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Cost Estimation Model for Mega-Constellation Deployment Missions

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ABSTRACT The economic problem is a primary consideration in mega-constellations design. This work aims to quantify the cost of mega-constellation deployment missions and analyze the contribution of reusable launch vehicles to cost savings. In this paper, the cost estimation model of mega-constellation deployment missions is investigated, consisting of the launch cost and satellite cost. Simulation examples demonstrate the high applicability of the cost estimation model and the considerable cost-effectiveness of the reusable launch vehicle in mega-constellation deployment missions.

INDEX TERMS Mega-constellation deployment, cost estimation model, reusable launch vehicle, partial least square regression.

I. INTRODUCTION

In recent years, along with the mass production and industrialization of satellite manufacturing [1], breakthroughs in reusable launch vehicle (RLV) technology [1] have reduced the cost of entering space drastically and made it possible to deploy a mega-constellation in low earth orbit (LEO). At present, many organizations and commercial corporations have proposed LEO mega-constellations plans [2]. Starlink system designed by SpaceX plans to launch 42,000 LEO satellites [3], of which 1,791 have been in orbit by the end of Oct 16, 2021. OneWeb initially plans to launch 648 satellites to form a global Internet constellation [4], [5]. For the unprecedentedly complex large-scale space system, funding issues are the primary constraint for deploying mega-constellation [6]. Huge costs are the crucial factor in determining whether the plan can be implemented smoothly. The cost estimation of the mega-constellation program plays a vital role in effectively controlling the mission cost.

Cost estimation and cost analyses are indispensable steps for space mission project management [7]. The "NASA Cost Estimating Handbook 4.0" [8] Summarizes three cost estimation methodologies: analogy cost estimating, parametric cost estimating, and engineering build-up methodology (also known as "bottom-up" estimating). As the most common method, parametric cost estimating keeps the advantages of objectivity, consistency, and speed compared to other methods. Parametric cost estimating depends on historical data and regression analysis to create Cost Estimating Relationships [9] (CERs). In recent decades, parametric cost estimation models widely used mainly include Unmanned Space Vehicle Cost Model [10] (USCM), Small Satellite Cost Model [11] (SSCM), NASA Instrument Cost Model [12] (NICM), Mission Operations Cost Estimating Tool [13] (MOCET), NASA Air Force Cost Model [14] (NAFCOM), Spacecraft/Vehicle Level Cost Model [15] (SVLCM), and Project Cost Estimating Capability (PCEC) [16], etc. Specifically, SSCM is developed by The Aerospace Corporation, which estimates the development and manufacturing costs of small satellites. USCM is another cost model developed by The Aerospace Corporation, which estimates the Unmanned, earth-orbiting spacecraft cost, but does not include launch vehicles. NASA develops NICM, NAFCOM, PECE, and SVLCM. NICM provides CERs for specific types of instruments; NAFCOM estimates the cost for launch vehicles, Landers, and other flight hardware elements; SVLCM is used for calculating the development and production cost for spacecraft and launch vehicle stages based on NASA/Air Force Cost Model database.

Although there are many existing cost estimation models for spacecraft or space missions, many of them have restricted access, and an available cost estimation model for mega-constellation deployment missions does not yet exist. In addition, a CER ultimately depends on a particular historical dataset. It only reflects the nature of that set. In other words, a given CER can only predict the future based on trends

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in the historical dataset, and a paradigm-shifting mission may be inappropriate. Therefore, it is necessary to create a specific cost estimation model for the mega-constellation deployment missions based on the parametric cost estimating method.

Launch cost is one of the most critical parts of the mega-constellation deployment missions that this paper focuses on. At the same time, the Reusable Launch Vehicles (RLVs) have been proven to be an effective cost-cutting tool [17]. The RLVs share the cost by reusing some devices multiple times, thereby reducing the mission's total cost. The Falcon 9 used by the Starlink system [18] offers a very competitive price depending on its reusability, and it has been reused up to 10 times. However, the RLV cannot be reused indefinitely, and its lifetime determines the upper limit of the number of times it can be used. On the one hand, extreme thermal cycling conditions lead to uneven heat distribution and instantaneous changes in the internal structure of the engine's high-temperature components, causing changes in the thermodynamic properties of the material. Multiple reuses will cause the high-temperature components to fatigue failures, which is the main constraint on the lifetime of the RLVs. On the other hand, the engine's moving components (including turbopumps and bearings) are severely worn under high-speed and high-pressure environments, limiting the number of times the RLVs can be used. Apart from the technical aspect, the lifetime of the RLVs is also determined based on the highest economic efficiency criteria. When the increase in the number of used times cannot contribute to cost-saving, the RLV's lifetime has reached an end. In conclusion, how the lifetime of the RLV affects the mission cost should be put into consideration. It is significant to evaluate the cost-effectiveness of the RLVs, compared with Expendable Launch Vehicles (ELVs), in mega-constellation deployment missions.

This paper provides a cost model based on the parameter estimation method to estimate and perform quantitative analysis for the cost of a mega-constellation deployment mission. The mega-constellation deployment cost is divided into two parts in this work, launch cost and satellite cost. At first, establish the cost estimation model for launch vehicles by parameter estimation method. The CER is obtained by the partial least square regression (PLSR) method based on small sample data. Then, considering various factors affecting the cost of the RLV, we create the RLV cost estimation model on the foundation of the ELV cost model. Meanwhile, we calculate the small satellite cost with mass customized production. The last, the cost model of mega-constellation deployment is obtained. Summarized, the main contributions of this paper are as follows: First, the total cost of mega-constellation deployment is analyzed quantitatively and systematically, and the impact of ELV and RLV on the total cost is compared. Second, this paper gives a specific cost model for the constellation rather than theoretical analysis compared with [19]. Third, Reference [20] proposed a bottom-up approach to estimate the costs linked to RLV operations and recovery with simplified assumptions. However, it didn't quantify the contribution of the RLV to controlling the cost of space missions. This paper can supplement the above shortcomings. In conclusion, this paper systematically analyzes the total cost of mega-constellation deployment missions, and the final results could provide some reference for the designers of mega-constellations.

The remainder of the paper is structured as follows. Section II presents the theory and method for establishing the cost estimation model of mega-constellation deployment missions. Section III develops the cost model in detail, and a corresponding numerical simulation is performed. Finally, conclusions are drawn.

