Planning of Vehicle Routing with Mixed Time Windows Based on the Improved Genetic Algorithm (IGA)

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Abstract. In recent years, the rapid expansion of urban distribution business and the increase use of traditional fuel logistics trucks have resulted in a lot of environmental, traffic and resource problems. "Green logistics" has become the direction of urban distribution transformation, and replacing fuel vehicles with pure electric logistics vehicles has become a way to meet the requirements of urban end distribution. In this paper, the characteristics of electric logistics vehicles are combined with the constraints of cargo capacity to meet the demand for sufficient power and driving range in the distribution process. Charging operations are carried out using charging piles at fixed locations when necessary, and the time windows of customers at each node are considered and penalty factors are set so that the distribution path of electric logistics vehicles can be well planned, which makes the total logistics cost lowest.

1. Research Background
With the adjustment of urban industrial layout, the planning of inter-regional cooperation and synergy, and the improvement of residents' living standards, urban distribution has gradually become the focus of attention in the logistics industry. Most of the urban distributions are transported by traditional fuel trucks, and with the expansion of business and the increase of vehicles, its emission of pollutants is also increasing dramatically. Under huge pressure from many aspects, the contradiction between the strong demand for urban distribution and the pollution caused by fuel vehicles needs to be solved. In the context of energy saving and emission reduction as well as policy support for the development of new energy vehicles, "green logistics" has become the direction of transformation, and the state and the government are encouraging the development of urban green distribution based on electric logistics vehicles.

Based on the urban distribution vehicle path problem, this paper combines the characteristics of electric logistics vehicles, the weight and volume in distribution, electricity, and the constraints of the customer's soft and hard time windows, and conducts a detailed analysis with the aim of minimizing the total logistics cost. At the same time, the best distribution scheme and delivery and charging routes are reasonably planned by using scientific methods, thus helping logistics enterprises to achieve the goal of cost reduction and efficiency increase.

2. Research Significance
In regard of theory, most studies focusing on the VRP model and its solution algorithm in both domestic and foreign studies are about traditional fuel vehicle, and there have been many academic achievements in this aspect. The research on the vehicle path problem based on pure electric vehicles is still in the
primary stage, for which there are relatively few relevant achievements. Meanwhile, because EVRP takes into account the dynamic nature of the external driving environment, the power and range of the vehicle, the geographic location of the charging pile and other factors, the model and algorithm still have many shortcomings.

In terms of practical significance, this study can help enterprises design distribution routes to reduce costs and increase efficiency; for the industry, it can help make full use of social public infrastructure and further promote the development process of electric vehicles in the field of urban distribution; for the society, it can promote the development of China's logistics industry in the direction of green and wisdom.

This paper integrates the characteristics of short driving range of electric logistics vehicles and the possible need for charging during the distribution process, constructs a VRP model with soft and hard time windows, which considers the load limit and charging demand. Meanwhile, an improved genetic algorithm suitable for solving this problem is designed, which further enriches the relevant theory of VRP.

3. Literature Review
The traditional vehicle routing problem, namely VRP (Vehicle Routing Problem), was first proposed by Dantzig and Ramser in 1959, and when pure electric logistics vehicles replace traditional fuel trucks as transportation vehicles, the problem becomes EVRP (Electric Vehicle Routing Problem). In addition to satisfying the basic conditions such as vehicle load, it is also necessary to combine the characteristics of electric vehicles and customer demand, and then make reasonable and optimal scheduling of vehicle distribution routes.

