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# Research on COVID-19 Vaccine Supply Chain Disruption Recovery Strategy from Resilience Perspective

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**Abstract:** The COVID-19 pandemic has greatly exacerbated the uncertainty of the external environment, meanwhile, the COVID-19 vaccine supply chain is highly complex and fragile, so its probability of disruption is higher and it is more difficult to recover, resulting in delays and shortages of vaccine supply. In order to develop the disruption recovery strategy of the COVID-19 vaccine supply chain and optimize the disruption recovery process, a multi-objective model was established and solved. Taking the shortest disruption recovery time, the largest reliability of the supply chain system, and the lowest recovery cost as the objective function, and taking the four dimensions of resilience, namely redundancy, robustness, resourcefulness and agility, as the decision variables, the model uses the nondominated ranking genetic algorithm with elite strategy (NSGA-II) to solve the problem, and uses the Pareto frontier analysis method to optimize the solution set, and the sensitivity analysis of the key parameters in the model is analyzed. Finally, the redundancy, robustness, resourcefulness and agility of the COVID-19 vaccine supply chain disruption recovery combination strategy under different decision-making preferences are given.

**Keywords:** COVID-19 Vaccine Supply Chain; Supply Chain Resilience; Supply Chain Disruption Recovery; Resilience Triangle.

## 1. Introduction

As of February 2023, the Corona Virus Disease 2019 pandemic (hereinafter referred to as the COVID-19 pandemic) caused by the SARS-CoV-2 is still in the global raged across the range. The number of confirmed cases worldwide has exceeded 608 million, and the total number of deaths has exceeded 6.7 million (Source: Worldmeter official website.). As a new type of infectious disease, people are generally susceptible to SARS-CoV-2. Under such circumstances, reactive vaccination is not only an effective means to protect susceptible people, but also a powerful measure to block the spread of infectious diseases [1]. Reactive vaccination is a type of medical intervention and the last link in the vaccine supply chain, so its successful implementation cannot be separated from the support of the normal operation of the supply chain. However, since the vaccine supply chain generally involves five links of research, development, registration, production, distribution, and vaccination, compared with the general supply chain, it in turn involves more links, more complex subjects, more special products, higher vulnerability and complexity, as well as the higher requirements for timeliness. Under the dual impact of the COVID-19 pandemic and its control measures, the supply chain of the COVID-19 vaccine that has been urgently developed and put into emergency application is more prominent. Poor capacity, high probability of disruption, and poor recovery ability have seriously hindered the survival and normal operation of the COVID-19 vaccine supply chain, and are not conducive to alleviating the tense relationship between vaccine supply and demand. For example, the joint vaccine supply chain of Pfizer and BioNTech, because it did not obtain the government's "priority rating" in time, was in severe supply constraints on some components, so it encountered a serious shortage of input when expanding production capacity. Modern also encountered similar situation. Meanwhile, although Johnson & Johnson received the first batch of support from the U.S. government and successfully expanded its production capacity, it encountered serious quality control and cross-infection problems, which led to the destruction of tens of millions of vaccines and the suspension of production for several months, affecting vaccination in several regions [2][1]. Such problems are finally intuitively manifested in vaccine production, and further have an impact on the number of confirmed cases: as of December 2021, the cumulative global production of COVID-19 vaccines is about 11.15 billion doses, and about 4.5 billion doses are produced in China, accounting for 40.35% of the total; nearly 950 million doses were produced in the United States, accounting for only 8.52% of the total (Source: Airfinity official website.). At the same time, the cumulative number of confirmed cases in the world is 268 million, of which, the cumulative number of confirmed cases in China is 128,000, accounting for only 0.048% of the total; while the cumulative number of confirmed cases in the United States has exceeded 50.42 million, accounting for approximately 16% of the total (Source: Worldmeter official website.). This intuitively illustrates the importance of ensuring the normal operation of the COVID-19 vaccine supply chain to ensure the supply of vaccines to control the spread of the epidemic. Therefore, under the circumstances that the COVID-19 pandemic has greatly increased the probability of disruption, it is necessary to fully study the disruption recovery strategy of the COVID-19 vaccine supply chain, shorten the disruption recovery time as much as possible, reduce the disruption recovery cost, and ensure the continuous normal operation of the supply chain, and in turn provide products and services in sufficient quantities.

Since the outbreak of the COVID-19 pandemic more than two years ago, relevant research has gradually been enriched, but there is no literature specifically on the recovery strategy of the COVID-19 vaccine supply chain disruption. In the literature on other related topics, part of the literature revolves around the optimization of the supply chain of the COVID-19 vaccine. On the one hand, quantitative methods are used to conduct optimization research from the perspective of

traditional supply chain management such as supply, transportation, and inventory, such as Georiadis et al. [3], which develops a new mixed integer linear programming model, which aims to minimize total cost and optimize the inventory level of different nodes in the COVID-19 vaccine supply chain, the vaccine flow on the distribution network, and the daily vaccination plan of the vaccination center. Sun et al. developed a combination of route optimization and dynamic simulation to improve the logistics efficiency of COVID vaccine distribution [4]. On the other hand, qualitative methods are used to guide the transformation and development direction of the COVID-19 vaccine supply chain from a more holistic and macro perspective. For example, Alam et al. used DEMATEL and IFS methodologies to identify the main challenges facing the COVID vaccine supply chain and their interrelationships, and provided practical guidance for stakeholders and government policymakers around the world [5]. Golan et al. extended the study of supply chain resilience to the field of vaccine supply chain for the first time, pointing out through literature analysis that existing research on vaccine supply chains mostly focuses on efficiency rather than resilience, which is the basis for ensuring the continued availability of vaccines to the public after the COVID-19 pandemic and its control measures have a chain reaction to the supply chain, causing disruptions in the development and expansion of COVID-19 vaccine production [6]. The study identified gaps in this vaccine supply chain resilience modeling through literature analysis and made recommendations. In addition, researches from Golan et al.[7] and Rele [8] are similar.

