Cost Estimation Model for Mega-constellation Deployment Mission

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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-constellations and analyze the contribution of reusable launch vehicles to saving the mega-constellations cost. In this paper, the cost estimation model of mega-constellation deployment mission 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 mission.

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 [2] 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 [3]. The most concerning Starlink system designed by SpaceX plans to launch 42,000 LEO satellites [4], 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 [5], [6]. For the unprecedentedly complex large-scale space system, funding issues are the primary constraint for deploying mega-constellation [7]. 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 [8]. The “NASA Cost Estimating Handbook 4.0” [9] 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 [10] (CERs). In recent decades, parametric cost estimation models widely used mainly include Unmanned Space Vehicle Cost Model [11] (USCM), Small Satellite Cost Model [12] (SSCM), NASA Instrument Cost Model [13] (NICM), Mission Operations Cost Estimating Tool [14] (MOCET), NASA Air Force Cost Model [15] (NAFCOM), Spacecraft/Vehicle Level Cost Model [16] (SVLCM), and Project Cost Estimating Capability (PCEC) [17], 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 mission 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 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 mission based on the parametric cost estimating method.

Launch cost is one of the most critical parts of the mega-constellation deployment mission that this paper focuses on. At the same time, the Reusable Launch Vehicles (RLVs) have been proven to be an effective cost-cutting tool [18]. The RLVs share the cost by reusing some devices multiple times, thereby reducing the mission’s total cost. Falcon 9 used in the Starlink system [19] offers a very competitive price depending on its reusability, and it has been reused up to 10 times. However, RLV cannot be reused indefinitely, and its lifetime determines the upper limit of the used times. 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, which restricts the RLVs’ used times. 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 mission.

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 [20]. Third, reference [21] 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 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 mission, 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 mission. 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

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 ground system responsible for satellite operation and control. Because 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.
FIGURE 1. The total cost of mega-constellation deployment mission breakdown.

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 [22]. Obviously, larger sample datasets will lead to a better accuracy estimation. However, it is challenging to collect large accurate launch vehicles dataset. 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 [23]. 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 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.

\[
C_{ELV} = F(P_1, P_2, \ldots, P_n)
\]

(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 where the regression accuracy is consistent with expectations.

| FUNCTIONAL RELATIONSHIPS |
|--------------------------|
| **Function Name**          | **Expression**          |
| Power function            | \( f(x) = ax^b \)       |
| Exponential function      | \( f(x) = ae^{bx} \)     |
| Fourier function          | \( f(x) = a + bx \cos(wx) + by \sin(wx) \) |
| Gaussian function         | \( f(x) = a + b \frac{e^{cx}}{1 + e^{cx}} \) |
| Linear function           | \( f(x) = ax + b \)      |

2) MODELING STEPS OF PLSR

PLSR is a practical technique that generalizes and combines features from principal component analysis and multiple least-squares regression [24]. 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.

\[
X = [x_i]_{i=1}^{n} \quad Y = [y_i]_{i=1}^{n} \quad i = 1, \ldots, n \quad j = 1, \ldots, k
\]

Where \( x_i \) represents the \( j \) th independent variable of the \( i \) th observation and \( y_i \) is the dependent variable of the \( i \) th observation.

Step 1: Standardize \( X \) and \( Y \) denoted as \( E_0 \) and \( F_0 \):

Step 2: Regression analysis. Extract the first principal component \( t_1 \) from \( E_0 \) : \( t_1 = E_0 w_1 \), and

\[
w_1 = \frac{E_0^T F_0}{||E_0^T F_0||}
\]

(2)

\( E_0 \) and \( F_0 \) are regressed on \( t_1 \) :

\[
E_0 = t_1 p_1 + E_1 \quad F_0 = t_1 r_1 + F_1
\]

(3)

where \( p_1 \) and \( r_1 \) are the regression coefficients, and

\[
p_1 = \frac{E_1^T t_1}{||t_1||} \quad r_1 = \frac{F_1^T t_1}{||t_1||}
\]

(4)

Step 3: Accuracy analysis. If the regression equation of \( y \) on \( t_1 \) meets the accuracy requirements, continue to the next step; else, \( E_0 = E_1, F_0 = F_1 \), 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 \( F_0 \) can be derived by PLSR:

\[
\hat{F}_0 = r_1 t_1 + r_2 t_2 + \cdots + r_h t_h
\]