Conrad and Figliozzi (2011) [1] considered the mileage constraint, thus allowing vehicles to travel to pre-defined locations for charging during the delivery trip or to perform charging operations at some customer stations. They proposed a charging vehicle path problem with a final prediction of the average distance traveled; Erdogan et al. (2012) [2] focused on the problem of low electric vehicle range and lack of charging facilities, added constraints on the time window, and proposed a green vehicle path problem that minimizes the total distance traveled by two heuristic algorithms; based on electric vehicle characteristics, Liu(2012) [3] combined electric vehicle technology and common distribution vehicle scheduling, focusing on range, charging time and demand constraints, finally established a logistics distribution scheduling model with electric vehicles as a tool, which solves and analyzes the rationality of the distribution plan with ant colony algorithm. Schneider et al. (2014) [4] introduced a path optimization and scheduling model for electric logistics vehicles when studying the "last mile" problem. This model takes into account the weight of goods, service time, and range constraints, avoids the delivery of useless routes, and requires the timely selection of a suitable charging station when the remaining mileage is insufficient; Gao (2015) [5] combined the time window problem with the characteristics of electric vehicles from the perspective of energy saving and emission reduction, built a vehicle path problem model with the objective of minimizing the total delivery cost, and solved it with an improved genetic algorithm; Guo (2017) [6] considered the soft time window constraint of customers and built a multi-objective EVRP model to maximize customer satisfaction with time, minimize driving cost and vehicle ineffective distance; Shao (2017) [7] used a nonlinear regression model to estimate the remaining mileage of vehicles in EVRP model considering dynamic customer demand and proposed an update time based route update strategy to achieve real-time optimization of distribution schemes. Li (2018) [8] concluded that partial charging strategy is more satisfying to customers compared to full charging strategy through comparative analysis; Song (2019) [9] constructed an EVRP model with time windows that allows vehicle midway charging, queuing time variability, which also takes into account the network time variability and the effect of driver style on power consumption.
4. Problem Description
In this paper, genetic algorithm is used as the solution algorithm of the research problem for JD logistics data, and the chromosome coding method and genetic operator suitable for solving this model are chosen and designed. Finally, the feasibility and effectiveness of the model and algorithm are verified by numerical experiments.

4.1. Research Contents
Based on JD logistics data, a problem with a single distribution center, multi-trip, capacity-constrained, charging piles, soft and hard time window-constrained was set based on the VRPTW problem for electric vehicles. There is no vehicle number limitation, and the optimization objective is minimizing the expected integrated cost (including transportation cost, waiting cost, charging cost and fixed usage cost).

4.2. Conditions and Constraints

4.2.1. About Vehicle Use. (1) The vehicle departs from the distribution center and returns to the distribution center after serving the customer; the vehicle can make multiple round-trip cycle deliveries; the departure time is after 8:00 am (inclusive) and the latest time to return to the distribution center is 24:00 on the same day.
(2) The first departure of the distribution center is not counted into the waiting cost, and the rest of the waiting are counted; if the vehicle is not used (i.e. not visiting the customer) then no cost is spent, and the number of vehicles is not limited.
(3) Vehicles departing from the distribution center (including multiple trips to the distribution center scenario) are fully charged and do not count charging costs and charging time, but for multiple trips scenario, the second departure from the distribution center requires 1 hour to wait at the distribution center, and the waiting cost is calculated.
(4) The relevant information of the vehicle is shown in Table 1:

| Maximum load volume | Approved load weight | Number of vehicles | Transportation cost per kilometer | Vehicle usage cost |
|---------------------|---------------------|--------------------|-----------------------------------|-------------------|
| 4.5m³               | 0.8t                | Unlimited          | 12 RMB                            | 200 RMB per day   |

4.2.2. About Delivery for Service Station. (1) The vehicle must arrive before (and including) the latest time requested by the customer, at the same time, there is a waiting cost if it arrives earlier.
(2) Customers are all to be served, and each customer can only be served by one vehicle a day. The unloading time is constant at 0.5 hour, in which the loading time is not counted.
(3) The cost coefficient of waiting is 24 RMB per hour.

4.2.3. About the Use of Charging Piles. (1) There is no restriction on charging piles. The vehicle needs to be charged at the charging station before the endurance mileage is reached. The vehicle is fully charged at one time;
(2) The cost of charging in charging station is 50 RMB per hour; each charging time is constant at 0.5 hour.
5. Problem Modeling