In addition, most of the relevant literature focuses on the recovery strategy of supply chain disruption, and most of the research focuses on the cost issue, such as Yang Yi et al., which analyzes two recovery strategies, namely supplier preset emergency inventory and manufacturer product changes, and uses simulation to verify the effectiveness of the two strategies [9]. Wang Jing et al. aimed at maximizing the expected benefits of the supply chain, and analyzed the advantages and disadvantages of coping strategies such as retaining redundant capacity, stockpiling inventory, and using alternative manufacturers in the event of production disruption of manufacturers [10]. Chen et al. proposed a supply chain disruption recovery strategy aimed at maximizing total profits in the context of the COVID-19 pandemic, the main method of which is to change the original product type [11]. Only a few studies consider the recovery time, such as He et al. when solving the production disruption recovery problem of the tertiary supply chain, the triangular fuzzy number and the relevant probability are used to evaluate the disruption duration, and then the production disruption recovery model is constructed, and a heuristic algorithm is proposed, which reduces the supply chain recovery time to a certain extent [12]. Gao Cong et al. analyzed the problem that a distribution center in a tertiary distribution network failed and could not accept supply considering the transit time and the customer's maximum tolerance of out-of-stock time, established a mixed integer programming model, and proposed an improved MILP algorithm [13].

In summary, there are still shortcomings in relevant research: most of the existing literature on the COVID-19 vaccine supply chain is based on the normal operation of the supply chain and optimizes it through traditional means, and rarely takes into account the supply chain disruption caused by the COVID-19 epidemic and its control measures. However, considering the supply chain disruption in the context of the epidemic, there is a lack of quantitative analysis of disruption recovery strategies. In addition, when considering disruption recovery strategies, studies have focused more on cost rather than recovery time, and only consider a single scenario, not the situation that the environmental changes in the context of the pandemic may have impact on decision-making.

Therefore, a multi-objective optimization model was established to optimize the disruption recovery process of the COVID-19 vaccine supply chain, and a non-dominated sorting genetic algorithms with elite strategy (NSGA-II) was written to solve the model.

## 2. Problem Description and Mathematical Model

Consider a three-stage COVID-19 vaccine supply chain consisting of production, distribution and use, as shown in Fig 1.

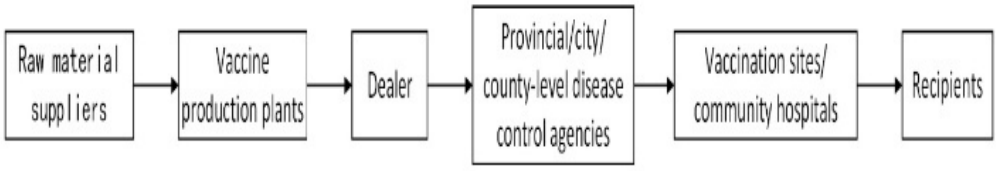



**Fig 1.** COVID-19 vaccine supply chain

When there is no disruption, the supply chain operates normally, when vaccine factories are normally produced and shipped to distributors, who sell to provincial, municipal, or county CDCs and then further distribute them to district or community hospital vaccination sites. When the vaccine arrives at the vaccination site, it is accompanied by medical supplies such as syringes, alcohol and cotton swabs, and vaccination is administered by trained medical personnel. Disruptions at any stage of production, distribution and use, such as lack of bottles and caps that prevent filling, problems with cold chain distribution and end-of-line storage, lack of aids (e.g., syringes, alcohol, cotton swabs, and personal protective equipment), and lack of trained medical personnel, can disrupt the entire vaccine supply chain and hinder vaccine production, distribution and use.

Once a disruption occurs, the supply chain enters the disruption recovery process. Taking into account the background of the COVID-19 epidemic and the particularity of COVID-19 vaccine products, that is, the need for the COVID-19 vaccine supply chain to provide vaccines in a timely, sufficient and stable manner, the shortest disruption recovery time, the maximum supply chain reliability and the lowest disruption recovery cost are taken as the objective function of the model, which respectively reflect the requirements for the timeliness, reliability and economy of the disruption recovery process of the COVID-19 vaccine supply chain.

Comprehensively considering the characteristics of the three objective functions, the concept of supply chain resilience is introduced. This study defines it as: an inherent ability of the supply chain to respond quickly and carry out recovery activities after disruption, thereby effectively reducing the recovery time of the disruption and minimizing the negative impact of the disruption; At the same time, supply chain resilience can also allow the supply chain to retain a certain level of operation after disruption, so that a certain number of products or services can be provided before the completion of the disruption recovery activity, without completely losing the ability to supply. Supply chain resilience can affect the process of supply chain disruption recovery from multiple angles, so if the level of supply chain resilience changes, the process and outcome of supply chain disruption recovery will also change.

