

A Multi-Method Integrated Study on Parameter Constraint Analysis and Optimization for Emergency Maneuver Launch Missions

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Abstract. With the intensifying competition in space capabilities, emergency maneuver launches have emerged as a critical research area due to their unique military value and application prospects. Efficient and safe responses to emergency launch requirements are paramount, especially for the co-ordination of multiple tasks within the same launch window. This study integrates various data sources, including rocket depot numbers and satellite depot numbers, to analyze constraints such as launch windows, satellite types, and road traffic. Utilizing unsupervised cluster analysis, the relationships between different constraints and their classification rules are identified. A neural network algorithm establishes connections among various launch mission indicators, and a dynamic comprehensive planning and evaluation model is developed by adjusting S and H parameters in conjunction with a dynamic planning algorithm (DDP). This model optimizes planning schemes across different launch tasks and multiple windows. Additionally, Pearson's correlation coefficient is used to assess the dynamic impact of constraint changes on mission planning. The proposed optimal planning scheme, based on data analysis and dynamic optimization, offers theoretical support and practical guidance for the efficient execution of space emergency maneuver launches.

Keywords: Contingency Maneuvering Launch Mission, Coupled Constraints, Dynamic Planning, Spaceflight, Merging.

1. Introduction

Space emergency maneuver launch has emerged as a critical research area due to its significant military value and application prospects. It involves rapidly deploying backup satellites and other spacecraft using specialized rockets from emergency launch positions outside conventional launch sites. These launches play a crucial role in tasks such as emergency network replenishment, network reconfiguration, and regional enhancement, holding high strategic importance^[1].

However, developing a space emergency maneuver launch plan is extremely complex and urgent. The diversity and complexity of the missions require the plan design to fully consider multiple constraints, including the preparation time of rockets and satellites, the selection of launch windows, the configuration of launch positions, orbit design, and coordination with other missions. All of these need to be scientifically and rationally planned within a short period. Additionally, since emergency launches involve the scheduling of resources from multiple parties and have complex relationships, traditional planning methods often struggle to meet the demand for rapid response. Therefore, there is an urgent need to construct an intelligent emergency maneuver launch planning model to achieve automation and quick decision-making, ensuring the efficient execution of launch missions in emergency situations.

This study is based on the existing data of rocket and satellite depot numbers, combined with actual constraint conditions, and conducts a comprehensive analysis from three aspects: launch window, satellite type, and traffic factors. According to the constraints of the emergency mission and its regular characteristics, the interrelationships among the constraints are analyzed through unsupervised clustering, and corresponding planning classification rules are formulated. A neural network algorithm is used to establish the association between data, and the Fi coefficient and L-M optimization algorithm are employed to solve the data index score. Simultaneously, a comprehensive planning evaluation model is constructed through the DDP dynamic programming algorithm to

optimize the planning of launch tasks and launch windows, ensuring completion within the target time^[2]. Furthermore, this study utilizes the Pearson coefficient to analyze the dynamic correlation between constraint conditions, proposing the optimal constraints. Ultimately, based on these analysis results, an efficient space emergency maneuver launch planning scheme is developed.

2. Influence Analysis of Emergency Launch Parameters

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

The data of this study comes from mcm.gfk.d.mtn. In order to establish the emergency maneuver launch mission associated parameter influence model and introduce the constraint relationship data model, according to the attached data already in the form of text data of the rocket depot number, the star arrow depot number, the satellite depot number, the launch vehicle number, the star arrow test facility number and the launch position number, the fuzzy synthesis evaluation model is used for processing, and first the evaluation matrix R_K is made fuzzy operation to synthesize the relationship and get the affiliation vector B_K of the main factor layer: of each sub-factor level indicator U_{Ki} is made fuzzy operation to synthesize the relationship, and the membership vector B_K of the main factor level indicator X_K for the comment set W is obtained^[2].

$$B_K = A_K \cdot R_K = b_{K1}, b_{K2}, b_{K3}, b_{K4} \quad (1)$$

One of the very important steps in the analysis of this study is to choose the appropriate synthesis algorithm, two commonly used algorithms are weighted average type and main factor salient type. The establishment of R , i.e:

$$R = \begin{bmatrix} B_1 \\ B_2 \\ B_3 \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \end{bmatrix} \quad (2)$$

