of these factors is analyzed.

To evaluate the effectiveness of the space-based information and communication system in sea surface target detection tasks, this paper designed 8 experimental factors with different value ranges, adopting the Nearly Orthogonal Latin Hypercube (NOLHs) experimental design method. NOLHs absorbs the ideas of orthogonal Latin hypercube and uniform design, giving the method approximate orthogonality and excellent spatial filling properties. Hernandez et al. proposed some variants of this design method that are more effective and allow for the study of a larger number of design factors [10][11]. The filling and uniformity of the experimental design scheme are shown in the following figure 4.

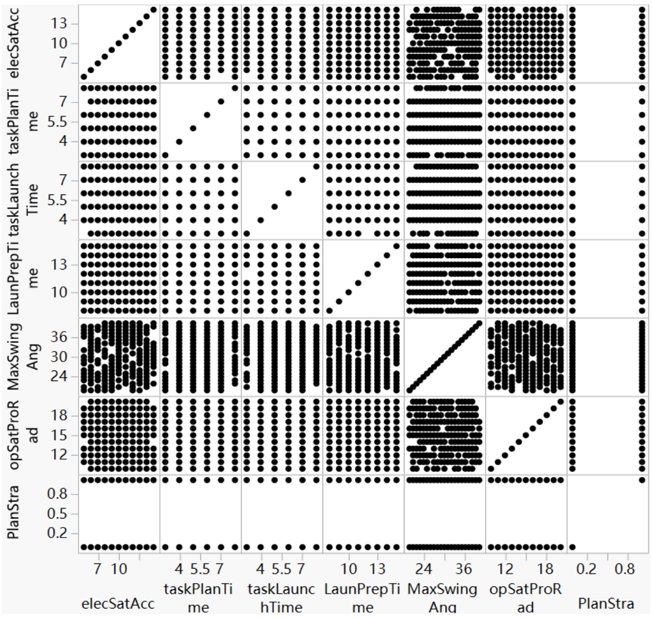


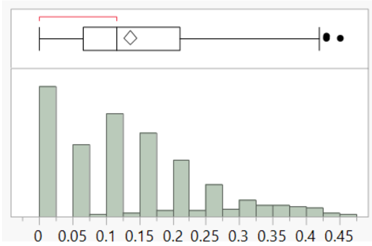
Fig. 4. Filling Property of Experimental Design Scheme.

5.2 Simulation Result Analysis

Based on the above experimental design scheme, the final experimental design includes 512 experimental schemes, each batch of simulation runs 10 times, for a total of 51,200 simulations. Each run takes about 4 seconds, and the total experimental time is about 57 hours in a general desktop computing environment.

1) Overall Data Statistical Analysis

Due to the differences in simulation models and experimental parameters, there will be statistical uncertainties in the simulation results, but the statistical results are basically within a certain deviation range. The following figure 5 shows the bar chart statistics of sea surface target detection rate.



Quantiles

100.0%	maximum	0.45215
99.5%		0.431347856795
97.5%		0.37975
90.0%		0.3068
75.0%	quartile	0.2105875
50.0%	median	0.115425
25.0%	quartile	0.06525
10.0%		0
2.5%		0
0.5%		0
0.0%	minimum	0

Summary Statistics

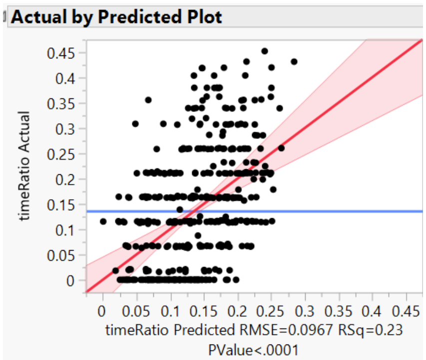
Mean	0.136424
Std Dev	0.1092921
Std Err Mean	0.0048301
Upper 95% Mean	0.1459133
Lower 95% Mean	0.1269348
N	512

Fig. 5. Statistical Chart of Sea Surface Target Detection Rate.