II. COST ESTIMATION MODEL OF MEGA-CONSTELLATION DEPLOYMENT MISSIONS

In order to quantitatively analyze the total cost of a mega-constellation deployment mission, an effective cost estimation model must be established. The cost of a mega-constellation deployment mission includes launch cost, satellite production and manufacturing cost, and the cost of the ground system responsible for satellite operation and control. The rental and construction costs of the ground system are affected by many complicated factors, such as the scale of construction, geographic location, economic conditions, and so on, leading to a considerable challenge for the cost estimation of the ground system. Therefore, this paper assumes that the mega-constellation makes full use of the existing ground system to provide satellite operation and control services, and regardless of the cost of the ground system. In conclusion, this paper's mega-constellation deployment cost estimation includes the launch cost estimation of the launch vehicle and the mass-produced satellite cost estimation. In addition, the cost of RLVs and ELVs are discussed in the launch cost estimation model.

A. ELV COST ESTIMATION MODEL

Using the parameter estimation method to determine the CER of ELV requires the launch vehicles dataset, including launch cost data and the cost drive factors data that directly affect the launch cost of ELV [21]. Obviously, larger sample datasets will lead to a better accuracy estimation. However, it is challenging to collect large amounts of accurate launch vehicles data. Due to the limited number of launch vehicles in service and the confidentiality requirements of certain types of launch vehicles, some data are unavailable. Moreover, some cost drive factors have high correlations, which means that there is multicollinearity between variables. PLSR method is a statistical tool designed to solve multiple regression problems with small sample data and overcome multicollinearity between variables [22]. Therefore, due to the lack of sufficient launch vehicle sample data and multicollinearity between variables, this paper utilizes the PLSR method to solve the cost estimation model.

1) ESTABLISHING CER OF ELV

The cost drive factors of the ELV mainly include payload capacity, lift-off mass, size dimensions, lift-off thrust, etc. In order to verify the validity of the selected factors, a correlation analysis of the data must be carried out. The cost drive factors that have a strong correlation with the launch cost are denoted as $P_1, P_2, \ldots, P_n$. There is a particular function relationship between each factor and launch cost, which is the CER of the ELV.

$$C_{ELV} = F(P_1, P_2, \ldots, P_n) \tag{1}$$

where C_{ELV} is the launch cost of the ELV.

To determine the CER relationship, we need to observe the regression fitting effect of the launch vehicle data on several common functional relationships, such as linear relationship, power function relationship, exponential function, Gaussian function, etc. The CER of the ELV is determined in which the regression accuracy is consistent with expectations.

2) MODELING STEPS OF PLSR

PLSR is a practical technique that generalizes and combines features from principal component analysis and multiple least-squares regression [23]. The steps of the PLSR method are described as follows.

The dependent variable y of n observations is described by a $n \times 1$ matrix. The k independent variables $x_1, x_2, \ldots, x_k$ are represented as a $n \times k$ matrix.

$$\boldsymbol{X} = [x_{ij}]_{n\times k} \quad \boldsymbol{Y} = [y_i]_{n\times 1} \quad i = 1, \ldots, n \quad j = 1, \ldots, k$$

where x_{ij} represents the j th independent variable of the i th observation and y_i is the dependent variable of the i th observation.

Step1: Standardize $\boldsymbol{X}$ and $\boldsymbol{Y}$ denoted as $\boldsymbol{E}_0$ and $\boldsymbol{F}_0$:

Step2: Regression analysis. Extract the first principal component $\boldsymbol{t}_1$ from $\boldsymbol{E}_0$. $\boldsymbol{t}_1 = \boldsymbol{E}_0\boldsymbol{w}_1$, and

$$\boldsymbol{w}_1 = \frac{\boldsymbol{E}_0'\boldsymbol{F}_0}{\|\boldsymbol{E}_0'\boldsymbol{F}_0\|} \tag{2}$$

$\boldsymbol{E}_0$ and $\boldsymbol{F}_0$ are regressed on $\boldsymbol{t}_1$:

$$\boldsymbol{E}_0 = \boldsymbol{t}_1 p_1 + \boldsymbol{E}_1 \qquad \boldsymbol{F}_0 = \boldsymbol{t}_1 r_1 + \boldsymbol{F}_1 \tag{3}$$

where p_1 and r_1 are the regression coefficients, and

$$p_1 = \frac{\boldsymbol{E}_0'\boldsymbol{t}_1}{\|\boldsymbol{t}_1\|^2} \qquad r_1 = \frac{\boldsymbol{F}_0'\boldsymbol{t}_1}{\|\boldsymbol{t}_1\|^2} \tag{4}$$

Step 3: Accuracyanalysis. If the regression equation of $\boldsymbol{y}$ on $\boldsymbol{t}_1$ meets the accuracy requirements, continue to the next step; else, $\boldsymbol{E}_0 = \boldsymbol{E}_1, \boldsymbol{F}_0 = \boldsymbol{F}_1$, and repeat step 1, step 2 to extract a new principal component from the matrix remnants

Step 4: If the extracted h th principal component meets the accuracy requirements, The regression equation of $\boldsymbol{F}_0$ can be derived by PLSR:

$$\hat{\boldsymbol{F}}_0 = r_1\boldsymbol{t}_1 + r_2\boldsymbol{t}_2 + \cdots + r_h\boldsymbol{t}_h \tag{5}$$

Eq. (5) can also be expressed as follow:

$$\begin{aligned} \hat{\boldsymbol{F}}_0 &= r_1\boldsymbol{E}_0\boldsymbol{w}_1^* + r_2\boldsymbol{E}_0\boldsymbol{w}_2^* + \cdots + r_h\boldsymbol{E}_0\boldsymbol{w}_h^* \\ \boldsymbol{w}_h^* &= \prod_{j=1}^{i-1}(\boldsymbol{I} - \boldsymbol{w}_j\boldsymbol{p}_j')\boldsymbol{w}_i \quad (i = 1, 2, \ldots h) \end{aligned} \tag{6}$$

$\boldsymbol{I}$ is a unit matrix, and Eq. (6) can finally be expressed as

$$\hat{\boldsymbol{y}}^* = \alpha_1\boldsymbol{x}_1^* + \alpha_2\boldsymbol{x}_2^* + \cdots + \alpha_k\boldsymbol{x}_k^* \tag{7}$$

where $\boldsymbol{x}_j^* = [x_{1j}^*, x_{2j}^*, \ldots, x_{nj}^*]^T$, $\boldsymbol{y}^* = [y_1^*, y_2^*, \ldots, y_n^*]^T$, and the regression coefficient α_j of $\boldsymbol{x}_j^*$ is

$$a_j = \sum_{i=1}^{h} r_i w_{ij}^* \tag{8}$$

w_{ij}^* is the j th element of $\boldsymbol{w}_i^*$.