The fuzzy transformation of R is then performed, i.e., the membership vector of the target layer metrics X with respect to the set of categories W is obtained as B :

$$B = A \cdot R = [a_1 a_2 a_3] \cdot \begin{bmatrix} B_1 \\ B_2 \\ B_3 \end{bmatrix} = A \cdot \begin{bmatrix} A_1 \cdot R_1 \\ A_2 \cdot R_2 \\ A_3 \cdot R_3 \end{bmatrix} = [b_1 b_2 b_3 b_4] \quad (3)$$

In this study, the indicator T was chosen for this emergency maneuver launch mission-associated constraint parameter influence $t1$, respectively, and the model was used to calculate the emergency maneuver launch mission-associated constraint parameter influence.

2.2. Correlation Analysis of the Task Force for the Emergency Launch of Mobile Devices

In order to effectively analyze the relationship between emergency mobile launch task groups, this study processes the distribution of parameter point indices of emergency mobile launch task associations, and then derives their distributions over a certain period of time. First, we consider the correlation between the emergency mobile launch task association and the distribution of changes in emergency mobile launch task types, eliminating some virtual indices with low correlation, and at the same time establishing a correlation analysis model. Assuming that $X \in Rn$ and $Y \in Rm$, the equation $Y = AX$ can be established as follows:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m1} & w_{m2} & \cdots & w_{mn} \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix} \quad (4)$$

Where $y_i = w_i^T x$, the form is the same as linear regression, which must be trained m times to get m w_i . Pearson's correlation coefficient is then used:

$$\rho_{X,Y} = \text{corr}(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y} \quad (5)$$

To measure the relationship between u and v . The expectation is to find a set of optimal solutions a and b that maximize $\text{Corr}(u, v)$, so that the resulting a and b are the weights that then make u and v maximally related. Finally, it is computed that $\text{Corr}(u, v)^{[2]}$.

$$\text{Corr}(u, v) = \frac{a^T \Sigma_{12} b}{\sqrt{a^T \Sigma_{11} a} \sqrt{b^T \Sigma_{22} b}} \quad (6)$$

Finally, a correlation can be derived. A dynamic exponential distribution is then obtained based on an initial dynamic exploration of the above correlation and a preliminary model.

Table.1. Distribution of Dynamic Correlation Coefficients

Time series	Dynamic coefficients	Time series	Dynamic coefficients	Time series	Dynamic coefficients	Time series	Dynamic coefficients
1	0.531634	18	0.002315	35	0.28654	52	0.324244
2	0.596371	19	0.003303	36	0.00011	53	0.270305
3	0.118859	20	0.01395	37	0.040451	54	0.034561
4	0.142329	21	0.114081	38	0.096251	55	0.000503
5	0.930866	22	0.00635	39	1.765557	56	0.343749
6	0.080387	23	0.069535	40	0.159538	57	0.0001
7	0.274233	24	0.199524	41	0.068693	58	0.0001
8	0.020527	25	1.92505	42	0.009653	59	0.071666
9	---	26	0.852365	43	0.098917	60	0.000165
10	0.197598	27	0.00153	44	0.28385	61	0.050258
11	0.028067	28	0.000587	45	1.079424	62	0.00077
12	0.303821	29	0.000376	46	0.013055	63	0.365113
13	0.133649	30	0.002376	47	0.046971	64	0.167387
14	0.024248	31	0.741613	48	0.581439	65	0.000551
15	0.017456	32	2.340303	49	0.000956	66	0.12189
16	0.047111	33	1.072792	50	2.33E-05	67	0.101668
17	0.008465	34	0.081912	51	0.250406	---	---