The task completion rate statistics show the binomial distribution characteristics of sea surface targets being detected: discovered (1) or not discovered (0). The average task completion rate is 13.64%, indicating that the detection task for sea surface targets in this type of scenario can achieve a 13.64% completion rate. Although the proportion is not high, achieving this result in the dynamic search for targets on the entire sea surface is quite high.

2) Important Influencing Factor Analysis Based on Stepwise Regression

Considering all controllable input factors and treating quadratic effects and bidirectional effects as implicit conditions of the regression fitting model, the stepwise regression method is applied to fit the sea surface target detection rate. The experimental results are shown in the following figure 6.

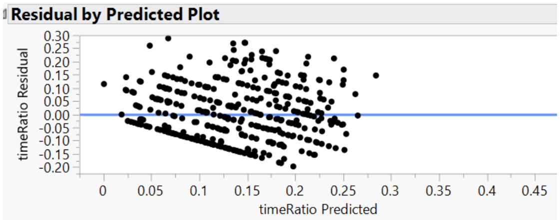


Summary of Fit

RSquare	0.229081
RSquare Adj	0.21682
Root Mean Square Error	0.096721
Mean of Response	0.136424
Observations (or Sum Wgts)	512

Fig. 6. Summary of Fitting and Variance Analysis of Sea Surface Target Detection Rate.

According to regulations, those main influencing factors with extremely large associations or quadratic effects will be retained in the regression model, as shown in the following figure 7.



Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
MaxSwingAng	0.009929	0.000926	10.72	<.0001*
taskLaunchTime	-0.008506	0.003209	-2.65	0.0083*
opSatProRad	-0.003411	0.001699	-2.01	0.0452*
Intercept	-0.090001	0.055115	-1.63	0.1031
taskPlanTime	0.0048911	0.003228	1.52	0.1304
TrackTarget	-0.036486	0.024116	-1.51	0.1309
LaunPrepTime	0.0014305	0.002242	0.64	0.5238
PlanStra	0.0050389	0.015361	0.33	0.7430
elecSatAcc	8.6686e-5	0.00137	0.06	0.9496

Fig. 7. Parameter Estimation Value Analysis of Sea Surface Target Detection Rate.

The figure above shows that considering the experimental samples, factors with a probability > |t| value < 0.001 or smaller parameter estimates are considered to have significant differences or a great association with influencing factors. It shows the basic order of optical satellite maximum side swing angle, launch preparation time, optical satellite projection radius, etc. This indicates that in this scenario, the optical satellite maximum side swing angle, task planning time, and optical satellite projection radius are the main factors affecting the detection rate of sea surface targets by the space-based network information system, and other factors such as launch preparation time and task planning strategy are general strategies. Accordingly, a multiple linear regression model is fitted between these experimental factors and the sea surface target detection rate as follows:

$$\begin{aligned} Y_{\mathbf{timeRatio}} = {} & -0.09000675 + 0.00008669\bar{x}_{\mathrm{elecSatAcc}} + 0.0048911\bar{x}_{\mathrm{taskPlanTime}} \\ & - 0.00850602\bar{x}_{\mathrm{taskLaunchTime}} + 0.00143051\bar{x}_{\mathrm{launPrepTime}} \\ & + 0.00992897\bar{x}_{\mathrm{maxSwingAng}} - 0.00341101\bar{x}_{\mathrm{opSatProRad}} \\ & - 0.0364856\bar{x}_{\mathrm{trackTarget}} \end{aligned}$$

3) Importance Analysis of Influencing Factors Based on Decision Trees

Decision tree analysis is an important tool for determining influencing factors. The figure 8 below shows the decision tree using the average detection rate as the response variable and all controllable input factors. The decision tree has 9 branches with an R-squared value of 60%, which has a good significant impact. Analyzing the decision tree from top to bottom, the top elements have a greater impact on the corresponding variables. Since the higher the average detection rate, the better, the right branches are the better branches, and the left branches are the worse branches. For example, the first branch on the far right, when using an efficiency-priority task detailed survey strategy, the average detection rate can reach 24.14%, and the far left branch can only reach 13.08%; then based on this branch, the second branch is the optical satellite maximum side swing angle. When the maximum side swing angle reaches more than 30 degrees, the average detection rate can reach 25.33%, otherwise, it can only reach 13.61%.