According to the above mechanism of action, the resilience triangle theory is introduced as shown in Fig 2, and the resilience capacity model of the COVID-19 vaccine supply chain is established, and the four dimensions of supply chain resilience defined in the theory - redundancy, robustness, resourcefulness and agility - are used as decision-making variables, and the three stages of supply chain disruption recovery are quantitatively described by using the time-varying supply chain operation level curve and corresponding parameters, and then the COVID-19 vaccine supply chain disruption recovery strategy is studied.

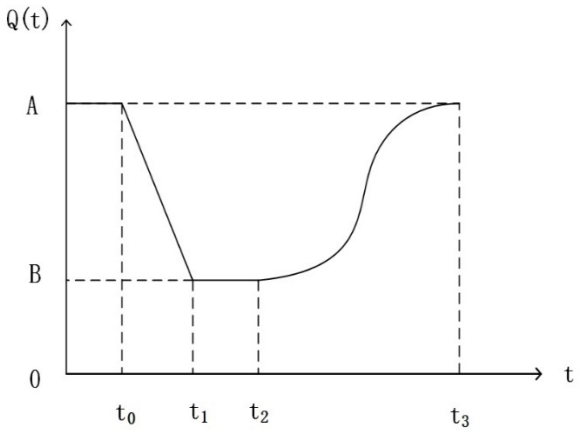



**Fig 2.** Resilience triangle

The meaning of the four decision variables is as follows:

1) Redundancy: refers to an additional part of the capacity and resources retained in the daily operation of the supply chain, which can make up for part of the loss of capacity and resources caused by the disruption event.

2) Robustness: refers to the resistance of the supply chain in the face of disruption events, the higher the robustness, the higher the operational capacity retained by the supply chain after being impacted by the disruption event.

3) Resourcefulness: refers to the dynamic response ability of the supply chain in the face of disruption events, and promotes the disruption recovery process by allocating capabilities and resources outside itself.

4) Agility: directly affects the speed of recovery from supply chain disruptions.

## 2.1. Symbols and Assumptions

### 2.1.1. Symbols

**Table 1.** Symbols of major related parameters and variables

| Symbols | Parameter variables | Symbols | Parameter variables |
|---|---|---|---|
| $t_0$ | The moment at which the disruption event occurred | R | Supply chain system reliability |
| $t_1$ | The time when redundancy is exhausted | g | Daily consumption of vaccines |
| $t_2$ | The moment of preparation is complete and the recovery begins | C | Total cost |
| $t_3$ | The moment the recovery is complete | $C_1$ | Cost of redundancy |
| $Q(t)$ | Supply chain operation level curve | $C_2$ | Cost of robustness |
| $A$ | Initial operational level | $C_3$ | Cost of resourcefulness |
| $B$ | The level of operations remaining after the disruption | $C_4$ | Cost of agility |
| $R_1$ | Redundancy coefficient | $k_1$ | Cost coefficient for redundancy |
| $R_2$ | Robustness coefficient | $k_2$ | Cost coefficient for robustness |
| $R_3$ | Resourcefulness coefficient | $k_3$ | Cost coefficient for resourcefulness |
| $R_4$ | Agility coefficient | $k_4$ | Cost coefficient for agility |
| T | Disruption recovery time | δ | Robustness conversion coefficient |

### 2.1.2. Assumptions

**Hypothesis 1:** Before the disruption event, supply and demand are balanced within the supply chain, and external demand for products is consistent before and after the disruption event, so the decline in supply chain operation level $Q(t)$ is essentially caused by the supply volume that significantly deviating from the expected target because of the supply chain disruption.

**Hypothesis 2:** Ignoring the time difference between production, circulation, and use stages, the production and supply capacity of the supply chain can be directly reflected in the operational level of the supply chain.

**Hypothesis 3:** At the end of the recovery process, the operational level of the supply chain is restored to its initial state, i.e.:

$$Q(t_0) = Q(t_3) = A \tag{1}$$

**Hypothesis 4:** The daily consumption of the vaccine is known as constant $g$.

**Hypothesis 5:** At the $t_1$ moment, the remaining level of operational capacity is exactly equal to the level of operation that can be retained after the impact of disruption due to the robustness of the supply chain, and there will be no sharp drop in operating level. Namely:

$$Q(t_1) = R_2 \quad (2)$$

**Hypothesis 6:** The ability to mobilize internal and external resources, represented by resourcefulness, requires a certain amount of reaction time to become effective. Due to the strict storage conditions of the vaccine and the high daily consumption, resulting in a short first phase, it is assumed that the length of reaction time is equal to the length of the first phase $[t_0, t_1]$, i.e., the ability does not work in the first phase and only works after the $t_1$ moment.

**Hypothesis 7:** Assuming that the supply chain does not preset the resilience capability to facilitate the disruption recovery process before the disruption event occurs, the values and descriptions of the four resilience coefficients are as follows:

1) Redundancy coefficient $R_1 = 1$: it means that there is no redundancy in the supply chain to compensate for part of the loss of capacity and resources caused by disruption.

2) Robustness coefficient $R_2 = 0$: this means that after a disruption, the operational level of the supply chain eventually drops to 0.

3) Resourcefulness coefficient $R_3 = 20$ : the role of resourcefulness is to shorten the time required to mobilize internal and external resources, thereby optimizing the disruption recovery process. When resourcefulness is not preset, the time available to mobilizing resources in the supply chain is not infinite, so a reasonable upper limit needs to be set for $R_3$. Assuming that the supply chain that is not preset with resourcefulness can only meet the minimum needs of normal vaccination of vaccines after disruption, taking the six types of COVID-19 vaccines vaccinated in China as an example, the vaccination interval is between 21-56 days, and the supply chain redundancy and robustness are 0 without preset resilience, which means that after the disruption event, the upstream nodes of the supply chain cannot supply vaccines to the downstream at all, and vaccination is completely stopped. In this case, if the vaccine is to be as regular as possible, the maximum time required for mobilization activities should be less than 21 days, so as to ensure that the recovery process can start in time and ensure the normal vaccination of subsequent vaccines.