(5)

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

\[
\hat{F}_0 = r_1 E_0 w_1^* + r_2 E_0 w_2^* + \cdots + r_h E_0 w_h^*
\]

(6)

\[
w_h^* = \sum_{i=1}^{h-1} (I - w_i p_i^T) w_i \quad (i = 1, 2, \ldots, h)
\]

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

\[
\hat{y}^* = \alpha_1 x_1^* + \alpha_2 x_2^* + \cdots + \alpha_h x_h^*
\]

(7)

Where \( x_j^* = [x_{j1}, x_{j2}, \ldots, x_{j,n}]^T \) and \( y^* = [y_1, y_2, \ldots, y_n]^T \), and the regression coefficient \( \alpha_j \) of \( x_j^* \) is

\[
\alpha_j = \sum_{i=1}^{h} r_i w_{ij}^* \quad w_{ij}^* \quad j \quad i
\]

(8)

\( w_{ij}^* \) is the \( j \) th element of \( w_i^* \).
Step 5: Reversing the process of standardization and converting to the regression equation of $y$ on $x_1, x_2, \ldots, x_k$.

### B. RLV Cost Estimation Model

Taking advantage of RLV in deploying the LEO mega-constellations is a cost-effective and efficient manner. 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 [25]. In addition, loss of payload capacity due to the landing process, number of used times, and reusable rate are the key factors directly affecting the total cost of mega-constellation deployment [26].

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 [21] of RLV recovery cost is given:

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

(9)

Where $L$ is the launch rate, $m_{\text{rec}}$ 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 [21].

$$
C_{\text{mr}} = k_r C_{\text{RLV}}
$$

(10)

Where, $k_r$ is the ratio coefficient of RLV maintenance and refurbishment cost to launch cost.

3) **USED TIMES**

The RLV’s used times 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 launched 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 of the LOX/ kerosene engine can be reused more than 30 times [27]. 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 [28]. 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 degree.

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 [29]. 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:

$$
\Delta v_i = g_0 \cdot I_{sp,i} \cdot \ln \left( \frac{m_0}{m_f} \right)
$$

(11)

Here $g_0$ is the standard gravity. All other variables are for the $i$th stage. $\Delta v_i$ 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:

$$m_{p_{\text{recovery}}} = m_{s,1} \left( e^{\eta \Delta v_{\text{recovery}}} - 1 \right)$$  \hspace{1cm} (12)

Where, \( m_{p_{\text{recovery}}} \) is the propellant mass consumed by the recovery process, and \( \Delta v_{\text{recovery}} \) 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:

$$\Delta v_1 = g_0 I_{sp,1} \ln \left( \frac{m_{p,1} + m_{p,2} + m_{s,1} + m_{s,2} + m_{pl}}{m_{p_{\text{recovery}}} + m_{p,2} + m_{s,1} + m_{s,2} + m_{pl}} \right)$$  \hspace{1cm} (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:

$$\Delta v_2 = g_0 I_{sp,2} \ln \left( \frac{m_{p,2} + m_{s,2} + m_{pl}}{m_{s,2} + m_{pl}} \right)$$  \hspace{1cm} (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:

$$\Delta v_{1}' = g_0 I_{sp,1} \ln \left( \frac{m_{p,2} + m_{s,2} + m_{pl}}{m_{s,2} + m_{pl}} \right)$$

$$\Delta v_{2}' = g_0 I_{sp,2} \ln \left( \frac{m_{p,2} + m_{s,2} + m_{pl}}{m_{s,2} + m_{pl}} \right)$$  \hspace{1cm} (15, 16)

Where, \( m_{pl_{\text{max}}} \) 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:

$$\Delta v_1 + \Delta v_2 = \Delta v_{1}'+\Delta v_{2}'$$  \hspace{1cm} (17)

$$\Delta v_{\text{recovery}} = \Delta v_1$$  \hspace{1cm} (18)

