Research Article

A Multiobjective Optimization Model for Prevention and Control of Coronavirus Disease 2019 in China

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It is a global issue to set up a practical, sensitive, and useful model to eradicate or mitigate the coronavirus disease 2019 (COVID-19). Taking Central China’s Hubei Province for example, three models were established. Firstly, a susceptible-probable-infectious-recovered (SPIR) model was proposed to predict the monthly number of confirmed and susceptible cases in each city. Next, an epidemic prefecture clustering model was set up to find proper vaccine delivery sites, according to the distance of each city. Finally, a dynamic material delivery optimization model was established for multiple epidemic prefectures, aiming to speed up vaccine production and storage in each delivery site.

1. Introduction

Coronavirus disease 2019 (COVID-19) is a serious and fatal disease, which threatens the public health of the entire world. Some susceptible cases were found in Wuhan, China, as early as December 2019 [1]. On January 12, 2020, the World Health Organization (WHO) named this highly contagious disease 2019-novel coronavirus (2019-nCoV) [2] and announced that the disease has no specific medicine, but routine antiviral treatment. Therefore, it is a global issue to set up a practical, sensitive, and useful model to eradicate or mitigate the disease. Otherwise, COVID-19 will upgrade and spread like Ebola, put the fundamental survival of the society at stake, and might even paralyze countries. China’s experience in upgrading personal protective equipment, building mobile labs, mobilizing medical staff, and real-time tracking of epidemic spread has played an important role in COVID-19 prevention and control [3].

Li and Bai [4] established an infectious disease model constrained by nonlinear incidence and maximum treatment capacity. Comparing recent cumulative and predicted cases, Kumar and Bhagavathula [5] forecasted that the confirmed cases, deaths, and recoveries will double in all the observed countries except China, Switzerland, and Germany, and the death and recovery rates will increase faster than confirmed cases in the next two months. Agusto [6] modeled the transmission dynamics of Ebola with relapse and reinfection and discovered that high efficacy control measures can effectively curtail Ebola in the community. Yi et al. [7] proved that the joint prevention between the government, the masses, and hospitals is a scientific way to prevent and control the epidemic, using the five-early model (early detection, early screening, early diagnosis, early quarantine, and early recovery). Kennedy et al. [8] suggested that the magnitude and duration of social distancing required to control the pandemic can be reduced, if people exercise caution in public by protecting themselves. Using the S(usceptible) U(nidentified infectious) I(dentified infectious) H(ospitalized) R(ecovery) model (SUIHR), Zhen et al. [9] justified the extremely strict border control in entities of China. Rui and Tian [10] divided the population into susceptible, infective, recovered, and dead populations and then reveal the law of epidemic transmission by the SIRD model. Wu et al. [11] established a generalized-growth model to present the evolution of the number of the total confirmed cases changing with time.

In the light of the above, this article aims at modeling COVID-19 trend based on factors such as spread rate,
vaccine demand, delivery site, and vaccine production rate, to name but a few, and optimize the model by bringing in other key factors. Specifically, three models were established to provide the optimal scheme to allay the severe COVID-19 epidemic. Firstly, the susceptible-probable-infectious-recovered (SPIR) model was employed to predict the situation at the outbreak of the disease. Then, the k-means clustering (KMC) model [12–14] was introduced to optimize the delivery sites of vaccines and medical staff. Finally, a dynamic material delivery optimization model was constructed to deliver sufficient vaccines and medical staff in the shortest time and at the minimum cost. Figure 1 is the roadmap of this research.

2. Hypotheses and Symbols

2.1. Hypotheses

H1: the objects form an ideal, uniformly mixed group. The total number of objects remains at N, without death caused by immigration, emigration, or other reasons.

H2: those infected with COVID-19 will eventually recover and acquire long-term immunity through treatment.

H3: the infected are immediately contagious, because COVID-19 is mildly infectious, despite its long incubation period.

H4: the objects are divided into four classes: the susceptible, the probable, the infected, and the removed.

