"AI + Orbit Design": A Preliminary Exploration of Intelligent Orbit Optimization Based on Data Generation Using STK

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Abstract: With the continuous breakthrough of technology in the aerospace field, the demand for compound innovative talents is becoming more and more urgent. The traditional orbital design or orbital dynamics and control teaching mainly depends on theoretical explanation, case teaching and problem calculation, and the evaluation ability to solve complex problems and practical engineering needs is insufficient. With the rapid development of artificial intelligence and computing capabilities, the integration of AI and platform visual simulation in teaching will guide students to master and use machine learning models for rapid orbit parameter selection and optimization. In this paper, a typical case of "comprehensive optimization of LEO constellation coverage performance" is designed. The constellation orbit is generated by STK simulation tool, and parametric modeling is carried out. Then Python is driven to call STK Connect to automatically extract performance indicators to form a structured data set. Then, AI model training is used to learn to use the optimization algorithm to quickly search the Pareto frontier. Finally, the optimal parameter combination obtained by calculation is re-entered into STK for high-fidelity simulation verification. This research design can not only greatly improve the computational efficiency and scheme optimization, but also significantly enhance the students' interest in learning and cultivate the cross-innovation ability of aerospace talents.

Keywords: AI+; Intelligent Orbit Design; STK; Aerospace Talent Cultivation.

1. Introduction

The rapid development of the aerospace field puts forward higher requirements for the innovation ability and engineering practice ability of talents. The traditional teaching mode of orbit dynamics and control related courses often focuses on theoretical derivation and static case analysis, which leads students to feel the gap between knowledge and practice in the face of complex task design, multi-parameter optimization and comprehensive evaluation of engineering systems [1]. At present, the integration of artificial intelligence technology and high-performance computing provides an unprecedented opportunity for innovating teaching methods and empowering complex problem solving [2]. The traditional teaching mode of orbit dynamics and control related courses often focuses on theoretical derivation and static case analysis, which leads students to feel the gap between knowledge and practice in the face of complex task design, multi-parameter optimization and comprehensive evaluation of engineering systems. At present, the integration of artificial intelligence technology and high-performance computing provides an unprecedented opportunity for innovating teaching methods and empowering complex problem solving. It has become a key path to cultivate future aerospace compound innovative talents by deeply integrating AI algorithm and high-fidelity visual simulation platform into teaching and guiding students to construct modern engineering thinking of 'modeling-simulation-data-driven-intelligent decision-verification closed-loop'.

At present, Yang [3] proposed problem-oriented teaching, which solves the frontier hot issues by simplifying the difficulty of tasks. While improving students' practical ability, it also improves students' enthusiasm. Wang [4] introduced a paradox of orbital perturbation in the teaching process to guide students to think from a unique perspective, which not only improved the difficulty and challenge of the course, but also achieved good teaching results.

Wang et al. [5] introduced and selected the classical Hohmann transfer orbit in teaching, and gave a simulation example of orbit maneuver design based on STK/Astrogator. The teaching practice shows that this method is helpful for students to construct spatial logical thinking, understand complex theoretical problems, cultivate practical application ability, and effectively improve the teaching effect. Zhang [6] proposed to take the space track design competition as the guidance of teaching practice. By guiding students to complete the previous years 'competition topics from simple to difficult in the learning process, a new long-term linkage mechanism of 'professional foundation-individual project practice-innovation and entrepreneurship project' is formed, which not only improves students' practical application ability, but also helps students to participate in the discipline competition.

In this context, this paper focuses on the typical space mission of "comprehensive optimization of ground coverage performance of low-orbit constellation" as a teaching case, aiming to propose a comprehensive practice that integrates professional simulation tools and intelligent algorithms. By integrating artificial intelligence technology, it provides a new way to innovate teaching methods and enable complex problem solving.