Step 5: Reversing the process of standardization and converting to the regression equation of $\boldsymbol{y}$ on $\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_k$.

B. RLV COST ESTIMATION MODEL

Taking advantage of the RLV in deploying the LEO mega-constellations is a cost-effective and efficient way. The recent Starlink constellation deployment by SpaceX has successfully proved this point. In this work, the RLV cost estimation model builds on the ELV cost estimation model and increases RLV recovery costs, maintenance and refurbishment costs [24]. In addition, loss of payload capacity due to the landing process, number of used times, and reusable rate of the RLV are the key factors directly affecting the total cost of mega-constellation deployment [25].

1) RECOVERY COST

The RLV recovery costs mainly include the transportation and operation costs of vehicles, vessels, and other ground infrastructure generated during the recovery process and the labor costs associated with recovery. Referring to the TRANSCOST, a top-down model, the estimation formula [20] of RLV recovery cost is given:

$$C_{recovery} = \frac{1.5}{L}(7 \cdot L^{0.7} + m_{rec}^{0.83}) \cdot f_i \tag{9}$$

where L is the launch rate, m_{rec} is the mass of the recovered stage, and f_i is the factor influenced by country and business.

2) MAINTENANCE AND REFURBISHMENT COST

Maintenance and refurbishment costs for RLV include repairing the damaged parts, refurbishing the worn parts, and replacing some disposable parts. At present, there is a lack of empirical data on the refurbishment cost of RLV for analysis since only SpaceX has successfully recovered and reused launch vehicles. Moreover, the maintenance and refurbishment cost is only a tiny part of the launch cost. The maintenance and refurbishment cost is calculated as a fraction of the RLV launch cost [20].

$$C_{m,r} = k_1 C_{\mathrm{RLV}} \tag{10}$$

where, k_1 is the ratio coefficient of RLV maintenance and refurbishment cost to launch cost.

3) NUMBER OF USED TIMES

The number of times the RLV is used as a critical cost driver plays an essential role in saving the total cost of the space mission, and its effect on total cost must be evaluated. SpaceX recently achieved that one of the Falcon 9 boosters be used 10 times, and this figure will likely keep rising. The reuse times of the RLV mainly depend on the lifetime of the engine. The fatigue resistance of the thermal structure and the friction and wear degree of the moving components are the main factors that affect the engine's lifetime. At present, the thrust chamber of China's LOX/ kerosene engine adopts various cooling methods. The seal and bearing of turbopump adopt surface spraying to reduce the wear. A preliminary evaluation that the LOX/ kerosene engine can be reused more than 30 times [26]. Based on the current technical status, this paper holds that each rocket booster should theoretically be able to launch up to dozens of times.

4) REUSABLE RATE

The reusable degree of RLV is another crucial factor affecting the mission cost. In order to describe the degree of reusable after the recovery process, this paper defines the reusable rate means that the cost of the reusable part accounts for the proportion of the entire launch vehicle cost. Since the speed of the upper stage far exceeds that of the first stage, it poses a considerable challenge to recover the upper stage. At the same time, the upper stage only accounts for about 20 % of the launch vehicle cost. In other words, the benefits of recovering the upper stage are difficult to make up for its price. Therefore, from the perspective of cost-effectiveness, there is no need for recovering the upper stage. Generally, if only the first stage is recovered, the reusable rate can be controlled at around 70 %. If the fairing is also recovered, the reusable rate is estimated to reach 80 %.

5) LOSS OF PAYLOAD CAPACITY

RLV's reusability comes at the expense of reduced payload capacity. Since the RLV must carry extra fuel for the reentry and landing process of the reusable first stage, and this will reduce the payload capacity of the RLV [27]. The loss of payload capacity has a considerable impact on the cost estimation of mega-constellation deployment. Thus, it is necessary to calculate the loss of payload capacity.

Assuming that the RLV is a two-stage rocket, and recovery the first stage can be realized. Moreover, the landing platform can be deployed in the first stage landing area when adopting the marine recovery mode. Then, large-scale lateral maneuvers are not required during the reentry and landing process, reducing the demand for propellant [28]. Therefore, assuming that the RLV adopts marine recovery mode, and regardless of the fuel consumption by the lateral maneuver. The Tsiolkovsky equation is the basis of the derived formulas for the propellant mass calculations:

$$\Delta v_i = g_0 \cdot I_{sp,i} \cdot \ln(\frac{m_0}{m_f})_i \tag{11}$$

Here g_0 is the standard gravity. All other variables are for the i th stage. Δv_i is maximum change of velocity, $I_{sp,i}$ is the vacuum specific impulse, m_0 is the initial total mass (including propellant) also known as "wet mass," and m_f is final total mass also called as "dry mass."

After the first stage separation, the wet mass of the first stage includes the structure mass and the propellant mass needed for the landing process. Assuming that the propellant is fully utilized in the recovery process, then the mass of the first stage after landing includes only the structure mass. The propellant mass required for the first stage recovery can be obtained as:

$$m_{p,recovery} = m_{s,1} \cdot (e^{\frac{\Delta v_{recovery}}{g_0 \cdot I_{sp,1}}} - 1) \tag{12}$$

where, $m_{p,recovery}$ is the propellant mass consumed by the recovery process, and $\Delta v_{recovery}$ is the velocity change in the landing process. $m_{s,1}$ is the structural mass of the first stage.

Under ideal conditions, the velocity change during the ascent of the first stage can be expressed as:

$$\Delta v_1 = g_0 I_{sp,1} \ln(\frac{m_{p,1} + m_{p,2} + m_{s,1} + m_{s,2} + m_{pl}}{m_{p,recovery} + m_{p,2} + m_{s,1} + m_{s,2} + m_{pl}}) \tag{13}$$

where, $m_{p,1}$ is the propellant mass of the first stage, similarly, $m_{p,2}$, $m_{s,2}$ stand for the mass of upper stage, and m_{pl} is the payload mass.

the upper stage's delta-v is calculated as:

$$\Delta v_2 = g_0 I_{sp,2} \ln(\frac{m_{p,2} + m_{s,2} + m_{pl}}{m_{s,2} + m_{pl}}) \tag{14}$$

If using the same launch vehicle but without recovering the first stage, the velocity change of the first stage and the upper stage are expressed as:

$$\Delta v_1' = g_0 I_{sp,1} \ln(\frac{m_{p,1} + m_{p,2} + m_{s,1} + m_{s,2} + m_{pl\,\max}}{m_{p,2} + m_{s,1} + m_{s,2} + m_{pl\,\max}}) \tag{15}$$

$$\Delta v_2' = g_0 I_{sp,2} \ln(\frac{m_{p,2} + m_{s,2} + m_{pl\,\max}}{m_{s,2} + m_{pl\,\max}}) \tag{16}$$

where, $m_{pl\,\max}$ is the maximum payload capacity when the first stage recovery process is not carried out.