4) Agility coefficient $R_4 = 1$: means that the supply chain is not preset for agility to speed up the third phase recovery process.

## 2.2. Mathematical Model

First, the $Q(t)$ curve is analyzed with the help of resilience triangle:

1) The first phase $[t_0, t_1]$: the production capacity is 0 due to the disruption, and the upstream nodes of the supply chain can only rely on their own redundancy to maintain continuous supply to the downstream nodes. In this phase, the $Q(t)$ curve decreases monotonically at a normal speed, which depends on $g$ and the magnitude of redundancy.

2) Phase 2 $[t_1, t_2]$: inventory is depleted, the supply chain relies on robustness to maintain a relatively low and stable level of operation during this phase, and internal and external resources are mobilized to prepare for formal recovery activities. The length of time this phase takes depends on the abundance of resources.

3) Phase 3 $[t_2, t_3]$: all preparations are in place and the supply chain enters the recovery process. In the early stage of the recovery process, the recovery speed of the supply chain was relatively slow due to lack of resources, imperfect structure, and imperfect relevant policies and laws and regulations. Over time, these factors are supplemented and optimized, resulting in faster recovery. In the later stage, the supply chain reaches a high degree of recovery, and the supply pressure is relatively reduced, so the recovery speed will gradually smooth out at this time. That is, the $Q(t)$ curve of the third stage will show a trend of "slow rise-rapid rise-slow rise", and the arctangent function has similar properties, so this study uses the arctangent function to simulate the $Q(t)$ curve of the third stage.

The final piecewise function for the $Q(t)$ curve is as follows:

$$Q(t) = \begin{cases} A - \frac{g*(t-t_0)}{R_1}, & t_0 < t < t_1 \\ R_2, & t_1 \le t < t_1 + R_3 \\ R_2 + R_4 * acrtan[b * (t - t_1 - R_3)], & t_1 + R_3 \le t \le t_3 \end{cases} \quad (3)$$

Secondly, the reliability of the supply chain system is analyzed. Defines reliability as the number of products or services that can be delivered to the market before the recovery process begins, relying on the redundancy and robustness of the supply chain. The more reliable the supply chain system, the more reliable it is to ensure that the supply chain can be supplied stably after a disruption. This echoes the study's definition of supply chain resilience. Modeled after the definition of resilience in the resilience triangle theory, reliability is expressed in the following form:

$$R = \int_{t_0}^{t_2} Q(t)dt \quad (4)$$

Finally, the cost is analyzed, and the cost is reflected by comparing the absolute value of the cost change before and after the preset resilience capacity:

1) Redundancy cost: let the redundancy cost factor be $k_1$, because the value of the redundancy coefficient $R_1$ is 1 when the redundancy is not preset, the relationship between the redundancy cost $C_1$ and the redundancy coefficient $R_1$ should meet the following linear relationship:

$$C_1 = k_1 * (R_1 - 1) \quad (5)$$

2) Robustness cost: let the robust conversion coefficient of the supply chain be $\delta$, and the robustness cost coefficient be $k_2$, because the value of the robustness coefficient $R_2$ is 0 when the robustness is not preset, there are the following equations:

$$\delta * A = Q(t_1) \quad (6)$$

$$C_2 = k_2 * \delta \quad (7)$$

Combined with (2), it can be seen:

$$C_2 = k_2 * \frac{R_2}{A} \quad (8)$$

3) Resourcefulness cost: the promotion effect of resourcefulness on the disruption recovery process is that it can shorten the time required for the second stage, so the size of resourcefulness can be expressed by the time $(t_2 - t_1)$ of mobilizing internal and external resources for preparatory activities before and after the supply chain is impacted by the disruption event, that is, the absolute value of the change in $R_3$. Given that the resourcefulness cost factor is $k_3$, and the $R_3 = 20$ is not preset from Hypothesis 8, the cost $C_3$ of the resourcefulness recovery strategy should satisfy the following relationship:

$$C_3 = k_3 * |\Delta(t_2 - t_1)| = k_3 * |20 - R_3| \quad (9)$$

4) Agility cost: it is directly reflected in the speed of recovery of the supply chain to disruption events, the higher the agility, the shorter the time it takes for the supply chain to recover from the disruption to the beginning, and the faster the recovery speed. Therefore, the size of the response agility can be $R_T$ using the temporal resilience, that is, the ratio of

supply chain disruption recovery time to supply chain disruption time, as defined $R_T$ as follows:

$$R_T = \frac{t_3 - t_2}{t_3 - t_0} \tag{10}$$

Since the agility coefficient calculated according to (3) and (10) is 0.86 when the resilience capacity is not preset, and it is easy to obtain according to (10), the higher the agility, the smaller the $R_T$. If the agility cost factor is $k_4$, the agility cost should satisfy the following relationship:

$$C_4 = k_4 * (0.86 - R_T) \tag{11}$$

In summary, a multi-objective model for disruption recovery of the COVID-19 vaccine supply chain is established.