Table 1 shows the dynamic correlation coefficients between the Emergency Maneuver Launch Task Index and the Constraint Category Index for different time series. These coefficients reflect the strength of the correlation between the two at different points in time. Observation shows that the correlation coefficients vary considerably over different time periods. For example, when the time series is 1, the correlation coefficient is 0.531634, indicating that there is a moderately strong correlation between the two at that time, while when the time series is 39, the correlation coefficient jumps to 1.765557, indicating an extremely strong correlation^[3]. This dynamic change reveals the complex and variable relationship between the emergency maneuver launch mission and the constraints. The fluctuation of the dynamic correlation coefficient can be affected by a variety of factors, such as the urgency of the launch mission, resource utilization, environmental factors, and so on. Therefore, these dynamic changes must be fully considered when formulating the emergency maneuver launch plan to ensure the smooth execution of the mission. In-depth analysis of these correlation coefficients can provide strong support for optimizing the launch plan.

Again, the distribution of the correlation between the Emergency Maneuver Launch Task Index and the Constraint Type Index is illustrated by a distribution of Q

Table.2. Correlation distribution of Q

Relevance	Q1	Q2	Q3	Q4	Q5	Q6
Q1	1.0000	0.8157	0.6624	0.2590	0.2713	-0.2690
Q2	0.8157	1.0000	0.5822	0.3064	0.3064	-0.1765
Q3	0.6624	0.5822	1.0000	0.2983	0.3119	-0.2737
Q4	0.2590	0.3064	0.2983	1.0000	-0.3440	-0.2544
Q5	0.2713	0.3064	0.3119	-0.3440	1.0000	-0.2840
Q6	-0.2690	-0.1765	-0.2737	-0.2544	-0.2840	1.0000

Table 2 also shows the correlation between the Emergency Maneuver Launch Mission and different types of constraints by calculating the correlation coefficients between Q1 and Q6. It can be seen that there is a strong positive correlation between Q1 and Q2 and Q3, while a negative or weak positive correlation is observed with Q4, Q5, and Q6^[4]. This indicates that there are differences in the impact of different types of constraints on the emergency maneuver launch mission. By analyzing Table 3, it is possible to identify which constraint types have a significant impact on the launch mission and which have a lesser impact. This helps to prioritize the resolution of critical constraints with limited resources, thereby improving the efficiency and success rate of the launch mission. The last case of relevance is given by the last quantitative question:

Table.3. Ultimate relevance

Constraint Factor for Launch Mission	Q1	Q2	Q3
A1	0.617	0.974	-0.037
A2	0.6005	-0.706	-0.399
A3	0.5887	0.437	0.719
A4	0.5796	0.856	0.006
A5	0.5725	-0.631	0.194
A6	0.5666	0.563	-0.753
A7	0.5616	-0.025	0.745
A8	0.5573	0.131	0.16
A9	0.5536	-0.334	0.23
A10	0.5503	0.467	0.24
A11	-0.612	-0.303	0.37
A12	0.431	0.676	-0.34
A13	0.156	0.182	0.17

Table 3 lists the final correlation coefficients between the various launch task constraint coefficients (A1 through A13) and Q1, Q2, and Q3. These coefficients provide a quantitative assessment of the importance of the launch task constraints. Looking at the data in Table 4, it is clear that there is a strong positive correlation between some constraint coefficients (e.g., A1, A2) and Q1, Q2, suggesting that these constraints are critical to the successful execution of the launch mission. Conversely, the weak or negative correlation between some constraint coefficients (e.g., A11, A13) and Q values indicates that these constraints may not be the critical factors in a particular context. Therefore, when developing a launch plan, the focus should be on those constraints that have a significant impact on mission success^[5].

3. Optimization and Solution of Constraint Parameters Using Neural Networks

3.1. Assessing the Quantitative Degree of Holding

According to the existing condition constraints basic principles, based on the above data fusion and research, here the use of neural networks to do constraints associated with the importance of

parameter judgment processing, because in the neural network model, there is feedback neural network model has a stronger corrective, in order to improve the accuracy of this model, this issue choose feed-forward neural network as the basis of model construction.

Optimizing the convergence of solving the neural network using the LM algorithm is shown as shown in Figure 1^[6].