5.1. Description of Variables and Symbols

Table 2. Description of Variables and Symbols

| Variables and Symbols | Explanation and Description |
|-----------------------|----------------------------|
| N                     | Customer Station set, \( N = \{n | n = 1, 2, 3...\} \) |
| O                     | Distribution Center        |
| M                     | Charging Pile set          |
| K                     | Electric Vehicle set       |
| V                     | The set of all points \( V = N \cup M \cup O \) |
| CM                    | The approved weight of electric vehicles |
| CV                    | Approved volume of electric vehicle |
| P                     | Maximum continuous mileage of electric vehicle |
| d_{ij}                | The length from point \( i \) to point \( j \), \( i, j \in V \) |
| t_{ij}                | The time from point \( i \) to point \( j \), \( i, j \in V \) |
| w_i                   | Weight of customer station \( i \) demand, \( i \in N \) |
| v_i                   | Volume of customer station \( i \) demand, \( i \in N \) |
| serv_i                | Service time of point \( i \): charging post represents charging time, distribution center represents full preparation time, and customer station represents unloading time |
| p_{ik}^{'}            | The remaining mileage of electric vehicle \( k \) to reach point \( i \), \( i \in V, k \in K \) |
| p_{ik}                  | Mileage remaining for electric vehicle \( k \) leaving point \( i \), \( i \in V, k \in K \) |
| e_i                   | The earliest service time requested by customer station \( i \) or the earliest departure time of the distribution center |
| l_i                   | The latest service time requested by the customer station \( i \) or the latest return time of the distribution center |
| s_i^{k}               | Time of electric vehicle \( k \) to arrive at point \( i \), \( i \in V, k \in K \) |
| wt_i^{k}              | Waiting time for electric vehicle at point \( i \), \( i \in V, k \in K \) |
| cw                    | Waiting Costs at Customer station |
| cm                    | Charging Costs at Charging Stations |
| cu                    | Vehicle usage cost |
| ct                    | Vehicle transportation cost |
| M                     | A large value |
| x_{ij}^{k}             | Whether the journey from point \( i \) to point \( j \) is done by electric vehicle \( k \) |
| y_{ik}                 | 0,1 variable to calculate the number of vehicles used |
5.2. Modeling

\[
\min z = \sum_{k \in K} \sum_{i \in N} w_t^k \times cw + \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} x_{ij}^k \times d_{ij}^k \times ct + \sum_{k \in K} \sum_{i \in O} \sum_{j \in V} x_{ij}^k \times cm + \sum_{k \in K} y_k^k \times cu 
\]

(1)

s.t.

\[
\sum_{k \in k} \sum_{j \in V} x_{ij}^k \geq 1, \forall i \in N 
\]

(2)

\[
\sum_{j \in V} x_{ij}^k - \sum_{j \in V} x_{ji}^k = 0, \forall i \in N, k \in K 
\]

(3)

\[
\sum_{i \in N} x_{ij}^k w_i^k \leq CM, \forall k \in K 
\]

(4)

\[
\sum_{i \in N} x_{ij}^k v_j^k \leq CV, \forall k \in K 
\]

(5)

\[
w_{t_i}^k = \max \{0, e_i - s_i^k\}, \forall k \in K, i \in N 
\]

(6)

\[
e_i + t_{ij} - s_j^k \leq M(1 - x_{ij}^k), \forall k \in K, i = O, j \in V 
\]

(7)

\[
e_i + t_{ij} + \text{serv}_i - s_j^k \leq M(1 - x_{ij}^k), \forall k \in K, i \in O, j \in V 
\]

(8)

\[
s_i^k + \text{serv}_i + w_t^k + t_{ij} - s_j^k \leq M(1 - x_{ij}^k), \forall k \in K, i \in V, j \in O 
\]

(9)

\[
s_i^k \leq l_i, \forall k \in K, i \in N 
\]

(10)

\[
p_{k_i}^1 = p_{k_i}^2, \forall k \in K, i \in N 
\]

(11)

\[
p_{k_i}^2 = P, \forall k \in K, i \in M \cup O 
\]

(12)

\[
p_{k_i}^2 - d_{ij} - p_{ji}^1 \leq M(1 - x_{ij}^k), \forall k \in K, i, j \in V 
\]

(13)

\[
p_{k_i}^1 > 0, \forall k \in K, i \in V 
\]

(14)

\[
\sum_{j \in V} x_{ij}^k - My_k \leq 0, \forall k \in K, i = O 
\]

(15)

\[
p_{k_i}^2 = P, \forall k \in K, i = O 
\]

(16)