It is generally a reasonable assumption that the final total velocity change of the ELV and the RLV is equal when the satellite is sent to the same altitude. Besides, the velocity change of RLV's first stage in ascent and descent is the same. Equations can be derived as:

$$\Delta v_1 + \Delta v_2 = \Delta v_1' + \Delta v_2' \tag{17}$$

$$\Delta v_{recovery} = \Delta v_1 \tag{18}$$

Combining Eq (17) and Eq (18) can obtain the maximum payload capacity of the RLV. We define the payload capacity loss rate as η which stands for the reduction degree of the RLV's payload capacity compared to the ELV under the same conditions. It can be calculated by:

$$\eta = \frac{m_{pl\,\max} - m_{pl}}{m_{pl\,\max}} \times 100\% \tag{19}$$

C. SMALL SATELLITE COST ESTIMATION MODEL

For small satellite cost estimation, the method of parameter estimation is usually used to give approximate results. The Small Satellite Cost Model (SSCM) model proposed by Aerospace Corporation is widely used to estimate the cost of small spacecraft with mass less than 1000 kg [29]. According to the SSCM model, when other factors are set as nominal values, the estimated relationship between cost and weight of small satellites is expressed as:

$$C_{sat} = -1.2 \times 10^{-8} \cdot m_{sat}^3 - 4 \times 10^{-5} \cdot m_{sat}^2 + 0.096 \cdot m_{sat} + 26 \quad (20)$$

where, C_{sat} is the cost per satellite, and m_{sat} is the mass of a satellite.

In addition, to deploy thousands of satellites in space, a volume production model of satellites is indispensable. With the expansion of the satellite production scale, the unit price will decrease accordingly. In industrial manufacturing, a learning curve [30] is used to describe the impact of volume production on the cost quantitatively and is defined as:

$$Y(N) = C_{sat} \times N^{1-\frac{\ln(1/S)}{\ln 2}} \quad (21)$$

where N is the number of satellites produced, S is the learning coefficient, and $Y(N)$ represents the total cost of N satellites in mass production.

For the aerospace industry, N and S have the following corresponding relations:

D. COST MODEL OF MEGA-CONSTELLATION DEPLOYMENT

Through the above analysis, the total cost of a mega-constellation deployment mission can be estimated. In order to obtain a comparative study of ELV and RLV cost-effectiveness for the space mission, the cost model of mega-constellations deployment missions using ELV and RLV was established, respectively.

1) COST MODEL OF TOTAL MISSION WHEN USING ELV

The cost using an ELV to launch the satellites is denoted as C_{ELV}, then, the number of launch vehicles needed to accomplish the entire constellation deployment mission is represented as n_{ELV} and calculated by:

$$n_{ELV} = \frac{N}{\left\lceil \frac{m_{pl\max}}{m_{sat}} \right\rceil} \quad (22)$$

Thus, the total cost of mega-constellation deployment missions is computed by:

$$C_1 = n_{ELV} \cdot C_{ELV} + Y(N) \quad (23)$$

2) COST MODEL OF TOTAL MISSION WHEN USING RLV

In order to estimate the total cost of deploying a mega-constellation with the RLVs, the number of satellites that can be carried by one rocket and the number of the RLVs required for the mission must be obtained. Furthermore, it is assumed that all launch vehicles have reached the upper limit of reusability, and all of them can be used for n_r times. In order to facilitate comparison with ELV, the parameters of the RLV are set to be consistent with it, that is, the first launch cost of the reusable rocket is C_{ELV}, then the i th launch cost of RLV expressed as:

$$C_{RLV,i} = \begin{cases} C_{ELV} & i = 1 \\ (1-\lambda)C_{ELV} + C_{m,r} + C_{recovery} & 2 \le i \le n_r \end{cases} \quad (24)$$

where, λ is the reusable rate of the RLV.

For the sake of calculation, we define the average cost per launch of RLV, and it represents the average cost of an RLV used for n_r times. Then, the average cost per launch of RLV can be computed as:

$$\begin{aligned} \overline{C_{RLV}} &= \frac{1}{n_r}\sum_{i=1}^{n_r} C_{RLV,i} \\ &= \frac{1}{n_r}[C_{ELV} + (1-\lambda)(n_r-1)C_{ELV} \\ &\quad + (n_r-1)C_{m,r} + (n_r-1)C_{recovery}] \end{aligned} \quad (25)$$

According to the payload capacity of RLV and the satellite mass, the maximum amount of satellites that RLV is capable of launching into space at one time can be derived:

$$n = \left\lfloor \frac{(1-\eta) \cdot m_{pl\max}}{m_{sat}} \right\rfloor \quad (26)$$

Subsequently, the quantity of the RLVs required to accomplish the deployment mission of the mega-constellation is expressed as:

$$n_{RLV} = \frac{N}{n \cdot n_r} \quad (27)$$

Consequently, when using the RLVs deploys the satellites, the total mission cost is calculated as:

$$C_2 = n_{RLV} n_r \cdot \overline{C_{RLV}} + Y(N) \quad (28)$$

III. CASE STUDY

Aim at the cost estimation problem of the mega-constellation deployment missions. This work refers to relevant literature and data. The cost model proposed in this paper is used to perform simulation analysis.

Before going into details, To ensure the rationality of the model, some necessary assumptions need to be clarified. The specific content is as follows:

a) It is assumed that the launch vehicle can reach the upper limit of its carrying capacity in each launch mission.
b) Suppose that the launch vehicle sends the satellites into a circular orbit at the height of 200km. Then the satellite relies on its propulsion system to lift to the pre-selected orbit.
c) Under the same conditions of all technical indicators, the launch cost of RLV when it is not recovered is the same as that of ELV.

TABLE 1. Functional relationships.

Function Name	Expression
Power function	$f(x)=a\cdot x^{b}$
Exponential function	$f(x)=a\cdot e^{bx}$
Fourier function	$f(x)=a_0+a_1\cos(wx)+b_1\sin(wx)$
Gaussian function	$f(x)=a\cdot e^{-(\frac{x-b}{c})^2}$
Linear function	$f(x)=a\cdot x+b$

TABLE 2. Relationship between N and S [30].