2. Analysis of Spacecraft Orbit Dynamics Course

2.1 Instructional Objectives

The course of spacecraft orbital dynamics is a comprehensive discipline that closely integrates basic theory and engineering practice. Based on celestial mechanics and control theory, the course systematically constructs a complete knowledge system from the ideal orbit of two-body problem to the real orbit under complex perturbation environment. This requires not only in-depth study and mastery of Kepler orbital elements, conic orbital characteristics and orbital energy conversion relations, but also focus on the mathematical models of the main perturbation sources such as earth shape perturbation, atmospheric resistance, solar light pressure, sun-moon three-body gravity and their effects on the long-term evolution of orbits (such as arch rotation, intersection drift) and periodic fluctuations. On the basis of this theory, the course focuses on cultivating students' ability to solve practical engineering problems, covering initial orbit determination, precision orbit prediction, and maneuvering design and optimization analysis for various mission scenarios (such as Hohmann transfer, orbit phase modulation, rounding, rendezvous and docking initial segment). Typical mission cases such as the deployment and maintenance of near-Earth satellite constellations, the fixed-point and decommissioning of geosynchronous satellites, and the escape orbit design and leveraging flight in deep space exploration will also be introduced in the course study. The core constraints and driving functions of orbital dynamics in the overall design of the mission will be explained, so that students can understand the design logic of key links such as launch, on-orbit operation, formation flight and mission life from the root of dynamics, and finally have the ability to carry out preliminary orbit design and analysis for a given space mission [7].

2.2 Instructional Mode

At present, the teaching mode of traditional spacecraft orbit dynamics course is usually based on the systematic theory teaching. The main part of the course focuses on the in-depth explanation of the dynamic equations under the framework of Newtonian mechanics, the analytical methods of typical orbital problems (such as Lagrange planetary motion equations, Gaussian perturbation equations), and the core concepts of orbital elements, perturbation sources, and orbital transfer. In this process, teachers will interspersed with case teaching. By analyzing the classic task cases such as the fixed-point maintenance of the geostationary satellite, the configuration design of the Beidou navigation constellation [8,9], and the Python programming of Hohmann orbit [10], the basic theory is explained in detail. How to apply it to engineering practice to help students establish preliminary engineering cognition. In the middle and late stages of the course, professional tools such as STK and MATLAB are usually introduced in teaching. Teachers demonstrate the process of orbit establishment, perturbation setting, maneuver simulation and result visualization through software, so that students can connect abstract formulas with intuitive dynamic orbit phenomena and data curves, so as to deepen their understanding. The assessment method of the course generally focuses on the examination of students' comprehensive application ability. Usually, students are required to cooperate independently or in groups, and comprehensively use tools such as STK and MATLAB to complete a relatively complete orbit design and analysis task. For example, the whole mission orbit of a remote sensing satellite (including launch window, orbit entry, orbit maintenance strategy during the life period) is designed and simulated to evaluate students' overall mastery of theoretical knowledge, software tools and engineering logic.

2.3 Teaching Reform Thoughts

With the rapid development of artificial intelligence technology and its deep application in aerospace system engineering, the future aerospace field puts forward new requirements for the skill matrix of talents. Among them, skilled use of intelligent algorithms to solve complex engineering problems has become a core accomplishment. To this end, this paper explores and proposes a future-oriented teaching mode reform, whose core is to deeply integrate artificial intelligence algorithms and high-fidelity visual simulation platforms into the spacecraft orbit dynamics curriculum system. Teaching no longer stops at traditional theoretical teaching and case demonstration, but guides students to build high-precision dynamic models by hand, simulate in high-fidelity platforms such as STK, and apply AI tools to independently complete frontier topics such as orbit optimization design under multi-objective constraints, collaborative configuration scheduling of cluster spacecraft, or rapid intelligent decision-making of on-orbit anomalies. This process aims to systematically guide students to build a complete closed-loop capability of 'modeling-simulation-data-driven-intelligent decision-verification', so as to cultivate their modern engineering thinking that is data-driven, intelligence-centered, and capable of system trade-off and independent optimization in a highly uncertain environment. This teaching path of deep integration of cutting-edge technology and basic theory is not only the key to improving students' ability to solve complex orbital system design optimization problems, but also a strategic way to cultivate compound innovative talents who can lead the development of intelligent aerospace in the future.