Equation (2) ensures that each customer station is served; Equation (3) is the flow balance constraint, i.e., the vehicle needs to be guaranteed to leave a point after reaching it; Equations (4) and (5) ensure that the vehicle load weight and cargo volume do not exceed the vehicle loading capacity; Equation (6) is the waiting time of the vehicle at the customer station; Equations (7) and (8) represent the first departure from the distribution center and non-first departure for the next customer station task; Equations (9) and (10) represent constraints on time, indicating time constraints between customer stations, returning to the distribution center after completing the task at customer station; Equations (11) satisfies the constraints on the time window; Equations (12) and (13) indicate that the vehicle does not charge when passing through a customer station and charges when passing through a charging post, respectively; Equations (14) indicates the power consumption constraint; Equations (15) indicates that
the remaining mileage needs to be greater than 0 when passing through and arriving at a point; Equations (16) is used to calculate the number of vehicles used; Equations (17) ensures that the departure is in a fully charged condition.

6. Model Solving

Since the model and the experimental network in this paper are relatively complex, it should not be solved by the exact algorithm, for which the genetic algorithm is selected as the solution method. The genetic algorithm has a good performance in solving the vehicle path problem of large networks, which is widely used.

6.1. Algorithm Introduction

Genetic Algorithm (Genetic Algorithm) follows the principle of "survival of the fittest" and is a type of randomized search algorithm that draws on natural selection and natural genetic mechanisms in the biological world. It uses randomization techniques to guide an efficient search of an encoded parameter space with all individuals in a population. Among them, selection, crossover and mutation constitute the genetic operation of the genetic algorithm. The five elements of parameter coding, initial population setting, fitness function design, genetic operation design, and control parameter setting form the core of the genetic algorithm. Figure 1 shows the basic flow of the algorithm.

![Figure 1. The Basic Process of Genetic Algorithm](image)

Each chromosome in the genetic algorithm corresponds to a solution of the genetic algorithm. Generally, the fitness function is used to measure the pros and cons of the solution, that is, the fitness from a genome to its solution forms a mapping. Therefore, the key steps of the genetic algorithm are as follows.

1. Randomly generate populations.
2. Determine whether the fitness of individuals meets the optimization criterion according to the strategy, and if so, end with outputting the best individual as well as its optimal solution. Otherwise, proceed to the next step.
3. Select the parents based on the fitness of the individuals, high individuals are with high probability to be selected and the lower ones are eliminated.
4. Crossover with the chromosomes of the parents according to a certain method to generate offspring.
5. Mutate the chromosomes of the offspring.
6.2. Improved Genetic Algorithm
For the research problem of this thesis, an improved genetic algorithm is constructed for solving the problem by applying different selection, crossover, and mutation operators as well as the adaptive mechanism of crossover probability. In addition, elitism strategy was added to avoid premature maturation and acceleration of convergence of the algorithm. To prevent the situation that the algorithm matures prematurely due to low population diversity, the generated populations are checked in this paper, and if the difference in individual fitness values between the two populations is found to be small, the populations with low diversity are updated once using the population update operation. The initial populations are randomly generated so that the initial populations are uniformly distributed in the solution space to ensure the diversity of the populations.

6.2.1. Chromosome Coding. Chromosomes are coded using the natural number coding method. In the process of generating chromosomes, firstly, the sequence of customer nodes is generated randomly, and the random sequence is the gene locus without representation of the division. Secondly, the nodes represented on each gene locus are inserted into the route of a vehicle sequentially in the order of the random sequence, and judge whether the vehicle satisfies the constraint, so that the vehicle that does not satisfy the constraint returns to the car park or runs to the charging pile for charging, thus gradually generating the actual vehicle path.

6.2.2. Selection Operator. In this paper, an improved roulette selection operator is designed. The roulette operator is a selection method that uses the proportion of individuals to the fitness value of the population to determine the next generation. The higher the relative fitness value of an individual, the higher the probability of being selected. The traditional roulette wheel operator has a large selection error due to random operation, and sometimes individuals with high fitness values are not selected, making the genetic algorithm results oscillating and difficult to converge. In this problem, the performance of the traditional roulette operator is not satisfactory, so the ideas of sorting and increasing the times of random number generation are integrated on the basis of the traditional roulette operator, which improves the selection performance of the selection operator. The specific steps are as follows.