Combining Eq (17) and Eq (18) can obtain the maximum payload capacity of the RLV. We define the payload capacity loss rate as \( \eta \) 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:

$$\eta = \frac{m_{pl_{\text{max}}}-m_{pl}}{m_{pl_{\text{max}}}} \times 100\%$$  \hspace{1cm} (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 [30]. 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:

$$C_{sat} = -1.2 \times 10^8 \cdot m_{sat}^3 - 4 \times 10^5 \cdot m_{sat}^2 + 0.096 \cdot m_{sat} + 26$$  \hspace{1cm} (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 [31] is used to describe the impact of volume production on the cost quantitatively and is defined as:

$$Y(N) = C_{sat} \times N^{\frac{\ln(1/S)}{\ln(2)}}$$  \hspace{1cm} (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:

| TABLE II | RELATIONSHIP BETWEEN N AND S [31] |
|---------|---------------------|
| N      | S       |
| <10    | 95%     |
| 10~50  | 90%     |
| >50    | 85%     |

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:

$$n_{ELV} = \frac{N}{m_{pl_{\text{max}}}/m_{sat}}$$  \hspace{1cm} (22)
Thus, the total cost of mega-constellation deployment mission is computed by:
\[ C_1 = n_{ELV} \cdot C_{ELV} + Y(N) \]  

(23)

2) COST MODEL OF TOTAL MISSION WHEN USING RLV

In order to estimate the total cost of deploying a mega-constellation with RLV, the number of satellites that can be carried by one rocket and the number of the RLV 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:
\[ C_{RLV,i} = \begin{cases} C_{ELV} & \text{if} \quad i = 1 \\ (1-\lambda)C_{ELV} + C_{m,r} + C_{recovery} & 2 \leq i \leq n_r \end{cases} \]  

(24)

Where, \( \lambda \) is the reuse 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:
\[ \overline{C}_{RLV} = \frac{1}{n_r} \sum_{i=1}^{n_r} C_{RLV,i} = \frac{1}{n_r} \left[ n_r C_{ELV} + (1-\lambda) \sum_{i=1}^{n_r-1} (n_r-i) C_{ELV} + \sum_{i=1}^{n_r-1} (n_r-i) C_{recovery} \right] \]  

(25)

According to the payload capacity of RLV and the satellite mass, the maximum quantities of satellites that RLV is capable of launching into space at one time can be derived:
\[ n = \left\lfloor \frac{(1-\eta) \cdot m_{pl,max}}{m_{sat}} \right\rfloor \]  

(26)

Subsequently, the quantity of the RLVs required to accomplish the deployment mission of the mega-constellation is expressed as:
\[ n_{RLV} = \frac{N}{n \cdot n_r} \]  

(27)

Consequently, when using the RLV deploys the satellites, the total mission cost is calculated as:
\[ C_2 = n_{RLV}n_rC_{RLV} + Y(N) \]  

(28)

III. CASE STUDY

Aim at the cost estimation problem of the mega-constellation deployment mission. 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.

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 [32]. 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 III.

| TABLE III | PARAMETERS OF LONG MARCH SERIES LAUNCH VEHICLE |
|-----------|-----------------------------------------------|
|           | Height (m) | Diameter (m) | Lift-off mass (t) | Payload to LEO (t) | Thrust (kN) | Launch cost (FY2020 SM) |
| 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.
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:

\[ r_{xy} = \frac{\sum_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \overline{x})^2 \sum_{i=1}^{n} (y_i - \overline{y})^2}} \]  

(29)

Where, \( n \) is the sample size, \( x_i \) and \( y_i \) are the individual sample points indexed with \( i \). \( \overline{x} \) and \( \overline{y} \) are the sample mean.

Table IV 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.