The objective function is:

$$minT = \frac{tan\left(\frac{A-R_2}{R_4}\right)}{b} + \frac{(A-R_2)*R_1}{g} + R_3 \tag{12}$$

$$maxR = \frac{(A^2 - R_2^2)*R_1}{2g} + R_2 * R_3 \tag{13}$$

$$minC = k_1 * (R_1 - 1) + k_2 * \frac{R_2}{A} + k_3 * |20 - R_3| + k_4 * \left( \frac{\frac{(A-R_2)*R_1}{g} + R_3}{\frac{tan\left(\frac{A-R_2}{R_4}\right)}{b} + \frac{(A-R_2)*R_1}{g} + R_3} - 0.14 \right) \tag{14}$$

$$1 \le R_1 \le 4 \tag{15}$$

$$0 \le R_2 \le 1 \tag{16}$$

$$0 \le R_3 \le 20 \tag{17}$$

$$1 \le R_4 \le 2 \tag{18}$$

The objective function (12) means to minimize the disruption recovery time $T$, and $T$ is derived from (1) and (3); the objective function (13) means to maximize the supply chain system reliability $R$, and $R$ is derived from (3) and (4); the objective function formula (14) means to minimize the disruption recovery cost $C$, and $C$ is obtained by adding (5), (8), (9) and (11).

The decision variables are $R_1$, $R_2$, $R_3$, $R_4$, and the corresponding constraints (15)-(18) are all derived from the definition of parameters in the model, which respectively define the redundancy coefficient, robustness coefficient, resourcefulness coefficient and agility coefficient. The value range of the coefficient is guaranteed to ensure its validity.

The value range of the parameter $R_1$ is set to $[1,4]$, which means that the redundancy of different values within the value range will cause the duration of the first stage to change within the range of $[5,20]$. The lower limit of the duration is set to 5, referring to the extreme shortage of vaccine stocks in Taiwan, China, in April 2022 (Source: Taiwan Health Bureau.). Based on the maximum daily vaccination volume in a week, there are only about five days left in stock. Set the upper limit of time to 20, referring to the inventory data of the world's largest vaccine manufacturer Serum Institute of India (SII) and China's COVID-19 vaccination data. April 2022, Adar Poonawalla, CEO of SII, said that in order to avoid vaccine waste, the research institute had to stop production in December last year after reaching 200 million doses of vaccine stocks. At the same time, based on China's COVID-19 vaccine vaccination data, the average daily vaccination volume from March 2021 to April 2022 was about 9.72 million doses (Source: Official website of the National Health Commission of China.). Based on this data, the stock of 200 million doses of vaccines equals the consumption of 20 days.

Set the value range of parameter $R_2$ to $[0,1]$, which means that the change in the robustness value within the value range will make the supply chain able to retain the operating level varies between 0-100% after being impacted by the disruption event.

Set the value range of parameter $R_3$ to $[0,20]$, which means that the change in the value of resourcefulness within the value range will cause the supply chain to mobilize internal and external resources for disruption and recovery activities within 0-20 days.

Setting the value range of parameter $R_4$ to $[1,2]$ means that the agility of different values within the value range will make the duration of the third stage change within the range of $[55,156]$. The lower limit of the duration is set to 55, referring to Yang Lijiao et al. 's research on the recovery time of manufacturing enterprises under the flood disaster scenario [14]. Since the COVID-19 pandemic is a public health emergency, the supply chain disruption caused by such incidents has certain similarities with the supply chain disruption caused by natural disasters such as floods, but the degree of negative impact is often deeper and longer-lasting, so choose 55 days as the lower limit for the predicted recovery time of traditional manufacturing enterprises under the most severe flood damage scenario. The upper limit of the duration is 156 days. This is because this study uses the arctangent function to simulate the $Q(t)$ curve of the third stage, so it takes about 156 days to return to the initial level without presetting the resilience capacity.

# 3. Model Solving

The model has three objective functions, which are Multiobjective Optimization Problems (MOPs), and the Evolutionary Algorithm (EA) has been recognized as the most effective optimization algorithm for solving such problems. In this study, the non-dominated Sorting Genetic Algorithms II. (NSGA-II) with elite strategy was selected to optimize the model.

The NSGA-II algorithm is based on a Pareto-dominated multi-objective genetic algorithm, proposed by Deb et al. in 2002, and has been further improved in terms of operation speed and algorithm robustness compared with traditional genetic algorithms [15]. The algorithm flow is shown in Fig 3, with the main steps as follows:

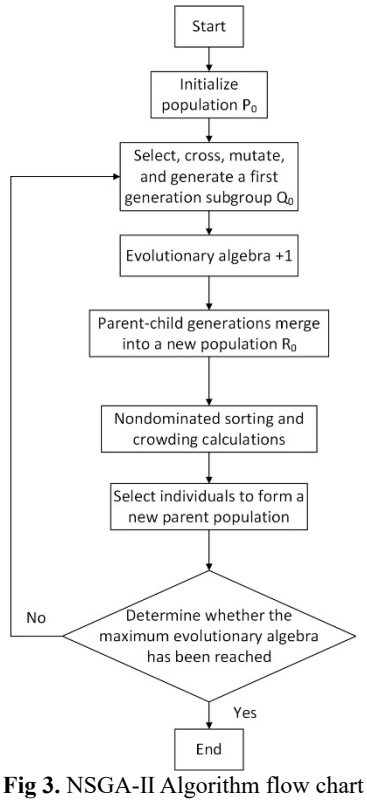



**Fig 3.** NSGA-II Algorithm flow chart

**Step 1:** Randomly generate an initial population $P_0$ of size n.

**Step 2**: Produce a descendant population $Q_0$ of the same size as the initial population by selection, crossing, and mutation.

