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*Article*

# Demand Forecasting for Emergency Supplies through Improved Dynamics Model: A reflection on the Post Epidemic Era

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**Abstract:** From ancient times to the present, mankind has struggled with infectious diseases that pose a serious threat to people's lives, COVID-19 pandemic has given a huge impact to the human society, which has triggered a lot of thinking. In the future, humans may encounter various unexpected disasters or awful events, therefore, should learn from COVID-19 pandemic incident that need to pay special attention to the emergency supply of manpower and materials, whether a major disaster or not. That is emergency medical management is very important in the event of a sudden outbreak. What's more, the preparation and scheduling of emergency medical supplies well safeguards people's lives, health, and safety. However, owing to the sudden onset of an epidemic and given the population trends, the scale of infections and the demand for supplies in the epidemic area are uncertain. The main influencing factors and mechanisms of emergency material demand under the development trend of emergencies can be studied, and materials can be allocated efficiently and effectively, so as to minimize damage. In this study, it improves upon the dynamics model of infectious diseases firstly, by establishing a demand forecasting model for a certain area, taking the Hubei province as an example. Furthermore, this dynamics model is used to predict demand for emergency supplies, such as masks, respirators, and food in the area where the disaster will occur. Experimental results demonstrate the effectiveness and reliability of this prediction model, which supports for the development of emergency material management systems, ulterior, this study provides a framework for the distribution of emergency supplies and a guideline for relief efforts.

**Keywords:** emergency materials; supply scheduling; dynamics model

## 1. Introduction

Given that major epidemics diseases are often highly contagious and widespread, they threaten the lives, health, and safety of the general public, and have a serious societal impact. After the COVID-19 pandemic, the suddenness of the infectious disease and the complexity and severity of the damage caused a great deal of concern.Throughout history, various types of infectious diseases have never stopped attacking humans, but playing in the fight against infectious diseases, human beings have very limited capabilities.Therefore, disposing timely of infectious diseases at the early stage and forecasting accurately the number of sick people and material needs are of great significance for curbing the spread of the epidemic. WHO (2020) was to gauge the need for supplies/equipment and health work force requirements during the COVID-19 pandemic, has developed a suite of complimentary surge calculators, called the WHO COVID-19 Essential Supplies Forecasting Tool (ESFT), which designed to help governments, partners, and other stakeholders to estimate potential requirements for essential supplies to respond to the current pandemic of COVID-19.

In addition to major public health emergencies, natural disasters in life can also cause outbreaks of infectious diseases. With the outbreak of the pandemic, the demand for various emergency medical supplies, such as protective equipment, biomedical equipment, diagnostic reagents and equipment, essential drugs for supportive care, and consumables, increased rapidly. Apparently, there was a huge shortage of various emergency medical supplies in key epidemic areas, and various external resources were needed to meet the demand. To address this shortage, this study devised an improved infectious disease dynamics model (Susceptible-Exposed-Infected-Removed, SEIR) (Bjørnstad et al., 2020; He et al., 2020) used COVID-19 case data, combined as well as a safety stock model, to predict and analyze the demand over time in an infected area to provide a reference for emergency relief efforts. Detailly, the true transmission characteristics of infectious diseases are considered based on the original SEIR model in this study, and then takes quarantined and hospitalized patients who need emergency supplies into account, classifying the incubators patients into two categories: quarantined and unquarantined, further improves the model adding the situation of rebound positivity of cured patients, to predict the demand, and finally verifies its validity by estimating the number of quarantined patients with safety stock theory.

The double-edged sword of repeated COVID-19 infection waves and Ukraine-Russia has brought the critical supply chains of healthcare supplies to a new low (Gleeson, 2022; Partida, 2022; Kumar et al., 2023), since diversity of infectious diseases and complex etiology, even becomes large-scale epidemics if are not well controlled. Therefore, the model is improved according to the real-life epidemic transmission characteristics on the basis of the SEIR model. Infectious disease dynamics models have been refined for a specific outbreak of a mass transmission, and the random demand predicted by stochastic planning methods, dynamic planning methods or assuming that the demand obeys a certain distribution. But, these methods may result in large errors in the estimated demand. Therefore, this article addresses an improved model considering the characteristics of the prevention and treatment of novel coronavirus pneumonia, can better predict the number of people in each category after the occurrence of infectious diseases, that is less error compared with the real data.. This is a relatively more accurate forecast of demand based on the number of people with each type of illness. However, it is not only limited to the prediction of the number of people of each type of novel corona virus, but also the outbreak of infectious diseases after the disaster and extreme weather events can be fine-tuned on the basis of this model and the demand for epidemic prevention materials can be predicted according to this.