H5: once the epidemic breaks out in a prefecture, the prefecture will be immediately quarantined, cutting off the flow of population.

H6: the storages of emergency materials in each prefecture have enough vehicles to deliver the materials in time.

2.2. Symbols. The main variables involved in this article are shown in Table 1.

3. COVID-19 Modeling

According to China’s National Health Commission (NHC), the nationwide distribution of COVID-19 epidemic on February 1, 2020, was obtained. The number of COVID-19 cases in Chinese provinces is shown in Figure 2.

As shown in Figure 2, Hubei, Zhejiang, and Guangdong led the country in terms of the number of COVID-19 cases. The number of infected people in Hubei province accounted for 63.1 percent of the total, higher than any other province in China. Therefore, Hubei was taken as an example in our research.

3.1. Models. As mentioned before, the objects form an ideal, uniformly mixed group. The total number of objects remains at N, without death caused by immigration, emigration, or other reasons. The objects were divided into four groups: the susceptible S, the probable P, the infected I, and the removed R. Figure 3 shows the relationship between the four groups.

The traditional susceptible, infected, recovered (SIR) model [15–18] can be expressed as

\[
\begin{align*}
\frac{di}{dt} &= \lambda si - \mu i, \quad i(0) = i_0, \\
\frac{ds}{dt} &= -\lambda si, \quad s(0) = s_0, \\
\frac{dr}{dt} &= \mu i, \quad r(0) = r_0,
\end{align*}
\]

where \(i\) is the number of the infected person, \(s\) is the number of the susceptible person, \(r\) is the number of the recovered person, and \(\mu\) is the recovered ratio.

3.2. Models Optimization. The transmission mechanism of COVID-19 differs from that of general infectious diseases, which involve the normally infected, patients, and the removed. COVID-19 has an additional group of objects: the susceptible. This group has similar symptoms with COVID-19, but cannot be diagnosed as infected with COVID-19 or general flus. Some of these objects might be transformed into
Table 1: Symbols of key variates.

| Symbol | Unit       | Description                                                                 |
|--------|------------|-----------------------------------------------------------------------------|
| $N$    | Person     | Total population                                                            |
| $s(t)$ | %          | Percentage of the infected at time $t$ in the total population              |
| $i(t)$ | %          | Percentage of patients at time $t$ in the total population                  |
| $e(t)$ | %          | Percentage of the susceptible at time $t$ in the total population            |
| $r(t)$ | %          | Percentage of the recovered at time $t$ in the total population              |
| $\theta_1$ | % | Percentage of the susceptible diagnosed as normally infected per day     |
| $\theta_2$ | % | Percentage of the susceptible diagnosed as infected per day                |
| $h$    | %          | Remove ratio (the sum of death rate and recover rate per day)              |
| $\lambda$ | Person | Daily contracting ratio (the mean number of people infected by a patient through contact) |
| $C_i$  | $\flat$    | Fixed cost of setting up $i$ storages                                      |
| $C_s$  | $\flat$    | Subsidy of medical staff                                                   |
| $C_d$  | $\flat$    | Transport cost of each dose per unit of distance                            |
| $t_{ij}$ | day | Travel time from $i$ to $j$                                                |
| $T_k$  | day        | Time threshold of vaccine delivery (violating the threshold will bring a penalty cost) |
| $M_{ij}$ | Dose | Quantity of vaccines delivered from $i$ to $j$                              |
| $X_{ij}$ | km    | Distance between $i$ and $j$                                               |
| $D_j$  | Dose      | Vaccine demand of $j$                                                       |
| $N_{ij}$ | Group | Number of medical groups delivered from $i$ to $j$                           |
| $\beta$ | —         | Ratio of the infected to medical staff                                      |
| $I$    | Person     | Number of the infected                                                      |
| $V_0$  | km/h       | Vaccine delivery speed from storages to the epidemic prefecture             |
| $V_p$  | Dose/day   | Vaccine production speed                                                    |
| $Y_{ij}$ | Person | Number of medical staff delivered from $i$ to $j$                           |
| $S_i$  | Dose       | The drug storage capacity of the $i$-th inventory point                    |

Figure 2: Top 10 provinces by the number of COVID-19 cases.

