Research on Emergency Mobile Launch Mission Planning Based on Dynamic Planning and Fuzzy Neural Network

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Abstract. Under the background of the high integration of space forces into joint operations and the increasingly fierce military struggle in space, emergency mobile launch capability, an important part of space forces, is a key supporting force for improving space combat capabilities. According to the research law of emergency mobile launch mission, the multivariable factory (warehouse) location and the number of satellites, rockets, and launch vehicles were included, and the constraint parameters were established and included in the model. T-SNE classifies the plane parameters through the SNE algorithm, then adjusts the continuity parameters and builds the evaluation model of dynamic planning to evaluate the distribution; the base model adjusts and analyzes the optimal emergency task constraint scheme, which has high loss performance and meets the value interval of the launch task constraint condition, and the construction cost is the lowest. Based on the heat relationship rule analysis of sensitivity and rationality, the experiment's comprehensive score is higher than all the established base models, then through the optimized emergency task constraints scheme, construction cost reduction of 15% to 20%, emergency motor launch mission loss compared to the basic model reduced by about 30%. This paper explores the characteristics, laws, and bottlenecks of constructing an emergency mobile launch force, and provides strong support for the performance of space missions.

Keywords: Emergency Mobile Launch Mission, Coupling Constraints, Space Launch, Fusion Algorithm.

1. Introduction

With the integrated development of modern military science and technology and space technology, the space emergency launch mechanism has become an indispensable key element in the system of space launch and recovery capabilities. This mechanism provides critical technical support for realizing the rapid response strategy, promoting joint operational effectiveness and meeting the urgent needs of space operations, and significantly enhances the strategic capabilities of space access, space resource utilization and space control in the future battlefield [1].

In the field of space emergency maneuver launch mission planning, the literature has provided a valuable foundation for mission planning and optimization. However, traditional launch mission planning strategies mostly rely on rules of thumb and linear optimization techniques, which are often difficult to cope with complex environments where multiple variables are intertwined and multiple constraints coexist when dealing with emergency maneuver launch missions. Many existing models lack sufficient flexibility and real-time performance when dealing with unexpected tasks and urgent requirements. Part of the literature in the modeling process, in order to simplify the problem, often oversimplify or ignore the real conditions, which leads to the accuracy and reliability of the model in practical application of the impact of some advanced optimization algorithms, such as genetic algorithm, particle swarm algorithms, etc., although it can find the global optimal solution, but its computational complexity is high, and it is difficult to give the planning plan quickly in an emergency situation, which affects the task execution of timeliness.

This study develops a comprehensive constrained parameter model for emergency mobile launch mission planning, incorporating factors such as facility locations, number of satellites, rockets, and launch vehicles. The model uses the T-SNE algorithm to categorize and downscale planar parameters, enabling better handling of multivariate complex environments. To enhance flexibility and real-time performance, a dynamic planning evaluation framework is built to formulate optimal constraint configurations by continuously adjusting the base model's structure and parameters. This allows for dynamic strategy adjustments based on the actual situation, ensuring quick decision-making in emergencies.

Given the tight time window for emergency mobile launch missions (e.g., under 72 hours), an optimization method using neural networks and genetic algorithms is employed to improve computational efficiency by reducing computation and increasing algorithmic convergence speed. The model is further verified and tested using simulation and modeling to minimize prediction error and boost result reliability. By constructing a multivariate coupling constraint model, implementing a dynamic planning and evaluation framework, considering realistic factors, and optimizing the algorithm, this study effectively addresses limitations in the existing literature on emergency mobile launch mission planning. The proposed approach provides strong support for efficient execution of such missions.