N	S
<10	95%
10~50	90%
>50	85%

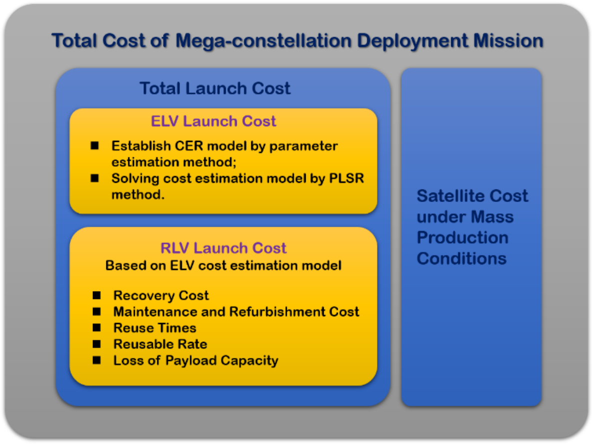

FIGURE 1. The total cost of mega-constellation deployment missions breakdown.

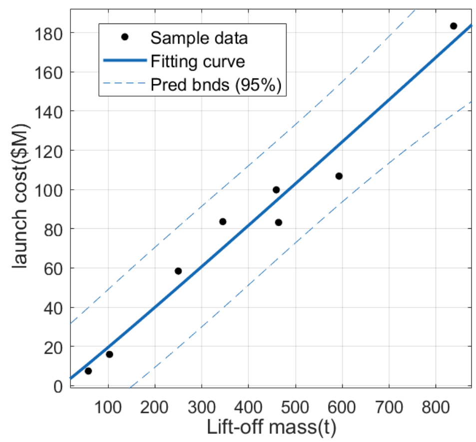

FIGURE 2. Fitting effect of lift-off mass.

A. COST ESTIMATION SIMULATION OF ELV

1) SIMULATION DATA COLLECTION AND ANALYSIS

Data is the basis for simulation using parameter estimation methods. This paper collects the technical parameter data and cost data of part of the Long March series launch vehicle in service [31]. The technical parameter data of the ELV includes the height, the diameter, the payload to LEO, the lift-off mass, and the thrust. It is shown in Table 3.

In order to measure the correlation degree between the technical parameter and the cost, the correlation coefficient between the observations must be calculated. It is calculated as:

$$r_{xy}=\frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{29}$$

where, n is the sample size, x_i and y_i are the individual sample points indexed with i. $\bar{x}$ and $\bar{y}$ are the sample mean.

Table 4 shows the correlation between the various parameters. According to the correlation coefficient matrix, it is evident that the correlation between the 5 technical parameters of the ELV and the launch cost is greater than 0.7. These studies suggest a strong correlation between the 5 parameters and the cost, and the technical parameters can be used as the cost drive factors of the ELV cost estimation model. In addition, some factors are also closely related. For instance, the correlation coefficient between the lift-off mass and the thrust is close to 1. It is proved that there is multicollinearity between the selected factors.

2) DETERMINATION OF CER

Table 5 to 7 show the regression effect of the data on the 5 classic functional relationships. In order to obtain a more accurate CER model, using the lift-off mass, the thrust, and the payload to LEO as the object of study on account of these three factors are highly correlated with launch cost. The least-squares regression method is used for comparative analysis, and the specific results are shown as follow:

The smaller the RMSE is, the smaller the deviation between the predicted and sample values, and the better the fitting effect is. If the R-square is closer to 1, it indicates that the function's independent variable has a more vital ability to interpret the dependent variable, which shows that the model fits the data. In Table 5, although the regression result of lift-off mass on the linear function is the best, the RMSE and the R-square value of the power function are extremely close to it. Table 6 and 7 show that the power function's results are the most ideal. A conclusion can be drawn from the results in multiple tables. When the relationship between the parameter and the cost is a power function, the RMSE and the R-square result are both outstanding and prove that the fitting effect is the best.

Figures 2 to 4 visually show the distribution of the sample points and the fitting curve. The line donates the regression curve of launch cost, and the two dashed lines indicate the 95% confidence interval of launch cost. In the three figures, the sample points are relatively evenly distributed on both

TABLE 3. Parameters of long march series launch vehicle.

	Height (m)	Diameter (m)	Lift-off mass (t)	Payload to LEO (t)	Thrust (kN)	Launch cost (FY2020 $M)
Long March 2F	58.3	3.35	464	8.1(200)	5920	83.21
Long March 3B/E	58	3.35	459	11.5(200)	5923	99.85
Long March 3C	56.5	3.35	345	8	5341	83.64
Long March 4C	47.977	3.35	250	4.2	3851	58.42
Long March 5B	53.66	5	837.5	25(200)	10620	183.40
Long March 6	29.287	3.35	103.2	1.5	1200	15.95
Long March 7	53.075	3.35	593	14	7200	106.85
Long March 11	20.8	2	58	0.75	1200	7.44
Long March 2F	58.3	3.35	464	8.1	5920	83.21
Long March 3B/E	58	3.35	459	11.5	5923	99.85

The "Payload to LEO" in Table III represents the maximum carrying capacity of the launch vehicle to send the payload to a near-circular orbit with a height of 200km.

TABLE 4. Correlation coefficient matrix of launch vehicle parameters.

	Height	Diameter	Lift-off mass	Payload to LEO	Thrust	Launch cost
Height	1					
Diameter	0.732	1				
Lift-off mass	0.927	0.814	1			
Payload to LEO	0.921	0.810	0.998	1		
Thrust	0.914	0.735	0.982	0.982	1	
Cost	0.962	0.822	**0.991**	**0.988**	**0.979**	1

TABLE 5. Regression results of lift-off mass on common functional relationships.

Lift-off mass	Coefficients	95% confidence bounds	RMSE	R-square
Power function	**a=0.1666; b=1.034**	**a: (-0.1291, 0.4622); b: (0.7568, 1.312)**	**11.36**	**0.9643**
Exponential function	a=29.87; b=0.002201	a: (14.45, 45.29); b: (0.001444, 0.002959)	18.07	0.9096
Fourier function	a_0=1.68e+08; a_1=-1.68e+08 b_1=-3.969e+05; w=-4.9e-07	a_0: (-2.641e+16, 2.641e+16); a_1: (-2.641e+16, 2.641e+16) b_1: (-3.119e+13, 3.119e+13); w: (-38.52, 38.52)	13.78	0.9649
Gaussian function	a=207.6; b=1105; c=705.4	a: (18.12, 397); b: (136.1, 2074); c: (57.62, 1353)	15.86	0.9419
Linear function	**a=0.2118; b=-2.479**	**a: (0.163, 0.2457); b: (-20.43, 18.29)**	**11.34**	**0.9644**

TABLE 6. Regression results of payload to LEO on common functional relationships.