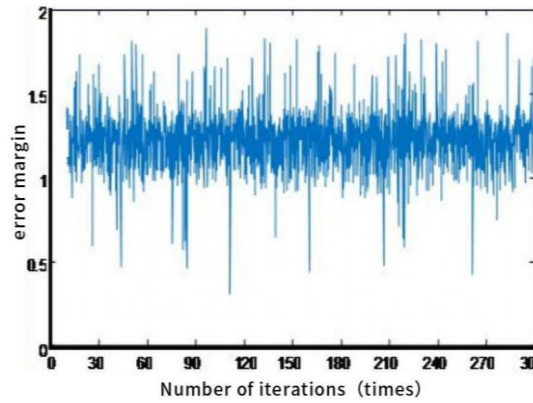


Figure 1. Output of the results

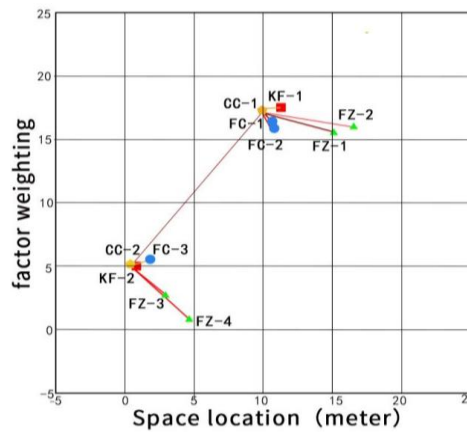


Figure 2. Trajectory plot of stacked factor weights

The neural network has better results after synthesizing the above integrated model for judging the data metrics, which is suitable for illustrating the computational problem. Finally, through the above neural network modeling algorithm, a suitable set of constraint scheme was established to give the factor weights on the trajectory, as shown in Figure 2.

3.2. Threshold setting and program optimization

Through the algorithm to determine the characteristics of multi-task planning constraints model, after the use of fuzzy comprehensive evaluation method, respectively, the constraints associated with the parameters of the indicators of the situation one by one analysis, to derive the required T-value (T1, T2, T3), will be classified as a collection of things divided into a number of categories, the information of a particular class (x_i) can be defined as follows.

$$I(X = x_i) = -\log_2 p(x_i) \quad (7)$$

$I(X)$ am used to represent the information about a random variable and $P(x_i)$ refers to the probability of x_i occurring^[7]. Entropy is used as a measure of uncertainty, when the entropy is greater, the uncertainty of $X = x_i$ is greater and vice versa. Considering the classification problem in machine learning, the greater the entropy, the greater the uncertainty of the category and vice versa. Information gain is used as an indicator for feature selection in decision tree algorithms, the larger the information gain, the better the selectivity of the feature. Next, Gini impurity, entropy and error rate are calculated.

(3) The function of the nonlinear activation function: making the neuron output signal within a certain range.

$$G_i n_i = 1 - \sum_{i=1}^n P(i)^2 \quad (8)$$

$$Entropy = - \sum_{i=1}^n P(i) \times \log_2^{P(i)} \quad (9)$$

$$Error = 1 - \max\{P(i) | i \in [1, n]\} \quad (10)$$

After that, this study integrates many decision trees into a forest and combine them to evaluate as well as regress the final results. The accuracy results show that the accuracy of the model is still relatively high, but it is difficult to directly achieve an objective evaluation of the model by accuracy alone, and ROC curves are constructed to analyze the value of AUC to further evaluate the model.

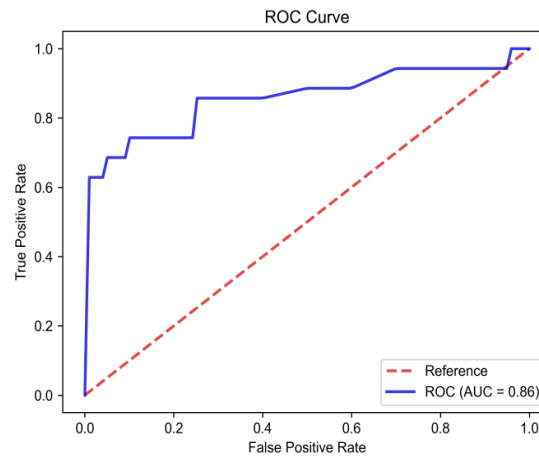


Figure 3. ROC plot

The ROC curve shows that the value of AUC is between 0.5 and 1, indicating that the model outperforms random guessing and can achieve better results when the thresholds are set properly.