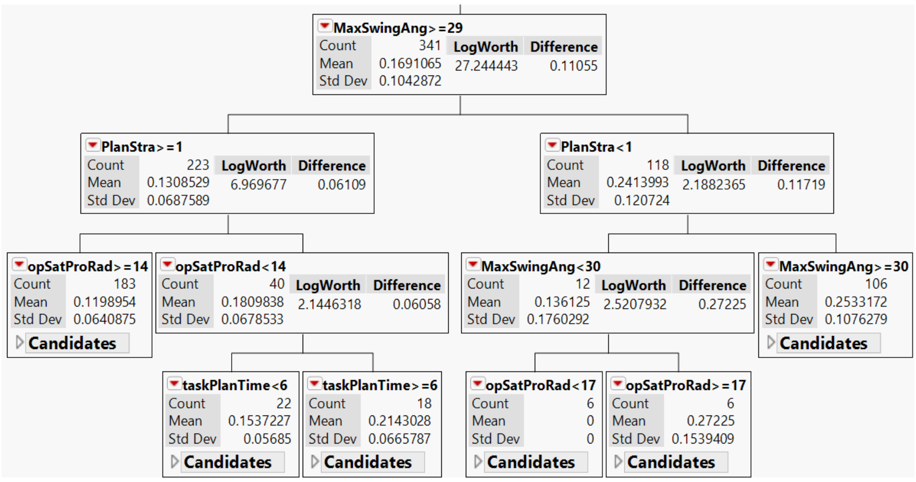


Fig. 8. Decision Tree of Sea.

Table 1. Ranking of Key Influencing Factors for Sea Surface Target Detection Rate Based on Decision Trees.

Importance	Key Factor	Analysis Result
1	Detailed Task Planning Strategy	When adopting an efficiency-first strategy for task planning, the average detection rate of sea surface targets is 24.14%
2	Maximum Side Swing Angle of Detailed Survey Satellite	When greater than or equal to 30, the average detection rate of sea surface targets is 25.33%

Many factors proven to be important in stepwise regression are also proven to be important in decision trees. The important influencing factors in stepwise regression analysis are the optical satellite maximum side swing angle, task planning time, and optical satellite projection radius, etc., and task planning strategy is a general influencing factor. The factors analyzed by the decision tree all include them, and the order is basically consistent.

The decision tree analysis conclusion in Table 1 quantifies the quantitative requirements for related influencing factors:

When the maximum side swing angle of the detailed survey satellite is greater than or equal to 30 and an efficiency-first strategy is adopted for detailed survey task planning, the average detection rate of sea surface targets is 25.33%.

4)Trend Analysis of the Impact of Maximum Side Swing Angle of Detailed Survey Satellite on Whether Sea Surface Targets Are Detected

The trend of the impact of the maximum side swing angle of the detailed survey satellite on whether sea surface targets are detected is shown in the figure 9 below. As the maximum side swing angle of the detailed survey satellite increases from 26 degrees to 31 degrees, the detection rate continues to rise and tends to level off after the maximum side swing angle exceeds 31 degrees. According to the aforementioned recursive partitioning decision tree, when the maximum side swing angle of the detailed survey satellite is greater than or equal to 30, the average detection rate is 25.33%. From the figure below, it can be seen that when the maximum side swing angle of the detailed survey satellite is greater than 30, the average detection rate does not increase, but it increases again from 38 degrees. Therefore, increasing the maximum side swing angle of the detailed survey satellite beyond 30 degrees has little marginal benefit.