2. Parameter Analysis of Launch Mission

2.1. Correlation Modeling of Task Force Constraints for Emergency Maneuver Launches

The data of this study are from mcm.gfkd.mtn. Considering that the actual emergency launch mission is usually completed within 3 days, this study increases the number of factory construction (library) sites, as well as the number of satellites, rockets, and the number of launch vehicles, and reset the target function. Based on the constraint principle of emergency maneuver launch mission, and the inclusion of a multivariable residual group, to effectively analyze the planning problems of different target functions, analyze the different conditions of the establishment of the planning parameters of emergency maneuver launch mission components, the different groups, here decided to integrate the plane parameters. To facilitate the analysis of the influence of the degree of characteristics, using the T-SNE algorithm to find the index for risk score weight, first using random adjacency embedded (SNE) can convert data points between high dimensional eucry distance into the similarity condition probability and start [2], data point x_i, x_j condition probability $p_{j|i}$ is given by the following equation:

$$p_{j|i} = \frac{e^{\frac{-\|x_i - x_j\|^2}{2\times\sigma_i^2}}}{\sum_{k\neq i} e^{\frac{-\|x_l - x_t\|^2}{2\times\sigma_i^2}}} \tag{1}$$

Similar conditional probabilities can be calculated for the low-dimensional correspondence sum of high-dimensional data points x_i and x_i:

$$q_{j|i} = \frac{e^{-\|y_i - y_j\|^2}}{\sum_{k\neq i} e^{-\|y_i - y_j\|^2}} \tag{2}$$

After that, to measure the sum minimum of the conditional probability difference, SNE uses gradient descent to minimize the KL distance. While the SNE cost function focuses on the local structure of the data in the mapping, it is very difficult to optimize this function, while t-SNE adopts a heavy-tailed distribution, alleviating the crowding problem and the optimization problem of the SNE [3]. Finally, define the confusion degree as follows:

$$\mathrm{perp}(p_i) = 2^{H(P_i)} \tag{3}$$

The Shannon entropy is:

$$H(P_i) = -\sum_j p_{j|i} \log_2^{p_{j|i}} \tag{4}$$

Then the dimension reduction data is visualized, where different colors indicate different categories of the data. After embedding the t-SNE into a two-dimensional space, you can see that the category information between the data points remains. After that, the composition relationship under various fields is obtained:

Table 1. Compositional relationships in various fields

Launch mission component parameters	1	2	3
A	-0.136	-0.198	0.292
B	0.211	0.175	0.534
C	0.575	-0.416	-0.166
D	-0.816	-0.606	-0.306
E	-0.206	0.546	-0.355
F	0.879	-0.186	0.061

Table 1 reveals the complex interactions of these parameters by showing the quantified relationships of different launch mission component parameters (A to F) in three different fields (1,2,3). The positive and negative parameter values reflect the different influence direction and intensity of each component parameter in different fields. For example, parameter A shows a negative correlation in domains 1 and 2, and turns to a positive correlation in domain 3, indicating that it may play different roles in different task stages. Similarly, both parameters B and F show a strong positive correlation in domain 3, implying their importance in specific task stages.

Later, the fused indicators will be used to map Fi, and finally get the degree of Fi of different indicators, as shown in Figure 1.

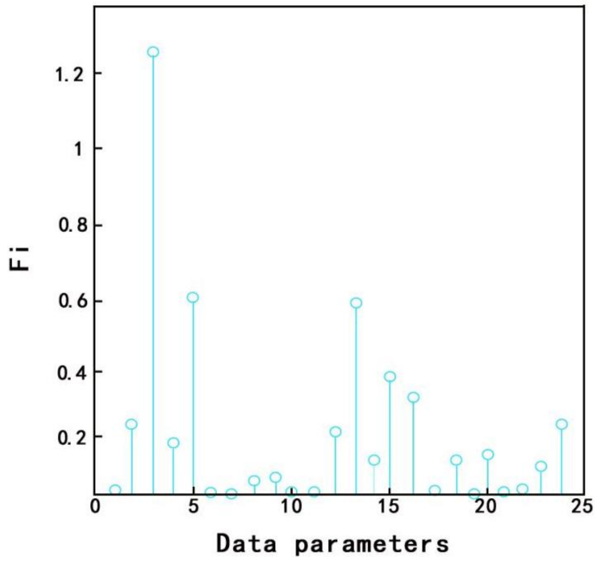

Figure 1. Contribution of different data parameters to Fi

3. Dynamic Optimization and Evaluation Models for Emergency Launch Missions

Later, a more detailed classification was established. First, this study considers that the threshold conditions of plane parameters have changed to a certain extent, and the planning objectives need to be adjusted to solve a truly suitable evaluation model.