### TABLE IV

| 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  | 0.979       |
| Cost   | 0.962    | 0.822        | 0.991           | 0.988  | 0.979       | 1 |

2) DETERMINATION OF CER

Table V to VII 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:

### TABLE V

| 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 | \( a=-1.68e+08; b=-1.68e+08 \) | \( a: (-2.641e+16, 2.641e+16); b: (-2.641e+16, 2.641e+16) \) | 13.78 | 0.9649 |
| Gaussian function | \( a=207.6; b=2105; c=705.4 \) | \( a: (18.12, 2074); b: (136.1, 2074); c: (57.62, 1353) \) | 15.86 | 0.9419 |
| Linear function | \( a=0.2118; b=-2.479 \) | \( a: (0.163, 0.2457); b: (-0.2043, 18.29) \) | 11.34 | 0.9644 |

### TABLE VI

| 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 | \( a_0 = -3.65e+07; a_1 = 3.656e+07 \) | \( a_0: (-2.378e+14, 2.378e+14); a_1: (-2.378e+14, 2.378e+14) \) | 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 VII

| 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 | \( a_0 = 78.76; a_1 = 19.36 \) | \( a_0: (42.98, 114.5); a_1: (-152.8, 114.1) \) | 31.27 | 0.8194 |
| Gaussian function | \( a=191.9; b=1.32e+04; c=7327 \) | \( a: (128.5, 255.2); b: (7659, 1.7e+04); c: (3628, 1.103e+04) \) | 10.17 | 0.9761 |
| Linear function | \( a=0.01768; b=-11.35 \) | \( a: (0.01552, 0.01985); b: (-0.2421, 1.501) \) | 7.322 | 0.9852 |

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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 V, 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 VI and VII show that the power function’s results are the most ideal. As the results of the comprehensive table shown, 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.

Figure 2 to 4 visually shows 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 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 Table V to VII 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 Figure 2 to 4 intuitively show that the launch vehicle data has a good regression effect on the power function. In addition, the TRANSCOST model [33] also uses a power function to establish the CER model. Therefore, through data analysis and reference to an existing model, this paper believes 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:

$$ C_{ELV} = a \times P_1^{b_1} \times P_2^{b_2} \times \ldots \times P_k^{b_k} $$ (30)

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:

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

Where $H, D, M, P, T$ are all cost drive factors of ELV. 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.
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 used times are 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 decrease significantly slower as the number of used times increases. At this time, it heavily reliance on increasing the reusable rate to reduce the cost.

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:

\[ M = 89.48 \cdot P^{0.6916}, \quad T = 1420 \cdot P^{0.1613}, \quad H = 30.18 \cdot P^{0.2247}. \]

Figure 6 compares the launch cost of ELV and RLV and the impact of the used times and 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 variation trend of average cost per launch with the used times of RLV ranging from 2 to 30 times and the reusable rate ranging from 50%
D. COST ESTIMATION SIMULATION OF MEGA-CONSTITELLATION DEPLOYMENT

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

![Figure 8](image_url)

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

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. What’s more, as the used times of RLV increase, the total launch cost gradually decreases. The entire launch cost of RLV and ELV is almost the same when the launch vehicle is reused once. When the launch vehicle is reused once, the total launch cost of RLV and ELV is almost the same. Only when the used times are greater than 2 can RLV save the total launch cost. If the booster flies at least three times, the savings are undeniable. However, as the used times continue to increase, 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 used times of RLV continue to increase. To sum up, increasing the payload capacity of the launch vehicle and utilizing the RLV to complete the mega-constellation deployment mission has a significant effect on greatly caving the total launch cost of the mission. However, when the used times and payload capacity increase to a certain extent, the reduction rate in the full launch cost of the mission slows down significantly.

![Figure 9](image_url)

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

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](image_url)

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

Figure 10 compares the total satellites costs and launch costs using RLV and ELV, respectively, in the mega-constellation deployment mission. The payload to LEO capacity of ELV is set to 20 tons, and the payload capacity of RLV loses 33.6% based on ELV, the reusable rate is set to 70%, and the 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 mission 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 and efficiency to a certain extent.

The accuracy and efficiency of the model proposed in this paper are 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 Tsiolokovsky equation, the LEO payload capacity loss rate of the RLV is derived in this paper. The simulation result is 33.6%, which is 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 [34]. 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 mission. 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 RLV to deploy mega-constellations has obvious cost advantages. Although increasing the used times and reusable rate of RLV is the significant way to reduce the cost of launch missions, the extent of mission cost is minimal if the reuses times exceed 10 times. Therefore, weighing the safety and reliability of the launch vehicle, blindly pursuing an increase in 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. And it is necessary to reduce satellite manufacturing costs by introducing new technologies, optimizing management mechanisms, and selecting commercial off-the-shelf (COTS) devices.

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