Figure 3: Relationship between different groups.
3.3. Parameter Evaluation. The above model contains the following key parameters: percentage of the susceptible diagnosed as normally infected $\theta_1$ per day; percentage of the susceptible diagnosed as infected $\theta_2$ per day; and the sum of death rate and recover rate per day (remove ratio) $h$. The values of these parameters can be approximated according to the official data released each day:

$$\begin{align*}
\theta_1 &= \frac{\text{newly added removal of suspected per day}}{\text{total suspected on the current day}}, \\
\theta_2 &= \frac{\text{newly added transformation of susceptible to patients per day}}{\text{total susceptible on the current day}}, \\
h &= \frac{\text{newly added recovered and deaths per day}}{\text{total susceptible on the current day}}.
\end{align*}$$

By our research hypotheses, the contracting probability of two persons is closely related to the population size. Therefore, it is assumed that the effective contracting ratio is the reciprocal of the population, $\lambda = 1/N$.

3.4. Model Solution. The epidemic severity in Hubei varies from prefecture to prefecture. It is necessary to optimize the material delivery sites for the province [19]. Before that, the number of COVID-19 patients should be predicted for each prefecture.

As shown in Figure 4, from 31 December 2019 to 1 February 2020, Wuhan had more infected than any other prefecture in Hubei. Several other prefectures also faced a serious epidemic: Huanggang, Xiaogan, Jingzhou, Ezhou, Suizhou, and Huangshi. In the said period, Wuhan and Jingzhou were the epicenters of the epidemic. Hence, this subsection attempts to predict the COVID-19 situation in each prefecture of Hubei with the SPIR model. However, it is impossible to directly drive $S$, $P$, $I$, and $R$ values with the SPIR model. To solve this problem, the Runge–Kutta method of MATLAB was called to obtain these solutions [21, 22]. And in the Runge–Kutta method, the initial value of parameters, $\theta_1$, $\theta_2$, $h$, and $\lambda$, are set as 0.001, 0.001, 0.0001, and 0.001, respectively.

The key parameters for Hubei were solved by differential equations (2). The solutions are given in Table 2. Then, the COVID-19 cases in the next month were predicted.

Figure 5 shows the number of diagnosed patients in Hubei. It can be seen that the epidemic reached its peak in the 10th week after the outbreak, as the patients took up 0.035% of the total population. In the 28th week, the epidemic was under control, when the percentage of patients dropped to 0.

3.5. Results and Analysis. The above model was applied to predict the COVID-19 situation of other preferences in four weeks. The results are given in Tables 3 and 4.

4. KMC Model

Under the condition of ensuring the safety of the epidemic, in order to quickly transport medical workers, medical supplies, and related materials to the affected areas, Hubei was divided into three regions according to the geographical coordinates of the cities and airports. For each region, a material delivery site was established [23, 24]. Once the epidemic breaks out, the local site will transfer vaccines and medical staff to the affected prefectures. If the local force is
insufficient to control the epidemic, the other prefectures will transfer vaccines and medical staff to this prefecture.

4.1. KMC. The distance from point \( i \) to point \( j \) can be defined as

\[
d_{ij}(q) = \left[ \sum_{k=1}^{p} |x_{ik} - x_{jk}|^q \right]^{1/q}.
\]

If \( q = 2 \), then the Euclidean distance

\[
d_{ij}(2) = \left[ \sum_{k=1}^{p} (x_{ik} - x_{jk})^2 \right]^{1/2}.
\]

The general steps of KMC [25, 26] are given in Figure 6:

Step 1: select a number of sample points as cluster heads by experience or basic knowledge of data

Step 2: compute the Euclidean distance between each sample point and each cluster head, and allocate the sample point to the cluster of the nearest cluster head

Step 3: classify one sample point at a time, and compute the mean of each cluster to update the cluster head

Step 4: repeat Step 2 with the new cluster head, and classify the sample points again

Table 2: Values of key parameters.

| Parameters | \( \theta_1 \) | \( \theta_2 \) | \( h \) | \( \lambda \) |
|-----------|---------------|---------------|---------|---------|
| Values    | 0.0035        | 0.0037        | 0.0003  | 0.00017 |

Figure 4: Epidemic distribution in Hubei [20].