Considering that the time dynamics equations of the system are usually used:

$$x_{k+1} = f(x_k, u_k) \tag{5}$$

The formula includes a certain state of the emergency maneuver launch mission into the allocation ratio, u is the control input of the plane distance, and then defines the objective function describing the loss size:

$$J(x_N, u_N) = \phi_f(x_n) + \sum_{k=1}^{N-1} L(x_k, u_k) \tag{6}$$

Where J represents the loss during the transmission of the emergency maneuver launch mission component, L represents a sum. The first term is the sum value [4]. The purpose of this study is to find a suitable set of emergency maneuver launch mission matching processes to minimize the value of the objective function. For the objective function of the nonlinear system, simplify to:

$$\mathrm{J} = \frac{1}{2} x_N^T W_N x_N + w_N x_N + \sum_{k=1}^{N-1} \left(\frac{1}{2} x_k^T W_k x_k + R_k u_k \right) + w_k x_k + r_k u_k \tag{7}$$

Which contains the positive definite and positive definite transport cost-weighted matrix. V represents the best assessment mode, Q represents the virtual assessment amount of the iterative process, and these two variables will be accumulated step by step at the time step. When the computational description of the optimal strategy and the optimality principle, the recurrence relationship can be expressed as:

$$\mathrm{J} = minQ_k^* \equiv \min \left(\sum_{k=1}^{N-1} \frac{1}{2} x_k^T W_k x_k + w_k x_k + \frac{1}{2} u_k^T R_k u_k + r_k u_k + V_k^*(f(x, u)) \right) \tag{8}$$

TabWhen such a process of combining the emergency maneuver launch mission component loss with the plane parameters is considered an iterative update process, this is the classic differential dynamic programming DDP algorithm [8]. Since the dynamic system presents a nonlinear relationship, during the initial change process, V requires a partial reduction:

$$V_k(x + \delta x, u + \delta u) \approx Q_k(x, u) \tag{9}$$

The total emergency maneuver launch mission component Q is approximately:

$$Q_k(x + \delta x, u + \delta u) \approx Q_k(x, u) + \frac{1}{2} \begin{bmatrix} \delta x \\ \delta u \end{bmatrix}^T \begin{bmatrix} Q_{xx} & Q_{ux} \\ Q_{xu} & Q_{uu} \end{bmatrix} \begin{bmatrix} \delta x \\ \delta u \end{bmatrix} + \begin{bmatrix} Q_x \\ Q_u \end{bmatrix} \begin{bmatrix} \delta x \\ \delta u \end{bmatrix} \tag{10}$$

The matrix is a matrix block form, and Q is a vector form of a gradient. If the matrix and gradient are calculated directly according to the above transport cost equation, it is the so-called classical algorithm differential dynamic planning.

$$\lambda = \begin{cases} \frac{\tau}{m+n+\tau} + 1 - \varsigma^2 + \beta & i = 0 \\ \frac{1}{2(m+n+\tau)} & i = 1, \ldots, 2(m+n) \end{cases} \tag{11}$$

$$\tau = \varsigma^2(m + n + \kappa) - (m + n) \tag{12}$$

The λ in the above formula is the type factor, the parameters often take minimal values, and K follows the principle of greater than or equal to 0. In the Gaussian distribution, β takes 2, and other values when in the non-Gaussian case. When the type of sample point is in the process of reverse transfer, the matrix is expressed as:

$$\begin{bmatrix} Q_{xx} & Q_{ux} \\ Q_{xu} & Q_{uu} \end{bmatrix} = \left\{ \frac{1}{2\lambda^2}^2 \sum_{i=1}^{m+n} \left\{ \begin{bmatrix} x_i^{s-} \\ u_i^s \end{bmatrix} - \begin{bmatrix} x_k \\ u_k \end{bmatrix} \right\} \left\{ \begin{bmatrix} x_i^{s-} \\ u_i^s \end{bmatrix} - \begin{bmatrix} x_k \\ u_k \end{bmatrix} \right\}^T \right\}^{-1} + \begin{bmatrix} W_k & 0 \\ 0 & 0 \end{bmatrix} \tag{13}$$