Payload to LEO	Coefficients	95% confidence bounds	RMSE	R-square
Power function	**a=17.05; b=0.7327**	**a: (11.03, 23.08); b: (0.6051, 0.8602)**	**7.809**	**0.9831**
Exponential function	a=41.37; b =0.06146	a: (20.99, 61.75); b: (0.03624, 0.08667)	22.65	0.8579
Fourier function	a_0 = -3.65e+07; a_1 = 3.656e+07 b_1 = 1.262e+05; w = 7.539e-05	a_0: (-2.378e+14, 2.378e+14); a_1: (-2.378e+14, 2.378e+14) b_1: (-4.103e+11, 4.103e+11); w: (-245.1, 245.1)	11.42	0.9759
Gaussian function	a=181.5; b=25.31; c=17.83	a: (138.2, 224.9); b: (14.47, 36.15); c: (7.435, 28.22)	16.19	0.9395
Linear function	a=6.91; b=16.75	a: (5.529, 8.291); b: (0.5306, 32.97)	11.79	0.9615

TABLE 7. Regression results of thrust on common functional relationships.

Thrust	Coefficients	95% confidence bounds	RMSE	R-square
Power function	**a= 0.003085; b= 1.185**	**a: (-0.001931, 0.0081); b: (1.003, 1.366)**	**6.716**	**0.9875**
Exponential function	a= 27.53; b =0.0001825	a: (14.14, 40.93); b:(0.0001264,0.0002387)	16.39	0.9256
Fourier function	a_0 =78.76; a_1=-19.36 b_1 = -71.6; w =0.001623	a_0: (42.98, 114.5); a_1: (-152.8, 114.1) b_1: (-121.5, -21.73); w: (0.001307, 0.001938)	31.27	0.8194
Gaussian function	a=191.9; b=1.23e+04; c=7327	a: (128.5, 255.2); b: (7659, 1.7e+04);c: (3628, 1.103e+04)	10.17	0.9761
Linear function	a= 0.01768; b=-11.35	a: (0.01552, 0.01985); b: (-24.21, 1.501)	7.322	0.9852

sides of the fitting curve, which means that the regression curve conforms to the distribution trend of the sample points. In general, the fitting effect is fairly ideal when the CER model is established based on the power function.

According to the above data analysis, the results in Tables 5 to 7 indicate that the smallest RMSE and R-square closest to 1 will be obtained when the launch vehicle's technical parameters and the launch cost are in a power function relationship. In other words, the regression effect of the vehicle data on the power function is the best. At the same time, the results in Figures 2 to 4 intuitively show that the launch vehicle data has a good regression effect on the power function. In addition, the TRANSCOST model [32] also uses a power function to establish the CER model. Therefore, through data analysis and reference to an existing model, it can be concluded that the relationship between the launch cost and the performance parameters of the ELV is a power function, and the final CER model can be expressed as:

$$C_{ELV} = a \times P_1^{b_1} \times P_2^{b_2} \times \cdots \times P_k^{b_k} \tag{30}$$

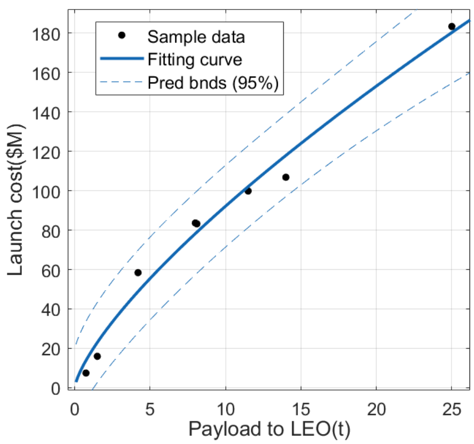

FIGURE 3. Fitting effect of payload to LEO.

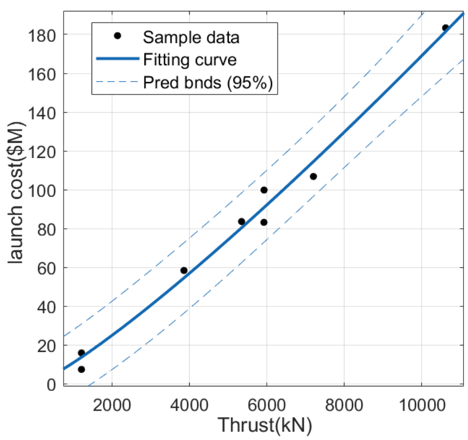

FIGURE 4. Fitting effect of thrust.

where, $a, b_1, b_2, \ldots, b_k$ are constant coefficients of the equation and $P_1, P_2, \ldots, P_k$ are k cost drive factors.

3) APPLICATION OF PLSR TO ELV COST ESTIMATION

This work takes the logarithm of both sides of Eq (29), which reduces to a linear equation. After that, we use the PLSR method to obtain the final CER of ELV as follow:

$$C_{LV} = e^{-4.4901} \cdot H^{0.9549} \cdot D^{0.5109} \cdot M^{0.224} \cdot P^{0.143} \cdot T^{0.3325}$$

where H, D, M, P, T are all cost drive factors of ELVs. Specifically, H is the height, D is the diameter, M is the lift-off mass, P is the payload to LEO, and T is the total thrust.

The histogram visually compares the actual value and the predictive value generated by the ELV cost estimation model. The model's predicted value is close to the true value, and the average deviation rate of the model estimation result is 2.507%. Moreover, RMSE = 2.432, which is significantly reduced compared to regression analysis results on the independent variables. In conclusion, the simulation results of the ELV cost model are in line with expectations and have an ideal predictive performance for the launch cost of the Long March series of rockets.

TABLE 8. Parameters of Falcon 9 block5.