Figure 5: Number of patients over time.
Table 3: Predicted new susceptible in four weeks.

| Prefecture | Prefecture | Week | Total |
|------------|------------|------|-------|
|            |            | 1    | 2     | 3     | 4     |       |       |
| Wuhan      | 1008.2     | 4035.7 | 8658.8 | 12510.4 | 26213.1 |
| Huanggang  | 66.8       | 212.4  | 604.4  | 878.6  | 1762.1 |
| Xiaogan    | 78.0       | 244.5  | 576.3  | 1045.7 | 1944.5 |
| Xiangyang  | 26.4       | 91.0   | 257.3  | 335.2  | 709.9  |
| Suizhou     | 31.6       | 88.4   | 248.6  | 336.8  | 705.5  |
| Yichang    | 23.2       | 68.5   | 185.5  | 239.1  | 516.3  |
| Jingzhou   | 34.6       | 114.3  | 304.6  | 492.0  | 945.5  |
| Jingmen    | 24.8       | 68.8   | 209.6  | 249.3  | 552.5  |
| Ezhou      | 29.6       | 88.1   | 280.5  | 362.0  | 760.1  |
| Huangshi   | 25.8       | 67.8   | 219.5  | 252.2  | 565.2  |
| Xianming   | 17.2       | 57.0   | 175.3  | 229.6  | 479.0  |
| Shiyan     | 15.8       | 45.5   | 123.5  | 156.5  | 341.3  |
| Xiantao    | 14.0       | 45.7   | 116.3  | 168.4  | 344.3  |
| Enshi      | 5.0        | 18.1   | 44.7   | 72.9   | 140.6  |
| Tianmen    | 9.3        | 33.2   | 88.0   | 121.2  | 251.6  |
| Qianjiang  | 4.6        | 16.9   | 39.4   | 59.0   | 120.0  |
| Shennongjia | 0.3      | 0.9    | 2.1    | 3.4    | 6.6    |

Table 4: Predicted new patients in four weeks.

| Prefecture | Week | Total |
|------------|------|-------|
|            | 1    | 3     | 4     |       |       |
| Wuhan      | 789.9 | 6506.6 | 9392.1 | 19341 |
| Huanggang  | 45.1  | 371.8  | 536.7  | 1105.1 |
| Xiaogan    | 55.1  | 453.5  | 654.6  | 1347.9 |
| Xiangyang  | 18.8  | 155.0  | 223.7  | 460.7  |
| Suizhou     | 20.0  | 164.7  | 237.7  | 489.5  |
| Yichang    | 14.7  | 121.0  | 174.7  | 359.8  |
| Jingzhou   | 25.5  | 210.2  | 303.4  | 624.9  |
| Jingmen    | 16.0  | 132.1  | 190.7  | 392.8  |
| Ezhou      | 21.0  | 172.7  | 249.2  | 513.2  |
| Huangshi   | 16.0  | 131.9  | 190.4  | 392.0  |
| Xianming   | 13.1  | 108.1  | 156.1  | 321.4  |
| Shiyan     | 10.3  | 84.8   | 122.4  | 252.0  |
| Xiantao    | 8.9   | 73.2   | 105.6  | 217.5  |
| Enshi      | 3.9   | 31.7   | 45.8   | 94.4   |
| Tianmen    | 7.2   | 59.0   | 85.1   | 175.3  |
| Qianjiang  | 3.1   | 25.6   | 36.9   | 75.9   |
| Shennongjia | 0.2  | 1.4    | 2.0    | 4.2    |

Figure 6: Flow of KMC.
Step 5: repeat Steps 2–4 cyclically and adjust the classes until no cluster head changes to obtain the final classes.