3. Simulation Teaching Mode based on “AI + Orbit Design”

The traditional STK simulation teaching usually relies on the manual interaction of the graphical user interface (GUI), which has the limitations of long calculation time and low optimization efficiency in the face of high-dimensional space search problems such as multi-objective optimization of giant constellations. To this end, this paper proposes a new simulation teaching model based on 'Python+STK+AI'. Its core is to generate massive data using automated interfaces, use machine learning to build high-speed agent models, and combine swarm intelligence algorithms to achieve multi-objective optimization.

3.1 Automatic Acquisition and Construction of Simulation Data

In the design of complex constellation configurations, system performance evaluation depends on the high-fidelity physics engine at the bottom of STK. This teaching mode first requires students to master the Python-based component object model (COM) interface call technology (STK Connect or STK Object Model). By writing Python automatic control scripts, Monte Carlo Sampling is performed within the preset orbital parameter boundaries, driving STK to automatically create scenarios, deploy constellations, calculate area coverage, and extract performance index reports. This process transforms the tedious physical calculations that originally require manual intervention into a batch process in the computer background, thereby constructing a structured data set containing multiple sets of ‘configuration parameters coverage performance’ mapping relationships, which lays a data foundation for the subsequent introduction of artificial intelligence algorithms.

3.2 Data-Driven Proxy Model Construction

The core innovation of this teaching mode is to introduce the concept of 'Surrogate Model' in artificial intelligence technology. In the traditional joint simulation, each parameter iteration needs to call STK for orbit extrapolation and occlusion calculation, which is extremely expensive. The role of the surrogate model is to perform mathematical approximation fitting on the physical calculation process of STK through machine learning algorithms, thereby achieving 'cost reduction and efficiency increase'. In the 'surrogate model', the input feature vector of the constellation configuration is set to $X \in R^d$, and the output coverage performance index vector is set to $Y \in R^m$. Based on the automatically acquired data set $D=\{(X_i,Y_i)\}_{i-1}^{N}$, a prediction model $Y=M(X;\theta)$ is constructed by introducing nonlinear regression algorithms such as random forest or multi-layer perceptron, where θ is the model parameter. By solving the empirical risk minimization problem:

$$\min_{\vartheta} L(\theta)=\frac{1}{N}\sum_{1}^{N}\left\|Y_i-M\left(X_i;\theta\right)\right\|^2 \quad (1)$$

After training convergence, the surrogate model is out of the STK environment, and can output high-precision prediction results with millisecond response speed, completely breaking the time bottleneck of traditional simulation optimization.

3.3 Multi-Objective Optimization based on Intelligent Algorithm

Constellation design in engineering practice usually faces the mutual restriction of cost and performance. After obtaining the high-speed surrogate model, the teaching mode will guide students to introduce swarm intelligence algorithms such as non-dominated sorting genetic algorithm (NSGA-II) to carry out multi-objective optimization. At this stage, the surrogate model is used as the computing engine to provide massive fitness evaluation support for the optimization algorithm. The optimization algorithm searches in a large solution space, and finally converges to the Pareto Front, providing students with a set of compromise schemes with optimal system cost-effectiveness ratio.

4. Application Example of Orbit Optimization Course Design

In order to verify the effectiveness of the above simulation teaching mode, combined with the teaching objectives of the orbital application module, an application example of the course design of "Integrated Optimization of LEO Constellation Ground Coverage Performance" is proposed. In this example, for a specific ground area, under the strict constraints of the specific space-time coverage performance indicators (such as revisit time, coverage elevation angle, and continuous coverage time) of the target area, the Walker constellation configuration parameters such as the number of satellites, the number of orbital planes, and the phase factor are collaboratively optimized. Finally, a global trade-off between coverage performance and full life cycle costs such as launch deployment and satellite development is performed, so as to optimize the equalization constellation scheme with the lowest cost and the best coverage performance. The experimental technology roadmap is shown in Figure.1.