Step 1: Calculate the fitness value of individual population;
Step 2: Calculate the total fitness value of the population;
Step 3: Calculate the probability of the individual being selected;
Step 4: Calculate cumulative probability \( q_i = \sum_{i=1}^{m} p_i \) and generate cumulative probability sequence \([q_1, q_2, q_3, \ldots, q_m]\);
Step 5: Rotate the wheel, and the number of rotations is the number of individuals in the population \(m\), the specific steps are as follows:

1. Generate \(m\) uniform random numbers \(k\) between \([0,1]\), using \(k\) as a selection indicator, if \(k \leq q_i\), then individual \(i\) is selected; if \(q_{i-1} \leq k \leq q_i\), then individual \(i\) is selected.
2. Calculate the number of random numbers \(x_i\) falling in each interval, and take the individual corresponding to the interval with the highest number of falling points as the selected individual. If more than one selected interval exists at the same time, the one with the higher value of individual fitness corresponding to the interval is selected.
3. The selected individuals are grouped into the offspring population, and the iterations are repeated until the target number of offspring populations is satisfied.

The improvement of the roulette operator is mainly reflected in two aspects, one is to accurately reflect the randomness. The traditional roulette operator in the generation of a random number to determine an individual, while the improved roulette operator is set to generate \(m\) random numbers to determine an individual, that is, the total number of random numbers generated from the original \(m\) to \(m^2\), more accurately reflect the role of random numbers to reduce the selection error; the second is to
ensure that the selection target. The improved roulette operator for the selection method may appear in the case of multiple selected intervals, to select the individual fitness value of the larger as the standard selection of individuals, to ensure that the selection target is the best.

6.2.3. Crossover Operator. In this paper, four crossover operators are designed, which are crossover operator A, partial matching crossover, sequential crossover and cyclic crossover, and sequential crossover is finally selected through numerical experiments.

The specific steps of sequential crossover are as follows.

Step 1: Randomly select the starting and ending positions of several genes in a pair of chromosomes (parent).

Step 2: Generate a zygote and ensure that the position of the selected genes in the zygote is the same as that of the parent.

Step 3: Find the position of the gene selected in the first step in the other parent, and then put the rest of the genes into the zygote generated in the previous step in order.

![Figure 2. Schematic Diagram of Sequential Crossover](image)

6.2.4. Mutation Operators. In this paper, two mutation operators, inverse mutation and disordered variation, are designed, and the former is chosen through numerical experiments. Inverse mutation refers to randomly selecting two mutation points r1 and r2 of a chromosome, and inverting the mutation region to obtain a new individual.

6.2.5. Adaptive Crossover Probability. The crossover probability is the key to the convergence and optimization effect of genetic algorithm, and a fixed crossover probability is often used in general genetic algorithm, although the phenomenon of scattered results may occur. Therefore, this paper introduces an adaptive mechanism to reduce the crossover probability for individuals with high fitness value and increase the crossover probability for individuals with low fitness value by dynamically adjusting the crossover probability, so that the algorithm can retain the better individuals and shorten the convergence time.

\[
p_c = \begin{cases} 
  k_1 \left( f_o - f' \right) / \left( f_o - \bar{f} \right) & f' \geq \bar{f} \\
  k_2 & f' < \bar{f} 
\end{cases} 
\]

The above equation is the adaptive crossover probability function, where \( f_o \) denotes the maximum adaptive value in the population; \( f' \) denotes the larger adaptive value among the two individuals that crossover; \( \bar{f} \) denotes the average adaptive value of the population. When \( f' < \bar{f} \), the crossover
probability is the larger \( k_2 \); When \( f' \geq \bar{f} \), its fitness value approaches \( f_0 \), and the crossover probability becomes lower, until \( f' = f_0 \), the crossover probability turns to 0.

6.2.6. Elitism Strategy. The elitism strategy separately records the best individuals of each generation in terms of fitness value, and when updating the new generation population, it makes them crossover and retain the recorded elite individuals to the new population, and increases the stock of elite genes in the population.

6.3. Example Solving
As mentioned earlier, chromosome encoding is done using natural number encoding, and crossover variation is done in the form of numerical arrangement when performing genetic operations. The Chromosome class is set up to decode chromosomes, and several conditions of the problem need to be considered when decoding - charging piles, multiple trips, capacity and volume constraints and time windows.