4.2. Solution of the Model. Table 5 sums up the coordinates of the central cities of the prefectures in Hubei.

According to the clustering results, Hubei was divided into three regions. The first region includes Yichang, Huanggang, Xiaoan, Suizhou, Ezhou, Huangshi, Xianning, Xiantao, Tianmen, and Qianjiang; and the third covers Xiangyang, Jingmen, Shiyan, and Shennongjia.

The coordinates of the head of each cluster were solved and taken as the location of the delivery site in the corresponding region, because the head is the closest point to any sample point in the cluster. The coordinates of the three heads were Yichang (8.31, 2.28), Wuhan (21.83, 2.04), and Xiangyang (11.54, 9.84).

5. Dynamic Material Delivery Optimization Model

By Model 1, it is possible to predict the number of patients in each prefecture in the near future and determine the newly added patients according to the distribution of the infected. From the perspective of emergency rescue, the number of patients and the growth of the infected must be suppressed by sufficient supply of vaccines. This is the only way to effectively control the epidemic [27, 28].

Based on SPIR model, this article establishes a dynamic emergency delivery optimization model for multiple epidemic prefectures [29, 30]. The model has two objective functions: the minimum delivery time $F_1(t)$ and the minimum transport cost $F_2(t)$.

5.1. Objective Functions

5.1.1. Minimum Delivery Time. Considering the high death rate of COVID-19, vaccines and medical staff should be delivered as soon as possible, that is, within the threshold of the arrival time. Otherwise, the severity and scope of the epidemic will go out of control. The penalty cost incurred by the violation of the threshold of the arrival time can be described as an exponential function:

$$\min F_1(t) = e^{\max\{0, t_i - T_i\}}. \quad (5)$$

5.1.2. Minimum Transport Cost. Besides delivery time, the transport cost must also be minimized to deliver vaccines and medical staff to the epidemic prefecture. The transport cost covers delivery cost, staff salary, and storage cost:

$$\min C(t) = \sum_{i=1}^{m} \sum_{j=1}^{n} \left( C_d X_{ij} M_{ij} + C_s Y_{ij} \right) + C_0, \quad (6)$$

where $C_0$ is the total fixed cost of setting up $i$ storages; $C_d$ is the subsidy of each medical staff member; $C_d$ is the transport cost of a dose per unit distance; $Y_{ij}$ is number of medical staff delivered from $i$ to $j$; $M_{ij}$ is the quantity of vaccines delivered from $i$ to $j$; and $X_{ij}$ is the distance between $i$ and $j$.

5.1.3. Composite Objective Function. The dynamic material delivery optimization model has two objective functions: the minimum delivery time $F_1(t)$ and the minimum transport cost $F_2(t)$. The two functions need to be normalized to unify their dimensionality:

$$\min F_i(t) = \frac{F_i(t) - F_i(t)_{\text{min}}}{F_i(t)_{\text{max}} - F_i(t)_{\text{min}}} \quad (7)$$

where $F_i(t)_{\text{max}}$ and $F_i(t)_{\text{min}}$ are the maximum and minimum expectations of $F_i(t)$, respectively, and $F_1(t)_{\text{max}}$ and $F_2(t)_{\text{min}}$ are the maximum and minimum expectations of $F_2(t)$.

Since two objectives have different priorities, weight coefficients were introduced to combine them into one composite objective function, turning the multiobjective optimization problem into a single-objective optimization problem:

$$\min F(t) = \alpha F_1(t) - (1 - \alpha) F_2(t), \quad \alpha \in (0, 1). \quad (8)$$

5.2. Constraints

5.2.1. Vaccine Demand. To control epidemic dissemination, the vaccine demand of each epidemic prefecture must be satisfied by the sum of vaccines and medical staff delivered to that prefecture:

$$\sum_{i=1}^{m} M_{ij} = D_j, \quad i = 1, 2, 3, \ldots, m; \quad j = 1, 2, 3, \ldots, n. \quad (9)$$