After that, the algorithm is used to fuzzify the three T-values to some extent, which finally results in the Q-value threshold case. And for the Q-value case, if $Q > C_0$ indicates that the constraint is allowed, and if $Q < C_0$ indicates that the risk is high and the constraint is not allowed.

And to determine the threshold C_0 , the pairwise comparison matrix is constructed using Sanity's consistent matrix method, and then a reasonable threshold is determined.

$$\int(r_i, r_j) = c_{ij}^{(r_i - r_j)/R} \quad (11)$$

The resulting matrix $C = (C_{ij})_{m \times n}$ is the consistency judgment matrix, where c_k is the relative importance of pairs of polar elements given by some criterion, and $R = r_{\max} - r_{\min}$ is called the polar difference^[7].

$$b_{ij} = \begin{cases} 2 & B_i \text{ is more important than } B_j \\ 1 & B_i \text{ is as important as } B_j \\ 0 & B_j \text{ is more important than } B_i \end{cases} \quad (12)$$

$$B_2 = \begin{bmatrix} 1 & \frac{1}{3} & \frac{1}{8} \\ 3 & 1 & \frac{1}{3} \\ 8 & 3 & 1 \end{bmatrix} \quad (13)$$

3.3. Decision making for ideal prognosis

Through the constraint modeling and solving the constraints associated with the parameters of 103 groups of parameters to meet the constraints, but for the case, the need to establish a separate

mathematical model, the purpose is to ensure that the risk of a certain premise to maximize the benefits of the resulting Q blended into the strategy model.

With Q/C0 level $K = V$, where K is the fuzzy slope of the constraint loss.

$$\rho(t) = \frac{m(t)}{v} \quad (14)$$

$$I(t) = \begin{cases} Q_1(t), t \in \Omega_{1,i} & i = 1, 2, \dots, n_1 \\ 0, other \end{cases} \quad (15)$$

$$E = \begin{cases} Q_1(t), t \in \Omega_{2,i} & i = 1, 2, \dots, n_2 \\ 0, other \end{cases} \quad (16)$$

$$Q_1(t) = CA \sqrt{\frac{2\Delta P(t)}{\rho(t)}} \quad (17)$$

$$Q_2(t) = \begin{cases} 100t', t' \in [0, 0.2) \\ 20, t' \in [0.2, 2.2) \\ 240 - 100t', t' \in [2.2, 2.4) \end{cases} \quad t' = t - t_0 + 100 \cdot (i - 1) \quad (18)$$

$$\Omega_{1,i} = [0 + (i - 1) \cdot (T + 10), T + (i - 1) \cdot (T + 10)]: i = 1, 2, \dots, n_1 \quad (19)$$

$$\Omega_{2,i} = [t_0 + 100 \cdot (i - 1), 2.4 + t_0 + 100(i - 1)]: i = 1, 2, \dots, n_2 \quad (20)$$

Afterwards, considering that there are also some relations between each other's constraint groups, let the total number of associated parameters remain K, D .

$$K_{100} \frac{\partial^2 \mu}{\partial x^2} + 2K_{120} \frac{\partial^2 \mu}{\partial x \partial y} + K_{220} \frac{\partial^2 \mu}{\partial y^2} - \beta \left(K_{220} \frac{\partial \mu}{\partial x} + \frac{\partial \mu}{\partial y} \right) = 0 \quad (21)$$

After that, take 50 groups of F-values to determine the curve, take the data 0.04-0.15 loss curve, the two groups of curves for adjustment, can be derived from the loss and F-value of the integrated curve. According to the conditions of the constraints of the nature of the situation, the calculation of F-value can finally give the appropriate, and for the determination of special cases take $N0 = F \wedge 2$ for the determination of the curve with 40%-97% to adapt to the results. Taken together, it can basically be realized to achieve the highest efficiency situation with a low loss rate. Through the above model construction, combined with effective data and fusion dismemberment data to finally solve the constraint program situation.