**Step 3:** Merge the parent and offspring populations to obtain a new population $R_0$, which twice the size of the initial population. Perform nondominated ordering and crowding calculations for new populations, and select new parent populations equal to the $P_0$ size of the initial population.

**Step 4:** Determine whether the maximum number of iterations has been reached, stop the search, otherwise go to Step 2.

Insert the basic input parameters of the algorithm as Table 2.

**Table 2.** Insert parameters of the algorithm

| The parameter type | Parameter definitions |
|---|---|
| Initial population size | 50 |
| Maximum evolutionary algebra | 300 |
| Mutation rate | 0.05 |
| Crossover rate | 0.8 |
| Select method | Tournament selection method |

Suppose the parameters in the model are: $g = 20\%$, $b = 0.01$, $A = 100\%$, $t_0 = 20$. The value of each cost factor: $k_1 = k_2 = k_3 = k_4 = 1$.

# 4. Results and Analysis

## 4.1. Solving and Pareto Frontier Analysis

The algorithm written by MATLAB 2016a software is used to solve the model, and the Pareto frontier solution set is obtained as shown in Fig 4:

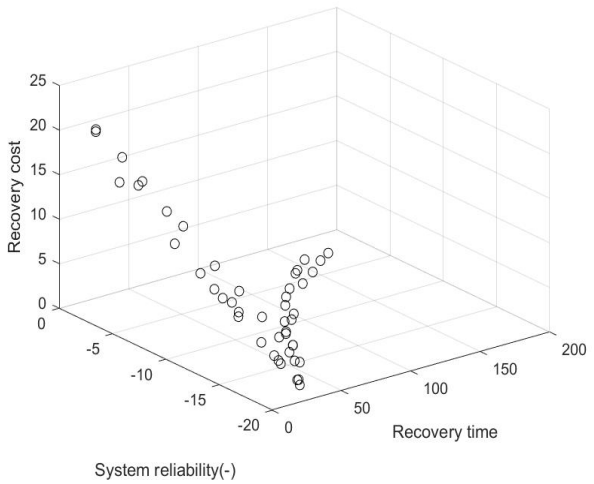



**Fig 4.** Pareto front solution set of three-objective optimization

Then, the Pareto frontier analysis method of Wu et al. was introduced to further screen and analyze the Pareto frontier solution [16]. The core idea of this method is to calculate the rate of change and sensitivity ratio of each point according to the distribution characteristics of each point of the Pareto front and its neighbors, and then form a Pareto non-inferior solution subset based on sensitivity ratio, and calculate the bias and imbalance degree of each point in the subset relative to each target. Therefore, the selection range of the optimal scheme can be compressed, and the bias degree and imbalance degree of each point in the non-inferior solution subset can be used, which provides important reference information for decision-makers to further judge.

Table 3 shows a comparison of the different decision results obtained using the Pareto frontier analysis method described above. Among them, $0^{\#}$ is interpreted as the situation of not preset resilience capacity, it is not difficult to find that if the supply chain does not preset resilience capacity, although there is no expenditure in this regard (C=0), but the reliability of the system is low (R=2.5) and the time required to resume normal operation is long (T=181), which does not meet the actual needs of the disruption and recovery of the COVID-19 vaccine supply chain. The other four solutions are non-inferior solutions selected according to different decision preferences based on the Pareto frontier analysis method: the $44^{\#}$ solution has the lowest imbalance relative to the three objective functions, and when the decision-maker wants to choose the Pareto non-inferior solution with the smallest imbalance relative to each optimization goal, this solution can be selected; $42^{\#}$ solution has the largest bias degree of shortest disruption recovery time; $50^{\#}$ has the largest bias degree of supply chain system reliability; $6^{\#}$ has the largest bias of the lowest disruption recovery cost. Considering the particularity of the COVID-19 vaccine supply chain, it is undoubtedly more appropriate to choose the $42^{\#}$ solution or the $50^{\#}$ solution to optimize the supply chain disruption recovery process by sacrificing certain economic benefits, and improve the reliability of the supply chain and ensure the timeliness of the supply chain.

**Table 3.** Comparison of different results

| Variables / Serial Number | R1 | R2 | R3 | R4 | T | R | C |
|---|---|---|---|---|---|---|---|
| 0# | 1 | 0 | 20 | 1 | 181 | 2.5 | 0 |
| 44# | 1.0144 | 0.3982 | 19.9933 | 1.0840 | 85 | 10.10 | 0.55 |
| 42# | 1.0144 | 0.9956 | 13.5822 | 1.0840 | 14 | 13.54 | 8.26 |
| 50# | 1.0144 | 0.5987 | 19.9933 | 1.0117 | 64 | 13.60 | 0.82 |
| 6# | 1.0144 | 0.0027 | 19.9933 | 1.0813 | 157 | 2.59 | 0.04 |

The significance of this result is that through quantitative analysis, how to preset the supply chain resilience capacity in different dimensions under different decision-making preferences, and put forward macro suggestions on how to optimize the disruption recovery process. This makes this study different from most existing disruption recovery studies, the results obtained by these existing studies are mostly micro, specific, static disruption recovery strategies such as inventory level, supplier location, node supply and order quantity, while the numerical results obtained in this study can be combined with a quantitative resilience evaluation index system, and according to the changes and development trends of the external environment of the supply chain, several key scenarios are constructed, and the resilience strategies applicable in different scenarios are combined to develop a long-term, changing, and more targeted disruption recovery strategy. In the context that the COVID-19 pandemic has had a huge negative impact on various industries, industrial chains and supply chains around the world, and this epidemic is likely to become normalized, it is undoubtedly very important to develop the "viability" of the supply chain by relying on the quantitative results of this model and through quantitative resilience evaluation index system and scenario analysis methods in the future.