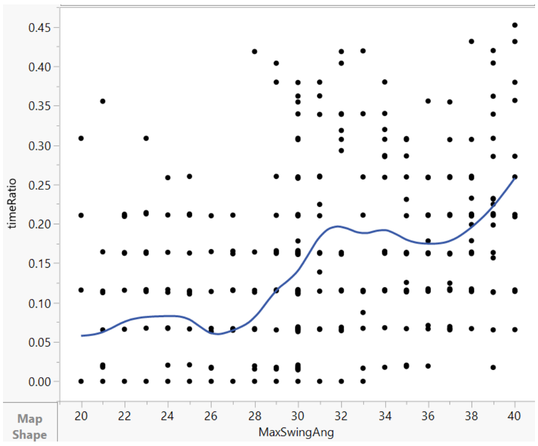


Fig. 9. Impact Curve of the Number of Maximum Side Swing Angle of Detailed Survey Satellite on Sea Surface Target Detection.

6 Conclusion

This paper aims at the effectiveness evaluation requirements of the space-based information and communication system, establishes a composable and reusable model framework for the space-based information and communication system oriented towards multi-domain connectivity, information processing, and resource management and control, and an agent behavior modeling method. A modeling, simulation, and effectiveness evaluation method based on ABMS is proposed. Experimental results of a certain space-based information and communication system for sea surface target detection applications show that the modeling method and framework can meet the needs of simulation evaluation of the space-based information and communication system. Using decision tree quantitative analysis methods to statistically analyze large-scale experimental results quantifies the contribution rate of different equipment elements of the space-based information and communication system to the detection effectiveness of sea surface targets and the impact trends of key elements. However, it is also found that when facing a much larger combat system, the description capability of agents needs to be improved, and related ABMS methods need further improvement, which will be the focus of future research directions.

References

1. Han Chi, Xiong Wei, Liu Wenwen, Yu Xiaolan, Jian Pin. Effectiveness Evaluation Method of Space-based Information Systems Based on SEM. Journal of System Simulation, 2022.08,34(8):1799-1810.
2. CHEN Yu, SHI Peng, MA Li. Modeling and effectiveness evaluation method of space-based information support system. Systems Engineering and Electronics,2024.12,46(10):3407-3415.
3. Yu Xiaolan, Xiong Wei. Operational Effectiveness Evaluation of Space-based Information Support Equipment System Based on Bayesian Network. Ordnance Industry Automation, 2024.03,43(3): 74-81.
4. XIONG Wei, YU Xiaolan, LIU Yali. Operational Effectiveness Analysis Method Based on Bayesian Network. Science Technology and Engineering,2023,23(17):7428-7435.
5. WANG Bintuan1, LYU Jinfeng2, DANG Puni. Research on the Design Factors and Assessment for Aircraft Structures Combat Survivability. ADVANCES IN AERONAUTICAL SCIENCE AND ENGINEERING,2022.07,13(3):50-58.
6. ZHOU Bo, KONG Depei, WANG Jianlu. Meta-synthesis method of SoS contribution rate for electronic information equipment. Journal of Terahertz Science and Electronic Information Technology, 2023.03,21(3):325-331.
7. Jamshidi, M. Theme of the IEEE SMC 2005[EB/OL], Waikoloa, Hawaii, USA.http://ieeesmc2005.unm.edu/, October 2005.
8. M. Jamshidi, Ed. System of Systems Engineering—Innovations for the 21st Century[J]. John Wiley & Sons, New York, 2008.
9. Wang Chengfei, Dong Yazhuo, Su Qianye, Zhang Xianglin. Research on Intelligent Countermeasure Behavior Modeling Methods in Combat Simulation[J]. Command Control & Simulation, 2022, 1: 79-85.
10. Hernandez, R., et al.. A review of variants and applications of the Latin hypercube sampling method. Reliability Engineering & System Safety, 2015, 142: 327-342.
11. Cioppa, T. M. A Latin hypercube design approach to parameter uncertainty and sensitivity analysis. Proceedings of the 2000 Winter Simulation Conference, 2000, 291-298.