## 2. Literature Review

Whether it is epidemics or natural disasters, such as earthquakes, floods, typhoons, et., they often occur and seriously affect people's lives and economic development (Wallemacq and House, 2018; Meng et al., 2023). The research theories and methods of related issues for emergency supplies are also consistent. The biggest difficulty in emergency material supply is randomness, a method of stochastic inventory model that characterized by multiple periods had been introduced (Taskin and Lodree, 2010). The randomness problem manifests in factors such as uncertainty in material demand and material transportation conditions, Yu (2023) proposed a two-stage robust model to locate emergency supply points and preposition the correspondin storage amount of supplies. However, there is also peculiar for emergency medical supplies. For instance, the limitations of electronic medical devices and differences in various types of medical drugs, etc. determine the importance of emergency logistics allocation. Mangla et al. (2023) designed an emergency order allocation strategy for facing the situation in a multi-supplier environment by a distributor while ensuring sufficient and timely availability for emergency consumption during pandemic peaks. Of course, it often need to discuss safety stocks and capital reserves together for emergency medical supplies, Zhang et al. (2023a) was the first to determine the combined optimal policy of these two aspects. Predict future demands according to the reported epidemic-related data is no enough, time parameter should be included in model, Zhang et al. (2023b) further proposed a time-space network of emergency resource allocation and Luo et al. (2022) addressed a multi-period location-allocation model for managing emergency medical supplies and infected patients both for the time-varying demands.

While the development and application of information technology and artificial intelligence (AI), AI also brought hope for the prevention of COVID-19 (Das et al., 2023), more and more machine-learning algorithms and mathematical models apply to forecast emergency material demands. For instance, case inference is an important research topic in the field of artificial intelligence for forecasting and dispatching of emergency supplies (Fang and Wang 2021). Gray system models have also been applied, Hu et al. (2019) proposed and validated an improved GM (1,1) dynamic prediction model in this field. Barrett et al. (2020) predicted the demand for ventilators and ICU beds using statistical models and information technique. Li and Su (2021) divided the epidemic into four stages of generation-outbreak-peak-recession, and then established a time-varying demand model and a Bayesian sequential decision model for medical supplies. Discuss and check whether the Bayesian model error is less than that of the time-varying model or not. Wan et al. (2023) proposed a hybrid multi-objective salp swarm algorithm and sine cosine algorithm (HMSSA-SCA) to minimize the unsatisfied demand, materials distribution cost, and the risk of choosing the path to distribute materials. Shah et al. (2023) emphasized various modelling and application techniques for AI and BDA (Big Data Analytics) in making the supply chain (SC) more resilient. AI, BDA, block chain, and simulation are the most important technologies employed in emergency supplies, however, the practical application of these emerging tools for managing disturbance and warranting resilience in the emergency supply chain has been examined only rarely (Arji et al., 2023). Therefore, there is a need to explore more real-time forecasting approaches based on intelligent information processing techniques, besides ARIMA, CBR and mathematical models, so as to achieve appropriate dynamic demand prediction in emergency situations (Zhu et al., 2019).

To sum up, emergency medical supplies involves the manufacturing and delivery of medicines at the right time, at the right place, and in the correct quantity, BDA-AI technology-based collaborative platform is becoming a mainstream solution (Bag et al., 2023). Since humans are unaware of new emergent infectious diseases, the case-based reasoning approach is not suitable for demand forecasting in this context. Moreover, a prominent feature of sudden public health events is the phase nature, having very different transmission characteristics in each phase, and the method chosen in this paper can more easily predict the demand for each phase.