Parameter	The first stage	The second stage
Stucture mass (t)	27.2	4.5
Propellant mass (t)	418.7	111.5
Sea level impulse (s)	283	/
Vacuum impulse (s)	312	348
Payload to LEO (t)	22.8	

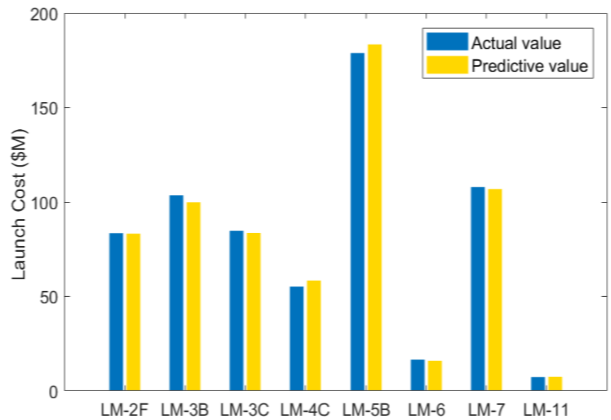

FIGURE 5. ELV cost estimation result based on the PLSR method.

B. COST ESTIMATION SIMULATION OF RLV

This paper refers to the performance parameters of Falcon 9, which is currently the only fully-used RLV in the world to estimate the loss rate of payload capacity caused by the RLV recovery process. Table 8 lists the performance parameters of Falcon 9 Block5.

After calculation, the Falcon 9 Block 5's first stage recovery will be at the cost of increasing 52.6 tons of propellant. At the same time, it will lead to a 33.6% reduction in the LEO carrying capacity of the launch vehicle. This result will be applied to subsequent simulation calculations.

In the following simulation for cost estimation of the launch vehicle, it is assumed that the diameter of all launch vehicles is 3.35 meters, the annual launch frequency is set to 24, and $k_1 = 1\%$. Moreover, this paper's launch vehicle cost estimation depends on five critical performance parameters, and some are closely related. Combining the parameter data of the Long March series of launch vehicles and the correlation analysis results, the consistent relationship between the performance parameters is obtained: $M = 89.48 \cdot P^{0.6916}$, $T = 1420 \cdot P^{0.6163}$, $H = 30.18 \cdot P^{0.2247}$.

Figure 6 compares the launch cost of ELV and RLV, the impact of the number of times the RLV is used, and the reusable rate of RLV on the average cost per launch. In the simulation, the payload to LEO capacity of ELV is set to 20 tons, and the payload capacity of RLV is reduced by 33.6% based on ELV. The curved surface in the figure describes the

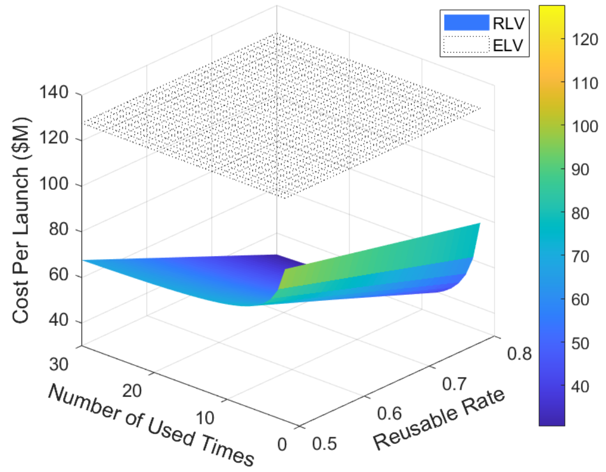

FIGURE 6. Comparison of the RLV and ELV cost per launch. The relationship between the number of used times, reusable rate and the cost per launch of the RLV.

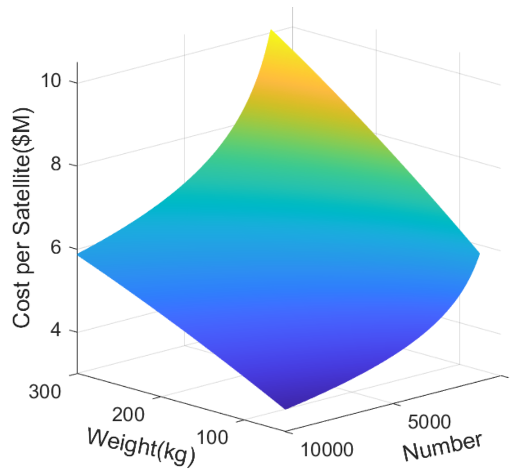

FIGURE 7. The relationship between the number of mass-produced satellites, weight and the cost per satellite.

variation trend of average cost per launch with the number of used times of RLV ranging from 2 to 30 times and the reusable rate ranging from 50% to 80%. It can be seen that RLV has a significant cost advantage compared to ELV. Even if it is reused only once, it can still save at least 24.3% of the cost per launch on average compared to ELV.

Furthermore, if the reusable rate is constant and the number of used times is less than 10, the average single launch cost of RLV decreases rapidly as the reuse times increase. If the number of used times is greater than 10 times, the average cost per launch of RLV decreases significantly slower as the number of used times increases. At this time, it mainly relies on increasing the reusable rate to reduce the cost.

C. COST ESTIMATION SIMULATION OF SATELLITES

Figure 7 depicts the trend of the cost per satellite with the satellite mass and the number of satellites. The curved surface clearly shows that the satellite cost will decrease significantly

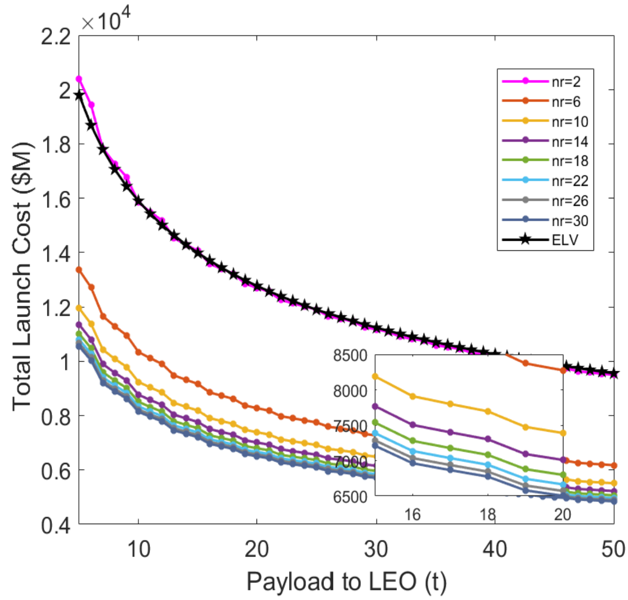

FIGURE 8. The total launch cost corresponds to payload capacity and the number of used times of RLV.

as the number of satellites increases in the case of mass production. However, if the number of satellites continues to increase, the cost of a single satellite decreases less and less.