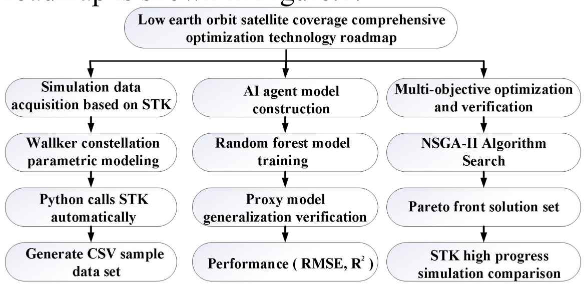

Figure 1. Experimental Technology Roadmap

4.1 Constellation Parametric Modeling and Sample Generation

The initial orbit altitude range is set from 200km to 500km, and the research object is Walker-Delta constellation. The key configuration parameters are extracted as decision variables $X=[h,i,P,S]^T$, that is, orbit height, orbit inclination, orbit surface number P and satellite number S per plane. The system size (total number of satellites) $C=P\times S$, the average visible time of the target area T_{agv}, and the maximum revisit period T_{max} in the STK coverage analysis module (Coverage Definition) are extracted as the system evaluation index Y. By using Python to call the STK interface circularly, 1000 groups of X_i satisfying the constraint conditions are randomly generated, and the corresponding Y_i is automatically solved by the STK, and the results are exported to the sample data set in CSV format.

4.2 Coverage Performance Surrogate Model Training

The collected data sets are divided into training sets and test sets, and machine learning libraries (such as scikit-learn) are imported into the Python environment. In view of the fact that the input features include discrete variables (number of orbital surfaces, number of satellites) and continuous variables (height, inclination), and there is a complex nonlinear mapping between the input features and the output indicators, this example uses a random forest regressor based on decision tree ensemble for model training. In the training process, students need to verify the generalization ability of the surrogate model. By comparing the real calculated value of STK in the test set with the predicted value of the surrogate model, the determination coefficient R^2 and the root mean square error $RMSE$ are used as the quantitative evaluation criteria. Experiments show that when $R^2 > 0.95$, the surrogate model has the ability to replace the STK physical engine for high-frequency calculations.

4.3 Pareto Front Search and High Fidelity Verification

Based on the well-trained surrogate model, a multi-objective optimization mathematical model for constellation coverage is constructed:

$$\min F(X) = (f_1(X), f_2(X))^T \quad \text{s.t.} \quad X \in \Omega \tag{2}$$

Among them, the objective function $f_1(X) = P \times S$ aims to minimize the size of the constellation system and control the cost; the objective function $f_2(X) = T_{\max}$ aims to minimize the maximum revisit period of the target area and improve the continuous coverage performance. X_k is the feasible region boundary of each orbital parameter.

The model is input into the NSGA-II multi-objective optimization algorithm. During the evolution process, the crossover and mutation operators are used to continuously generate new parameter combination populations. For each individual E in the population, the surrogate model constructed in Section 4.2 is called to instantaneously output the fitness evaluation value. The algorithm avoids time-consuming physical simulation and can complete tens of thousands of iterations in minutes. After the algorithm is running, a smooth Pareto frontier curve is output in the target space. Students select several representative non-dominated solutions at the 'inflection point' from the curve, and re-input these sets of optimal parameters into STK software for a high-precision simulation. The real simulation report of STK is compared with the prediction results of AI model, and the teaching closed loop of 'data generation-model training-optimization search-simulation verification' is completed.

5. Conclusion

In view of the disconnection between classical theory teaching and frontier engineering practice in the current spacecraft orbital dynamics course, although students are familiar with formula derivation, it is difficult to cope with the ability fault problem of complex multi-constraint practical task design. This paper systematically proposes and expounds a new teaching paradigm that deeply integrates high-fidelity simulation platform and artificial intelligence technology. This paradigm constructs a complete teaching closed-loop of 'modeling-simulation-data-driven-intelligent decision-making-verification'. The teaching practice shows that this mode not only enables students to master the modern methods of using intelligent algorithms to solve engineering problems, but also significantly breaks through the bottleneck of computational efficiency faced by traditional trial and error or numerical optimization. It also cultivates students' system engineering thinking based on data and centered on intelligent decision-making at a deeper level, and provides an effective reform path for the future development of intelligent and clustered aerospace and the cultivation of compound talents with solid theoretical foundation and cutting-edge technological innovation ability.

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