## 3. Data and Methods

### *3.1. Data Sources and Case Context*

In this paper, it encountered great difficulties in obtaining data, because the improved model divided patients into inpatients and confirmed cases who were not isolated, and then divided latent infections into isolated and non-isolated. The breakdown of the classification resulted in the absence of this category in the data published by the Hubei Provincial Health and Health Commission, that was the data of some categories not published after a period of time. After a long and fruitless search on various data sites, including national, Hubei, Wuhan's Health and Health Commission, for example, these data from Wuhan's list of 4 types of emergency material demand released by 26 hospitals during Feb. 22 to Mar. 8, 2020, and then had to turn to other data, which was derived from complex calculations based on other data.

### *3.2. Research Methodology*

This study develops a improved predictive model using the SEIR model (Hethcote, 2000), proposed by Hethcote in 2000, which is a classical infectious disease dynamic model during incubation period, to study the effect of the incubation period on the epidemiology of infectious diseases. Finally, considering artificial intelligence algorithms, the improved SEIR model is validated through data from Hubei province during the COVID-19 outbreak.

### *3.3. Model Description*

The infectious disease transmission dynamic model is the basic mathematical model of infectious diseases to study the speed of transmission, spatial scope, transmission pathway, and dynamic mechanism of infectious diseases and to aid effective prevention and control of infectious diseases.

Generally, infectious disease models are classified into SI (Susceptible-Infected), SIS (Susceptible-Infected-Susceptible), SIR (Susceptible-Infected-Removed), SIRS (Susceptible-Infected-

Removed-Susceptible), and SEIR (Susceptible-Exposed-Infected-Removed) models, according to the type of infectious disease. In accordance with their transmission mechanism, they are further divided into different types based on ordinary differential equations, partial differential equations, and network dynamics. Due to the complexity of SEIR model and is closer to such machine-learning algorithms and the real transmission law of infectious diseases, it can be well used to improve the predicted demand and the optimization problem of emergency supplies model.

As shown in Fig. 1, the SEIR model (Zhang et al., 2023b; Luo et al., 2022; Wang and Nie, 2023; Liu, 2022) divides the population into four parts: susceptible, denoted by S as the number of susceptible individuals; latent, denoted by E as the number of exposed individuals; infected, denoted by I as the number of infected individuals; and recovered, denoted by R as the number of recovered individuals.  denotes the probability of infection,  denotes the conversion rate, that is, the probability of viral transmission from one infected person, and  denotes the recovery rate. where N denotes the total number of people (N = S + E + I + R). The differential equations of the SEIR model are:

$$dS/dt = -\beta SI/N \tag{1}$$

$$dE/dt = \beta SI/N - \sigma E \tag{2}$$

$$dI/dt = \sigma E - \gamma I \tag{3}$$

$$dR/dt = \gamma I \tag{4}$$

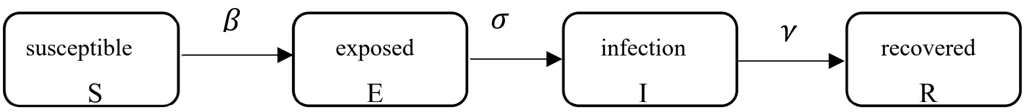


**Figure 1.** Schematic diagram of SEIR model.

Modeling studies based on infectious diseases have led to the generalization of infectious disease dynamics models. This model is an important method for theoretical quantitative research, which mathematical model reflects the dynamics of infectious diseases based on various relevant factors, and can analyze the process of disease development, reveal the epidemic pattern, predict the trends in change, and analyze the key causes of epidemics.

## 4. Infectious Disease Dynamics Modeling

### *4.1. Existing Models and Shortcomings*

The existing models are generally based on the classical model of infectious disease dynamics (SEIR) modified by adapting data from specific outbreak transmission cases (Zhou et al. 2020). Most of classical models are available in China emerged during the SARS period in 2003, applying the 2003 SARS epidemic transmission data. The classical SEIR model, however, cannot be applied to the third stage of COVID-19 due to the following shortcomings:

1. COVID-19 and many other infectious diseases are infectious for patients during the incubation period. Therefore, patients in the incubation period can also transmit.
2. No isolation phenomenon is included in the model. Usually susceptible persons with a history of exposure or latent infection or both are isolated. Latents who are isolated are not infectious. Eventually, the isolated uninfected susceptible person becomes susceptible again and the latent person is sent to the hospital for treatment.
3. Without considering asymptomatic infected persons, infected persons are similar to unisolated infection latents but have a higher infectious capacity than infection latents.
4. Cured patients are not considered to have a return of positivity or re-infection.