## 4.2. Sensitivity Analysis

### 4.2.1. Sensitivity Analysis of Parameter G

The parameter $g$ set in this study is the daily consumption of the COVID-19 vaccine, which also represents the rate of redundancy consumption in the event of supply chain disruption, which is closely related to the number of days between vaccinations. Taking the six types of COVID-19 vaccines vaccinated in China as an example, the vaccination interval varies from 21-56 days, with a difference of up to 25 days, indicating that the vaccinated individuals have strong differences in the choice of vaccination interval. In the event of a supply chain disruption, sensitivity analysis can be carried out to adjust the rate of consumption of vaccine stocks by controlling the vaccination interval, thus affecting the disruption recovery process of the supply chain. It should be noted that the change of parameter $g$ only affects the disruption recovery time and the supply chain reliability in the early stage of the disruption recovery, and does not affect the disruption recovery cost, because the disruption recovery cost in this study is generated by the preset resilience capability.

According to (12) and (13), it can be seen that the larger the value of $R_1$ and the smaller the value of $R_2$, the more sensitive the objective functions $T$ and $R$ are to changes in the parameter $g$. As shown in Fig 5, under the model constructed in this study, the change of $g$ within the value range can cause up to 16% reduction in disruption recovery time and 900% increase in system reliability.

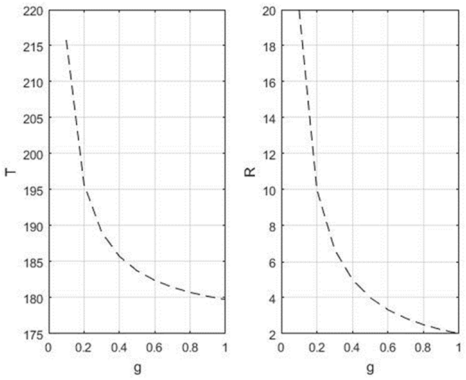



**Fig 5.** (a) Impact of $g$ on disruption recovery time; (b) impact of $g$ on supply chain reliability

In actual management, the significance of this result is as follows:

1) If a disruption occurs in the early stage of the mass vaccination process, when the vaccine supply chain capacity is relatively low, the supply gap is large, the supply and demand relationship is tight, and the inventory of each node of the supply chain is a drop in the bucket for the gap, so it is urgent to restore the disrupted supply chain to normal operation, so as to provide sufficient vaccines in a timely manner. At this time, decision-makers prefer the goal of shortening the disruption recovery time, and can choose to shorten the vaccination interval and call on the vaccinated person to receive follow-up shots as early as possible, thereby accelerating the disruption recovery process.

2) If an disruption occurs in the later stages of the mass vaccination process, when the national vaccination rate is high, most people have completed full vaccination, and the vaccination work is concentrated on the vaccination of booster shots, as well as the vaccination of minority groups such as the elderly and children, decision-makers can focus their decision-making preferences more on enhancing the reliability of the supply chain, that is, choosing to appropriately extend the vaccination interval to reduce the supply pressure faced during the recovery of supply chain disruption.

3) When the redundancy coefficient is larger and the robustness coefficient is smaller, the higher the sensitivity of disruption recovery time and supply chain reliability to parameter $g$. Therefore, when the preset redundancy of the supply chain is stronger and the robustness is worse, the more effective it is to assist in adjusting the disruption recovery process of the supply chain by adjusting the vaccination interval, and this does not cost additional costs, which provides a new idea and theoretical support for decision-makers to optimize the disruption recovery strategy.

4) Vaccination and inventory information can be collected, integrated managed exchanged, analyzed and sourced, and relevant data and information can be made open and transparent through the establishment and improvement of vaccination information system. This is conducive to the dynamic adjustment and allocation of vaccination groups by vaccination sites and higher-level management institutions according to the actual situation, alleviating the pressure of vaccine supply and demand, and regulating and promoting the disruption and recovery process of the COVID-19 vaccine supply chain.

### 4.2.2. Sensitivity Analysis of Four Resilience Parameters

Next, compare the degree of change of the three objective functions caused by the change of one parameter under the condition that the other three resilience parameters remain unchanged. Based on the initial situation without preset resilience capacity, the analysis results are shown in Fig 6, Fig 7, Fig 8 and Fig 9:

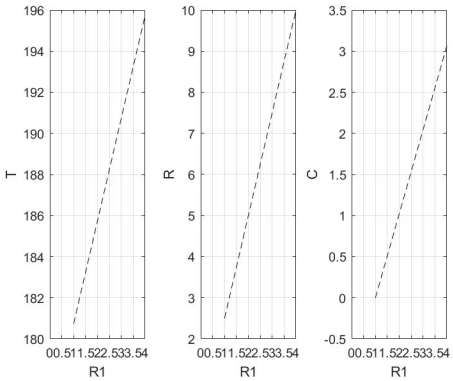



**Fig 6.** (a) Impact of $R_1$ on disruption recovery time; (b) impact of $R_1$ on supply chain reliability; (c) impact of $R_1$ on disruption recovery cost