Table.4. Distribution of constraint parameters under T1

parametric pair	X1	X2	X3	X4	X5	X6
N1	0.830949554*T1	0.018999691*T1	0.079433632*T1	1.579499655*T1	0.00109807*T1	0.139484587*T1
N2	0.536776037*T1	0.564216366*T1	0.037847166*T1	0.069541693*T1	0.058278542*T1	0.031101122*T1
N3	0.265030766*T1	0.008865604*T1	0.277054634*T1	0.060076981*T1	0.910390034*T1	0.002057686
N4	1.537390804*T1	0.001839619*T1	0.523583355*T1	0.176188517*T1	0.007913504*T1	2.702728462*T1
N5	0.309729357*T1	0.00333293*T1	0.726681881*T1	0.053288879*T1	0.00014061*T1	0.106388674*T1
N6	0.090619698*T1	0.008082933*T1	0.077675152*T1	0.182462358*T1	0.001298695*T1	0.029926319*T1
N7	0.072795877*T1	0.010664473*T1	0.898989906*T1	0.07215951*T1	0.000365629*T1	1.532905836*T1

Table.5. Distribution of constraint parameters under f1

parametric pair	X1	X2	X3	X4	X5	X6
N1	0.7*f1		7.68*f1	1.41*f1	1.73*f1	13.05*f1
N2	67.71 *f1		7.37*f1		1.35*f1	11.15*f1
N3	61.58*f1	3.04*f1	10.95*f1	3.12*f1	0.11*f1	4.16*f1
N4	65.23*f1		9.67*f1	7.12*f1	1.65*f1	6.44*f1
N5	61.71*f1	5.51**f1	12.37*f1	5.87*f1	1.11*f1	5.5*f1
N6	87.05*f1		5.19*f1	2.01*f1		4.06*f1
N7	69.61*f1		9.42*f1	6.11*f1	0.82*f1	3.93*f1

Tables 4 and 5 show the distribution of each constraint parameter at different T values (T1 and f1), respectively. These tables show the magnitude of the overall impact of each constraint parameter on the launch mission by quantifying their weights^[8].

Comparing the data in Tables 4 and 5, it can be seen that there are differences in the weights of each constraint parameter at different T values. This reflects that the degree of influence of each constraint on the launch mission changes under different scenarios^[9]. Therefore, when formulating the launch plan, it is necessary to flexibly adjust the priority and weight of each constraint according to the actual situation. At the same time, quantitative analysis of the distribution of each constraint parameter can provide a scientific basis for optimizing the launch plan^[10].

The distribution of model parameters, as well as the constraint coefficients, are integrated by the algorithm to solve the constraint scheme for the emergency maneuver launch mission pairs derived in the previous section and adjusted according to the local adjustment points^[11].

4. Conclusions

Focusing on the planning of Space Emergency Manoeuvre launch missions, this study investigates the key elements and their optimisation strategies. The basic dataset was constructed, unsupervised cluster analysis was used to categorise the constraints, and preliminary planning rules were formulated. Based on the multi-constraint, multi-stage ballistic flight procedure, the associated parameter influence model is established and each parameter is quantitatively evaluated, and the mission planning model is successfully constructed. Meanwhile, the optimal planning model is constructed based on the optimal planning of the launch mission with multiple launch windows, and the objective function parameters are set. The study also shows the distribution of the constraint parameters at different T-values and discusses their influence on the launch mission. Through methodological and empirical analyses, the main problems are solved, accuracy and efficiency are improved, and new ideas for related fields are provided. However, weak model validation, lack of actual data comparison and a single data source may limit the broad applicability and accuracy of the model.

In this study, key issues in space emergency manoeuvre launch mission planning are successfully addressed through systematic methodology and empirical analysis. The constructed model and optimisation strategy not only improve the accuracy and efficiency of mission planning, but also provide new ideas and methods for research in related fields. In the future, space emergency launch mission planning will strengthen model validation and data diversity, deepen the application of intelligent algorithms, enhance the flexibility and robustness of mission planning, and strengthen international cooperation to jointly build an efficient and intelligent global space emergency response system.

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