This can be calculated when projected onto the sample points used to calculate the equilibrium values.

$$V_1^s = V_{x|k+1}^T x_i^s \tag{14}$$

This is solved for the system of linear equations for:

$$\begin{bmatrix} x_1^{s-} - x_{n+m+1}^{s-} & \cdots & x_{n+m}^{s-} - x_{2(n+m)}^{s-} \\ u_1^s - u_{n+m+1}^s & \cdots & u_{n+m}^s - u_{2(n+m)}^s \end{bmatrix} \begin{bmatrix} f_x^T V_{x|k+1} \\ f_u^T V_{x|k+1} \end{bmatrix} = \begin{bmatrix} V_1^s - V_{n+m+1}^s \\ \cdots \\ V_{n+m}^s - V_{2(n+m)}^s \end{bmatrix} \tag{15}$$

When the emergency maneuver launch mission component is iterated to time k, the type changes are:

$$\delta V_k = -l_k^T Q_{uu} l_k - Q_u^T l_k \tag{16}$$

Start the process of forward operation and forward operation. The new state control U is brought into the algorithm model as a feedback correction and the new state X can be calculated. Then repeat the above process until the termination condition is satisfied and converge to the local optimum.

Considering the problem of designing the optimal scheme for the component propagation problem of the model emergency maneuver launch task, the evaluation algorithm is added based on dynamic planning. Therefore, this study constructs a T-S fuzzy neural network and combines fuzzy logic and neural networks to make better use of the advantages of both. T-S fuzzy neural network is mainly divided into an input layer, fuzzy layer, fuzzy rule calculation layer, and output layer. The fuzzy layer uses the membership function to obtain the fuzzy membership value, and the fuzzy rule calculation layer uses the fuzzy continuous multiplication formula∂.

In the learning of fuzzy neural networks, the error is calculated as follows:

$$e = \frac{1}{2}(y_d - y_c)^2 \tag{17}$$

Where z is the network output and the desired output; d is the actual network transmission; and e is the error of the desired and actual output [5].

Coefficient modification:

$$p_j^i(k) = p_j^i(k-1) - \alpha \frac{\partial e}{\partial c_j^i} \tag{18}$$

$$\frac{\partial e}{\partial p_j^i} = (y_d - y_c)\omega^i / \sum_{i=1}^{m} \omega^i x^j \tag{19}$$

Parameter correction:

$$c_j^i(k) = c_j^i(k-1) - \beta \frac{\partial e}{\partial c_j^i} \tag{20}$$

$$b_j^i(k) = b_j^i(k-1) - \beta \frac{\partial e}{\partial b_j^i} \tag{21}$$

For the input quantities $\mathrm{y} = [\mathrm{y}_2, \mathrm{y}_3, \dots, \mathrm{y}_\mathrm{l}]$, the membership of each input variable y k is calculated according to the fuzzy rule as:

$$uA_j^i = \frac{\exp(-(x_j - c_j^i)^2}{b_j^i} \quad j = 1,2,\dots,k; i = 1,2\dots,n \tag{22}$$

Where c and b are the center and width of the membership function respectively; k is the input parameter; and n is the number of fuzzy subsets. In each subordinate fuzzy calculation, the fuzzy operator used is the continuous multiplication operator, namely:

$$\omega^i = uA_j^1(x_1) * uA_j^2(x_2) * \dots * uA_j^k(x_k) \tag{23}$$

According to the results of the fuzzy calculation, the output value of the fuzzy model is calculated as y^i,

$$y^{\,i} = \sum_{i=1}^{n} \omega^i (p_0^i + p_1^i x_1 + \cdots + p_k^i x_k) / \sum_{i=1}^{n} \omega^i \tag{24}$$

In this study, the control amount of the set transportation algorithm is the same result in the figure below. The control amount is constantly changing in the time step and the control amount u is always within the threshold range. At the same time, it can be seen that the control amount size of the two algorithms is the same, and the convergence trajectory of the control amount U calculated by the two algorithms is the same, so the two achieve the effect of the same trend.