The problem is divided into different situations according to different constraint requirements, and different processing methods are employed for different situations. For example, for the vehicle that meets the vehicle transportation capacity, does not meet the power constraint or early arrival time window constraint after charging, measures should be taken. First, transport the vehicle to the nearest charging post, fully charged and then go to the next customer station, which is reflected in the operation of the chromosome to visit each customer station of the chromosome in order. Check the time window of the customer station, the load demand and whether the vehicle has enough power to reach the charging post or return to the distribution center after arriving at that customer station. Then the charging pile point is inserted into that vehicle path and the parameters of that vehicle are updated: power, travel time, load capacity. Next, the customer stations to be served are inserted into the vehicle path, and other situations are similar.

Firstly, the operators used in this experiment are determined by comparing the performance of different operators, and 10 experiments are conducted under each operator and the averaged is chosen to analyze the effect between different operators, after which the optimal operator combination is used to solve the results.

6.3.1. Determining Operator Combinations. Among the cross operators, the sequential cross operator has the best calculation performance, but the number of iterations is more; among the selection operators, the selection operator of improved roulette is obviously better than the tournament operator; among the mutation operators, using the inverse variation can get a better solution. The specific comparative analysis is shown in Table 3.
Table 3. Comparison Analysis Table of Different Operators

| Crossover operator (fixed selection operator for improved roulette, mutation operator for inverted variation) | Total Cost | Number of Vehicles | Number of Visits of Distribution Center | Number of Visits of Charging Pile | Number of Iterations |
|--------------------------------------------------------|-------------|-------------------|----------------------------------------|-------------------------------|---------------------|
| Crossover operator A                                   | 42325.352   | 13                | 16                                     | 4                             | 4500                |
| Partial matching crossover                             | 45450.724   | 13                | 17                                     | 5                             | 3000                |
| Cyclic crossover                                       | 46306.831   | 14                | 17                                     | 7                             | 3500                |
| Sequential crossover                                   | 37765.444   | 12                | 16                                     | 3                             | 5000                |
| Selection operator (fixed crossover operator is cyclic crossover, mutation operator is inverted variation) |             |                   |                                        |                               |                     |
| Binary Tournament                                      | 41333.1     | 13                | 16                                     | 3                             | 4000                |
| Improved Roulette                                      | 37765.444   | 12                | 16                                     | 3                             | 5000                |
| Mutation operator (fixed cross operator is circular cross, selection operator is modified roulette) |             |                   |                                        |                               |                     |
| Inverse mutation                                       | 37765.444   | 12                | 16                                     | 3                             | 5000                |
| Disordered variation                                   | 42956.123   | 14                | 17                                     | 2                             | 6000                |

The numerical experiments show that the better performing operators are: sequential crossover, inverse variation, and improved roulette, respectively. The corresponding operators are set up.

6.3.2. Results. Based on the JD logistics data, the problem is solved for 20 and 100 distribution sites respectively. In the cases of 20 distribution sites and 100 distribution sites, there are 4 and 20 charging posts respectively.

(1) The solution of 20 distribution sites calculation example
Figure 3. Genetic Algorithm Iteration Diagram – 20 Distribution Sites

When the algorithm solves for 20 points, it has converged at around 300 generations, and the calculation results are: 2 vehicles are used, visits to the distribution center 4 times, charge once, and a total cost of 8603.452, with each vehicle path as shown in Figure 4.

Figure 4. Vehicle Routing Diagram for 20 Distribution Sites

(2) The solution of 100 distribution sites calculation example
The algorithm has converged at about 5000 generations when solving for 100 points, and the results are calculated as using 13 vehicles, visiting the distribution center 16 times, charging 4 times, and a total cost of 42132.427, with each vehicle path as shown in Figure 6.

7. Summary and Outlook
In this paper, genetic algorithm is used as the solution algorithm, and after describing the problem and establishing the model, and the optimal combination of operators suitable for this problem is selected through numerical experiments. The number of vehicles used, the number of visits to the distribution center, the number of charging times and the routing of each vehicle are derived using the algorithm solution, which makes the total logistics cost the lowest in a certain range. Comparing the results under different experiments, it can be seen that this algorithm combination works well and has certain feasibility and effectiveness.
In order to further fit the reality and provide users with more effective solutions, more variables and constraints can be incorporated on the basis of this paper, such as the selection of different vehicle models, the road restriction policies for different models, and the influence of external environment on the range of electric vehicles.

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