D. COST ESTIMATION SIMULATION OF MEGA-CONSTELLATION DEPLOYMENT

The curves in Figure 8 respectively show the relationship between the payload to LEO capacity of an ELV, the payload to LEO capacity of an RLV, the number of used times of an RLV, with the total launch cost of the mega-constellation deployment missions. The simulation process assumes that 10,000 small satellites are deployed in low earth orbit, the satellite mass is 200kg, and the reusable rate of the RLV is 70%.

The simulation results illustrate that the payload to LEO capacity of the launch vehicle is negatively correlated with the total launch cost. Still, the downward trend of the entire launch cost will slow down when the payload capacity increases to a certain extent. Moreover, as the number of used times of RLV increases, the total launch cost gradually decreases. The entire launch cost of RLV and ELV is almost the same when the RLV is reused once. Only when the reused times of the RLV are greater than 2 can RLV save the total launch cost. However, when an RLV is used more than 10 times, the distribution of the curve in the figure becomes denser. In other words, the overall launch cost reduction effect becomes worse and worse as the number of used times of an RLV increases to a certain extent. To sum up, increasing the payload capacity of the launch vehicle and utilizing the RLV to complete the mega-constellation deployment missions has a significant effect on saving the total launch cost of the mission. However, when the number of used times and payload

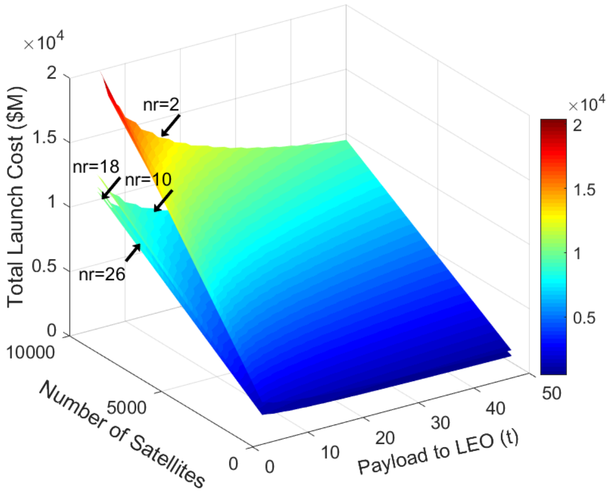

FIGURE 9. The total launch cost corresponds to the number of satellites, payload capacity of RLV, and used times of RLV.

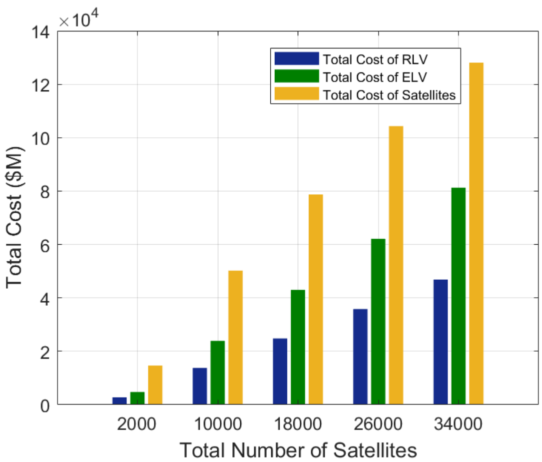

FIGURE 10. The total cost of mega-constellation deployment mission breakdown.

capacity increases to a certain extent, the reduction rate in the full launch cost of the mission slows down significantly.

Figure 9 analyzes the relationship between the total number of satellites in the mega-constellation, the used times, the payload capacity of RLV with the total launch cost. It can be seen that the total number of satellites is the main factor affecting the total launch cost, and the payload capacity has a significant impact on the total launch cost when the number of satellites is large. In addition, if the RLV can be reused more than 10 times, it has little effect on saving the mission's total cost.

Figure 10 compares the total satellites costs and launch costs using the RLV and the ELV, respectively, in the mega-constellation deployment missions. The payload to LEO capacity of ELV is set to 20 tons, and the payload capacity of RLV is reduced by 33.6% compared with ELV, the reusable rate is set to 70%, and the number of used times is 10 times. It can be seen that satellite costs account for the largest proportion of the total mission costs. As the quantity of satellites increases, the proportion of launch costs gradually increases. Besides, compared with ELV, RLV can reduce the launch cost by at least 42.3% under the same conditions.

IV. CONCLUSION

A cost estimation model for the mega-constellation deployment missions is proposed in this paper. As the mega constellation is a newly developed project, only two systems, Starlink and OneWeb, are currently being constructed and have not yet been completed. Therefore, it is difficult to verify the accuracy and efficiency of the model by comparing it with real data. However, in the simulation process, some mathematical statistics can be used to verify the model's accuracy to a certain extent.

The accuracy of the model proposed in this paper is illustrated from the following aspects. Firstly, the best RMSE and R-square results are acquired when the power function establishes the CER model. It proves the efficiency of using the power functions to develop the cost estimation model of the ELV. Then, the ideal average deviation and RMSE results between the predicted value and the real sample data show that using the PLSR to solve the cost estimation problem of the ELV has high accuracy and effectiveness. Moreover, based on the Tsiolkovsky equation, the LEO payload capacity loss rate of the RLV is derived in this paper. The simulation result is 33.6%, in line with SpaceX's official claim that Falcon 9's LEO payload capacity loss rate is less than 40%. Furthermore, the simulation results show that if the RLV is reused only once, it can save 24.3% of the cost per launch on average. This result is roughly consistent with the average launch cost reduction of 25.9% described in [33]. It means that the model related to the launch cost in this paper has a certain degree of credibility. In conclusion, the model proposed in this paper has certain accuracy and efficiency.

The following viewpoints can be obtained preliminarily by modeling and simulating the cost estimation of the mega-constellation deployment missions. Firstly, the cost estimation model of the launch vehicle based on the PLSR method can effectively estimate the launch cost of the Long March series of rockets. Secondly, compared with ELV, the application of the RLV to deploy mega-constellations has obvious cost advantages. Although increasing the number of used times and reusable rate of RLV is a significant way to reduce the cost of launch missions, the degree of the mission cost reduction will become very small if the number of used times exceeds 10. Therefore, weighing the safety and reliability of the launch vehicle, blindly pursuing an increase in the number of used times does not contribute much to the cost-saving of the mission. In addition, total satellite costs account for the largest proportion of total mission costs. It is necessary to reduce the satellite manufacturing costs by introducing new technologies, optimizing management mechanisms, and selecting commercial off-the-shelf (COTS) devices.

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