Finally, the appropriate evaluation scheme is determined through the calculation results. In order to verify the implementation effect of the program, the conclusion is drawn by comparing the actual evaluation and analysis with the existing data.

Through the above model, the evaluation model and specific rules are established, the influence of different laws on the constraints of emergency maneuver launch task is analyzed, the preliminary rules are obtained, and the classification is given. For the points of a new plant (warehouse) and launch positions, the factor weights on the trajectory are analyzed [6], as shown in Figure 2.

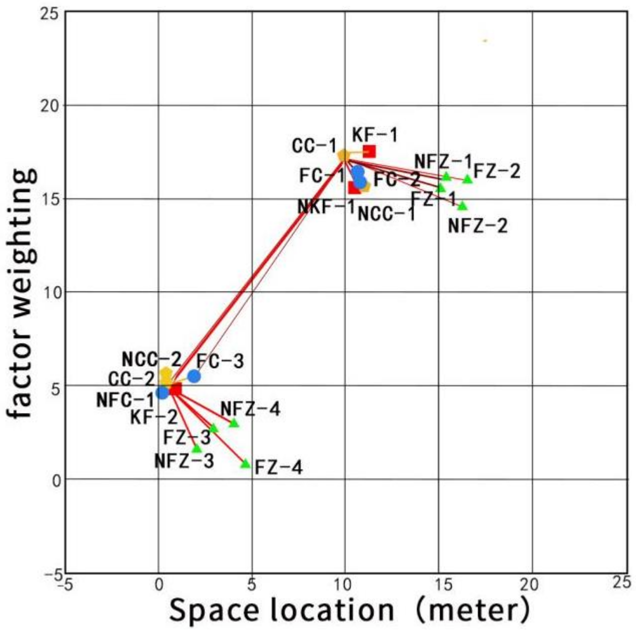

Figure 2. Track plot of the superimposed factor weights

4. Control Models and Resource Optimization for Launch Missions

Through the transformation analysis idea, the problem of emergency maneuver mission task is transformed into the relationship between positions as the position plane control system. The position plane coupling system takes full advantage of the high accuracy of the position plane and the active regulation of other emergency maneuver launch mission components. Compare the resulting position plane of the system with the measurement of the emergency maneuver launch mission component experiment [7]. The results show that the position-plane coupling system can not only evaluate the changes in the composition of the emergency maneuver launch mission but also for the model distribution performance test.

$$S' = (S_1, S_2, S_3)^T \tag{25}$$

$$F' = (F_1, F_2)^T \tag{26}$$

$$\max Z = \{\max S' + \min F'\} \tag{27}$$

Order F "=- F',

Turn the original problem into:

$$\max Z' = \max\{S' + F''\} \tag{28}$$

From this result, one can get that:

$$S_1(\mathrm{x}, \mathrm{y}, \mathrm{z}) = 6f_{(x_1,t)} - 5f_{(x_2,t)} + \mathrm{n}f_{(x,t)} \tag{29}$$

$$S_2(\mathrm{x}, \mathrm{y}, \mathrm{z}) = 12f_{(x_1,t)} - 5f_{(x_2,t)} + \mathrm{n}f_{(x,t)} \tag{30}$$

$$S_3(\mathrm{x}, \mathrm{y}, \mathrm{z}) = 6f_{(x_1,t)} - 50f_{(x_2,t)} + \mathrm{n}f_{(x,t)} \tag{31}$$

The model building yields the following optimization results:

Table 2. The optimized results

Optimize the variable	The optimized results
E_{F_X}	22.9208
E_{F_Y}	113.5736
E_{F_Z}	67.9281
D_{F_X}	0.0719
D_{F_Y}	0.1661
D_{F_Z}	13.4299

The data in Table 2 are the key parameter values obtained during the model optimization process, which represent the best state for each parameter to achieve optimal task performance and minimum cost under different constraints. The table includes the allocation number of key resources, the best level of efficiency index, and the weight coefficient. The data show that the scheme not only has high loss degree performance, but also meets the constraints of the launch task, and achieves the lowest construction cost [8]. In addition, by using the heat relationship rule analysis, as shown in Figure 3.