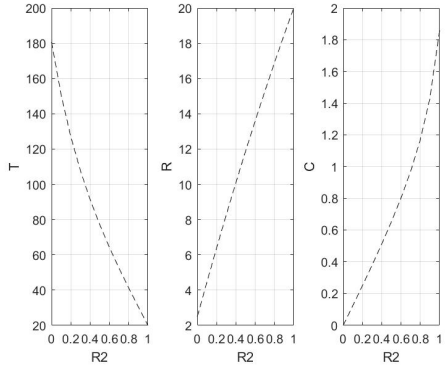



**Fig 7.** (a) Impact of $R_2$ on disruption recovery time; (b) impact of $R_2$ on supply chain reliability; (c) impact of $R_2$ on disruption recovery cost

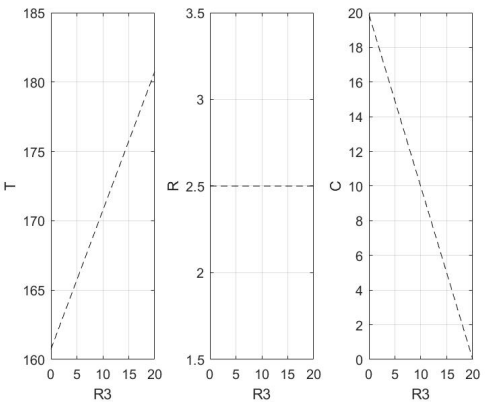



**Fig 8.** (a) Impact of $R_3$ on disruption recovery time; (b) impact of $R_3$ on supply chain reliability; (c) impact of $R_3$ on disruption recovery cost

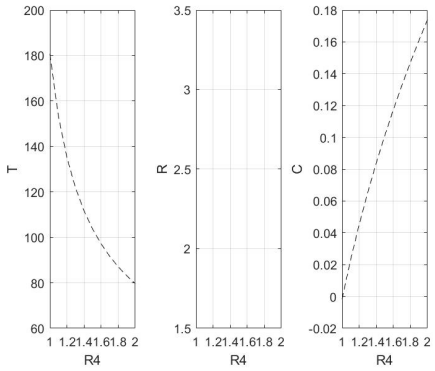



**Fig 9.** (a) Impact of $R_4$ on disruption recovery time; (b) impact of $R_4$ on supply chain reliability; (c) impact of $R_4$ on disruption recovery cost

As can be seen in these figures, taking the situation that the resilience capacity is not preset as the starting point, the effects of increasing redundancy, robustness, resourcefulness and agility on the three objective functions within the value range are shown in Table 4:

**Table 4.** Impact of four resilience parameters on objective function

| | $T$ | R | C |
|---|---|---|---|
| $R_1$ | (+)8.3% | (+)300% | (+)306% |
| $R_2$ | (-)88.9% | (+)700% | (+)186% |
| $R_3$ | (-)11.1% | (+)0% | (+)2000% |
| $R_4$ | (-)55.9% | (+)0% | (+)17.4% |

The significance of this conclusion lies in the following points:

1) Based on quantitative results to illustrate that, if the decision maker takes the shortest disruption recovery time as the primary optimization goal, then increasing robustness is the best choice, followed by increasing agility; If decision-makers prioritize maximum reliability of the supply chain system, then increased robustness is still the best choice, followed by increased redundancy. In addition, it can be observed that among the four optimization methods, the cost increase caused by increasing robustness is relatively low, indicating that this method is more economical. Therefore, for the supply chain of special products such as the COVID-19 vaccine supply chain, which requires timely supply, increasing its robustness is the most scientific and effective means to promote the disruption of the recovery process and reduce the negative impact.

2) Improving supply chain redundancy and robustness alone can correspondingly enhance the reliability of supply chain systems; If decision maker wants to enhance the reliability of the supply chain system by improving the resourcefulness, they need to pay attention to the robustness level of the supply chain at the same time, because when the robustness level of the supply chain is 0, the improvement of resourcefulness, will not have any impact on the reliability of the supply chain system.

3) Resourcefulness does not have an obvious effect on the optimization of disruption recovery time, and will not affect the reliability of the supply chain system, and the economy of this means is also the worst, so decision-makers can appropriately reduce the priority of improving resourcefulness when formulating disruption recovery strategies.

4) for shortening the disruption recovery time, agility is a method second only to robustness, and this means is the most economical.

# 5. Conclusion and Outlook

In this study, considering the background of the COVID-19 pandemic and the characteristics of the COVID-19 vaccine supply chain, a multi-objective optimization model for the COVID-19 vaccine supply chain with three functions, including the shortest disruption recovery time, the maximum system reliability, and the minimum disruption recovery cost, was established. According to the characteristics of the model, the NSGA-II algorithm is used to solve the model, and the Pareto frontier analysis method is used to further optimize and select the frontier solution set, and finally the effectiveness of the model and algorithm is verified by the comparison of different decision results and sensitivity analysis, and specific suggestions are put forward.

The innovation of this study lies in the establishment of a quantitative model of disruption recovery of the COVID-19 vaccine supply chain by linking time, reliability and cost through the resilience triangle theory, and proposing a realistic and dynamically developed quantitative strategy for the disruption recovery of the COVID-19 vaccine supply chain under the background of the epidemic. However, the application of this study needs to be combined with a quantitative vaccine supply chain resilience evaluation index system, which is also one of the problems to be solved in future research.

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