### Table 5: Coordinates of central cities of the prefectures in Hubei.

| Prefecture | $x$     | $y$     |
|------------|---------|---------|
| Wuhan      | 21.83   | 2.04    |
| Huanggang  | 24.87   | 1.75    |
| Xiaogan    | 20.00   | 3.94    |
| Xiangyang  | 11.54   | 9.84    |
| Suizhou    | 17.49   | 8.20    |
| Yichang    | 8.31    | 2.28    |
| Jingzhou   | 12.51   | 0.29    |
| Jingmen    | 11.91   | 4.02    |
| Ezhou      | 24.26   | 1.16    |
| Huangshi   | 25.61   | 0.00    |
| Xianning   | 22.20   | -2.12   |
| Shiyan     | 5.66    | 12.96   |
| Xiantao    | 18.10   | 0.45    |
| Enshi      | 0       | 0       |
| Tianmen    | 16.91   | 2.25    |
| Qianjiang  | 15.45   | 0.79    |
| Shennongjia| 4.76    | 8.07    |

### Table 4: Statics of Hubei’s prefectures.

| Prefecture | $x$     | $y$     |
|------------|---------|---------|
| Wuhan      | 21.83   | 2.04    |
| Huanggang  | 24.87   | 1.75    |
| Xiaogan    | 20.00   | 3.94    |
| Xiangyang  | 11.54   | 9.84    |
| Suizhou    | 17.49   | 8.20    |
| Yichang    | 8.31    | 2.28    |
| Jingzhou   | 12.51   | 0.29    |
| Jingmen    | 11.91   | 4.02    |
| Ezhou      | 24.26   | 1.16    |
| Huangshi   | 25.61   | 0.00    |
| Xianning   | 22.20   | -2.12   |
| Shiyan     | 5.66    | 12.96   |
| Xiantao    | 18.10   | 0.45    |
| Enshi      | 0       | 0       |
| Tianmen    | 16.91   | 2.25    |
| Qianjiang  | 15.45   | 0.79    |
| Shennongjia| 4.76    | 8.07    |
5.2.2. Vaccine Supply. Practically, it is impossible to deliver an infinite number of materials to epidemic prefectures. The total vaccines transferred from storage $i$ to each epidemic prefecture should not surpass the vaccine supply capability:

$$\sum_{j=1}^{n} M_{ij} \leq S_i, \quad i = 1, 2, 3, \ldots m; j = 1, 2, 3 \ldots n. \quad (10)$$

Every medical staff member involved in the rescue mission must be trained professionally, as medical staff have the highest infection rate of COVID-19 among all groups of people. According to the Health Commission of Hubei Province, there are a total of 54 million medical staff that could support the epidemic control in Hubei. This number should not be exceeded by the total medical staff delivered to epidemic prefectures. Let $N_{ij}$ be a group of eight medical staff. In addition, there is a correspondence between medical staff groups and the infected: one group is needed to treat every 15 infected. The two numbers should grow in proportionality. If not, the rounding-plus-one method was adopted to confirm the number of groups:

$$M_{ij} = \begin{cases} \beta I, & \beta I \in N^+ \\ \lfloor \beta I \rfloor + 1, & \beta I \notin N^+ \end{cases}, \quad Y_{ij} \leq 540000,$$

$$N_{ij} = 8Y_{ij}, \quad (11)$$

5.2.3. Arrival Time. The period from the epidemic outbreak to the arrival of vaccines and medical staff at the epidemic prefecture covers the following stages: the period from vaccine production to delivery at each storage; the period for vaccines and medical staff to move from the storage to the epidemic prefecture; and the response period of the emergency system to the epidemic:

$$t_{ij} = \frac{X_{ij}}{V_0} + \sum_{i=1}^{m} \sum_{j=1}^{n} \frac{M_{ij}}{V_p} + t_0, \quad (12)$$

where $t_0$ is the response period of the system; $V_p$ is the vaccine production speed; and $V_0$ is the delivery speed from storage to epidemic prefecture.