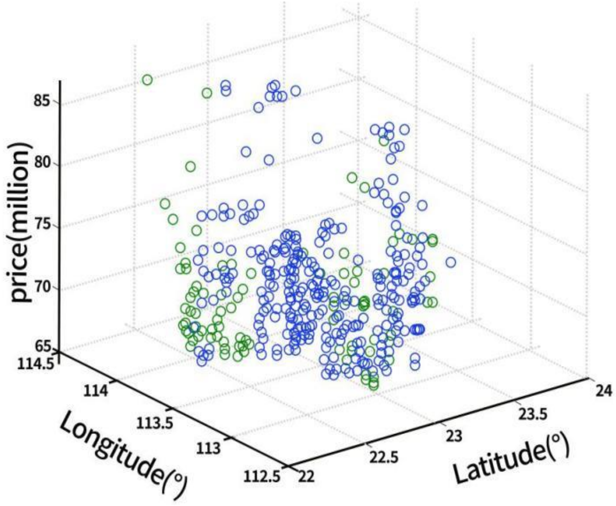

Figure 3. Model building

The combined score of this scheme outperformed all established base models, demonstrating its effectiveness and superiority in handling the planning problems of complex emergency maneuver launch missions.

Through the above model establishment, the results are analyzed by the algorithm, and the subsequent problem is processed to obtain the distribution of the planning parameters.

Table 3. Distribution of the planning parameters

Parameter number	Parameter distribution of the emergency maneuver launch mission	Constraint parameters
102900051010455	0.197598*T1	0.0001*F1
102900051004294	0.028067*T1	0.0001*F1
102900051000944	0.303821*T1	0.071666*F1
102900011009970	0.133649*T1	0.000165*F1
102900011008522	0.024248*T1	0.000551*F1
102900011006948	0.017456*T1	0.012189*F1
102900011001219	0.047111*T1	0.101668*F1
102900005125815	0.008465*T1	0.003786*F1
102900005125808	0.002315*T1	2.310549*F1s
102900005123880	0.003303*T1	0.718133*F1
102900005119975	0.01395*T1	0.068771*F1
102900005119944	0.114081*T1	1.006855*F1
102900005118831	0.00635*T1	0.039274*F1
102900005118824	0.069535*T1	0.011837*F1
102900005118817	0.199524*T1	0.015872*F1
102900005117209	1.92505*T1	0.209158*F1
102900005117056	0.852362*T1	0.002267*F1
102900005116943	0.00153*T1	0.146615*F1
102900005116912	0.000587*T1	0.390579*F1
102900005116790	0.000376*T1	0.852809*F1
102900005116714	0.081912*T1	0.012685*F1
102900005116547	0.28654*T1	0.455811*F1
102900005116530	0.00011*T1	0.000256*F1
102900005116509	0.040451*T1	0.008707*F1
102900005116257	0.096251*T1	0.87789*F1
102900005116233	1.765557*T1	0.132618*F1
102900005116226	0.159538*T1	0.412101*F1
102900005115984	0.068693*T1	0.012047*F1
102900005115960	0.009653*T1	0.000258*F1
102900005115946	0.098917*T1	0.508555*F1
102900005115908	0.28385*T1	0.031765*F1
102900005115823	1.079424*T1	0.389251*F1
102900005115793	0.013055*T1	0.035959*F1
102900005115786	0.046971*T1	0.113984*F1
102900005115779	0.324244*T1	0.17375*F1
102900005115762	0.270305*T1	0.139324*F1

Table 3 details the parameter distribution of the emergency maneuver launch mission, showing the specific values of the parameter distribution of the emergency maneuver launch mission and the constraint parameters under different parameter numbers. Some distribution patterns are revealed: each parameter number corresponds to a specific task parameter distribution value, which is expressed in the form of `*T1`, implying that they are proportional to the time or some task completion index [9]. The difference in constraint parameters means that different tasks have different limitations in resource allocation, time arrangement, technical requirements, etc., which directly affect the execution efficiency and completion of the task [10].

According to the distribution law of parameters, the rules are established through the above model, and the evaluation model and specific rules are established. By analyzing the influence of different laws, the preliminary rules are obtained, and the specific parametric scheme is given. For the new factory (warehouse) room location, as shown in the table 4.

Table 4. Location of the new plant (warehouse)

Sequence number	Point number	X coordinate (km)	Y coordinate (km)
1	NKF-1	10.65	15.87
2	NCC-1	10.43	16.03
3	NFC-1	0.72	4.79
4	NFZ-1	15.25	16.17
5	NFZ-2	15.98	14.72
6	NFZ-3	2.12	1.96
7	NFZ-4	3.85	3.07

Each warehouse of stars and arrows shall reserve the number of each type of satellites and rockets, and the number of each launching vehicle shall be equipped with each type of launching vehicle as shown in the following table below.

Table 5. Reserve status of Star Arrow Warehouse and launching vehicle workshop

Sequence number	NKF-1	NFC-1
Number of K-shaped rockets	7	-
Number of Z-shaped rockets	9	-
Number of Type A satellites	5	-
Number of Type B satellites	8	-
Number of Type C satellites	5	-
Number of Type D satellites	6	-
Number of Type K launchers	-	3
Number of Type Z transmitters	-	2

Table 5 details the storage of Star arrow warehouses (NKF-1 and NFC-1) and launch vehicle plants, including the number of different types of rockets and satellites, as well as the configuration of launch vehicles. It provides detailed information about the reserve of the Star arrow warehouse and launch vehicle plant. By rationally allocating the number of different types of rockets, satellites, and launch vehicles, it can ensure the smooth progress of space launch missions and improve the efficiency of resource utilization. At the same time, the timely adjustment of the reserve situation according to the mission requirements is also the key to ensuring the flexibility and response speed of the space mission activities.

5. Conclusion

In the process of dealing with the problem, due to some assumptions about some conditions, makes the model are subjective and may deviate from the actual situation. Although the study has improved the model and significantly reduced the error, the model for the research problem is still more complex. The operation and parameter setting are complicated, which may affect the efficiency of the application, still requiring further optimization and simplification of the algorithm and model structure, to be more widely applied to practical problems. Therefore, in the future, the model still needs to be further adjusted and optimized according to the specific situation to improve its universality. To further improve the practical application effect of the model, more realistic factors will be included in the model in the future, and the consideration of uncertain conditions will be increased to ensure that the model can be promoted and applied in more scenarios, to enhance its operability and applicability. In the process of model improvement, this study also plans to apply more simulation techniques to the verification and detection of the model, to reduce the prediction error and improve the reliability of the results. In addition, the introduction of simulation will help to better understand the behavior of the model and to make targeted adjustments to ensure that the accuracy and stability of the model in practical problems are further improved.

In this study, a parametric model including multi-dimensional variables (such as warehouse location, satellite, rocket and launch vehicle number) was constructed for space emergency mobile launch missions. Through the T-SNE algorithm classifies plane parameters, dynamic programming is used to evaluate the influence of new variables and formulate the optimal constraint scheme. To improve the efficiency and reduce the computational amount, the neural network method is adopted to conduct a comprehensive factor analysis to ensure accurate and scientific results. Combining fuzzy logic and neural networks, the T-S fuzzy neural network is constructed to improve the adaptability and accuracy of the model. The model considers multiple mission planning factors and provides a scientific basis for the efficient planning of space emergency motor launches.

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