5.3. Solution of the Model. Referring to epidemic situations in previous years [31], the values of key parameters can be obtained as shown in Table 6.

With $\alpha = 0.8$, the dynamic material delivery optimization model can be expressed as

$$\min F_1 (t) = 0.8F_1 (t) + 0.2F_2 (t),$$

$$\begin{align*}
\sum_{i=1}^{m} M_{ij} = D_j, & \quad i = 1, 2, 3, \ldots m; j = 1, 2, 3 \ldots n, \\
\sum_{j=1}^{n} M_{ij} \leq S_i, & \quad i = 1, 2, 3, \ldots m; j = 1, 2, 3 \ldots n, \\
\sum_{i=1}^{m} \sum_{j=1}^{n} Y_{ij} \leq 4116, \\
M_{ij} \geq 0, \\
t_{ij} = \frac{X_{ij}}{V_0} + \sum_{i=1}^{m} \sum_{j=1}^{n} \frac{M_{ij}}{V_p} + t_0.
\end{align*} \quad (13)$$
The distance between prefectures and delivery sites is shown in Table 7.

Through LINGO modeling, the optimal vaccine distribution scheme was obtained (Table 8). The vaccine quantities delivered from the three sites were $S_1 = 2560$, $S_2 = 27160$, and $S_3 = 4520$.

The vaccine production speed was $V_p = \sum_{i=1}^{m} \sum_{j=1}^{M_i} \frac{M_{ij}}{t_0} = 34240/28 \approx 1223$ doses/day.

Then, the number of medical staff delivered from the three sites to each epidemic prefecture was calculated (Table 9). The coordinates of the three delivery sites were $S_1$(8.31, 2.28), $S_2$(21.83, 2.04), and $S_3$(11.54, 9.84).

### 6. Conclusions

Based on the characteristics of the spread of COVID-19 and treatment procedures, three models of organic linkage were established to address the epidemic prevention and control issues systematically. The results reflect the stability and reliability of our models.

Model 1 considers the driving effect of COVID-19 diffusion on the distribution of materials and the inverse control of material flow on disease spread. The modeling results are reasonable and practical, because various factors were coupled with the SPIR infectious diseases model.

Model 2 relies on KMC to cluster the epidemic prefectures by the Euclidean distance. The modeling results lay the basis for optimizing the material delivery of Model 3 and help to choose the best delivery sites.

Model 3 takes account of the competition between epidemic prefectures for medical resources, and the distance between epidemic prefecture and delivery site, as well as the severity of the epidemic. In this way, the authors derived a practical distribution scheme for emergency materials.

### Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

### Conflicts of Interest

The authors declare that they have no conflicts of interest.

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**Table 8: The drug distribution scheme.**

| Vaccine quantity | S1-Jingzhou | S1-Enshi | S2-Huanggang | S2-Xiaogan | S2-Suizhou | S2-Ezhou | S2-Huangshi | S2-Xianning | S2-Xiantao | S2-Tianmen | S2-Qianjiang | S3-Jingmen | S3-Shiyian | S3-Shennongjia |
|------------------|-------------|----------|--------------|------------|------------|----------|-------------|--------------|------------|-------------|--------------|------------|-----------|----------------|
|                  | 1840        | 720      | 11040        | 4840       | 3200       | 2040     | 1720        | 1600         | 1720       | 680         | 320          | 3120       | 1400      | 0              |

**Table 9: Medical staff delivery scheme.**

| Number of medical staff | S1-Jingzhou | S1-Enshi | S2-Huanggang | S2-Xiaogan | S2-Suizhou | S2-Ezhou | S2-Huangshi | S2-Xianning | S2-Xiantao | S2-Tianmen | S2-Qianjiang | S3-Jingmen | S3-Shiyian | S3-Shennongjia |
|-------------------------|-------------|----------|--------------|------------|------------|----------|-------------|--------------|------------|-------------|--------------|------------|-----------|----------------|
|                        | 30          | 12        | 180          | 79         | 52         | 33        | 28          | 26           | 28         | 11          | 5            | 51         | 23        | 0              |
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