The following improvements to the model take into account the third-stage characteristics of COVID-19 and address the shortcomings of the classical model.

*4.2. Improved SEIR Model*

Refer to the actual epidemic situation, susceptible persons are divided into two non-infectious categories: those quarantined because of contact history, and those who are not quarantined and can move freely. There are also two types of infection latents: those infected after contact with an infected person and isolated during the incubation period, but do not transmit, and those who are undetected and can transmit. Infected people are divided into two categories: 1) Those who cannot infect others: people who are hospitalized with a confirmed diagnosis. They are not considered to be infectious because they are isolated in the hospital. This also includes asymptomatic infected people who are isolated. 2) Those with undetected infections, mainly asymptomatic people. They have a strong ability to infect others but are not noticed and belong to the risk category. Those who have recovered are likewise divided into two categories: those who recovered completely and those who were re-infected after recovery. The relationship diagram is shown in Fig. 2 (Zhuang and Wu, 2022).

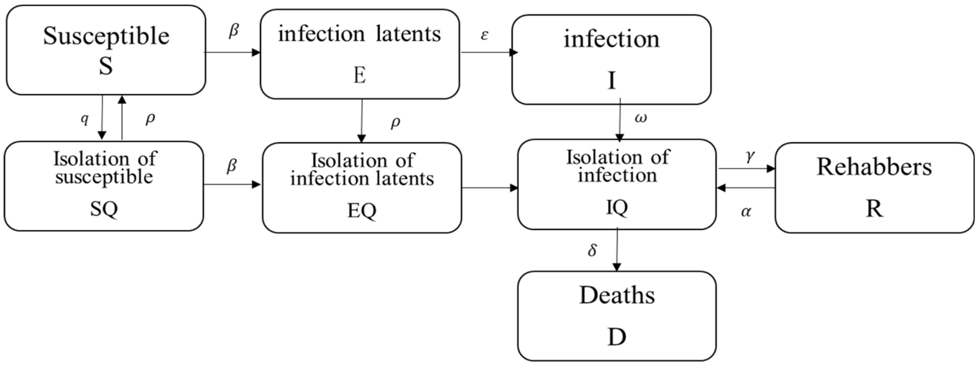


**Figure 2.** Schematic diagram of the improved model.

4.2.1. Subsubsection

The symbolic parameters used for modeling are as follows:

S: Susceptible persons, the general population that is not quarantined.

SQ: Isolated susceptible persons are those who have had contact with an infected person and have been isolated. Patients who are not symptomatic after 14 days of isolation revert to non-isolated susceptible persons.

E: Infection latents are people who are not quarantined but infected and are in the incubation period.

EQ: Isolation of infection latents, where those who are found to be infected in the latent phase for isolation can originate from latent patients found after exposure of susceptible persons to infected persons for isolation, or latent patients who may not have been previously isolated.

I: Infected persons, that is, confirmed cases who are not isolated, mostly refer to undetected asymptomatic infections.

IQ: Hospitalized infected persons, that is, infected persons in isolation.

D: Deaths, people who died after contracting COVID-19.

R: Recovered persons, those who recovered after treatment for the epidemic, and some of whom can be re-infected, considering that there are many cases of re-infection after recovery.

$\rho$: Isolation ratio.

$\sigma$: Exposure rate.

$\varepsilon$: Probability of incidence in exposed individuals.

$\beta$: Infection rate, the probability that a contact will be diagnosed with an outbreak.

q: Desegregation rate, where q = 1/14 because the isolation time is typically 14 days.

$\theta$: Rate of conversion of isolated exposed individuals to isolated infected individuals.

$\delta$: Probability of death among infected persons.

$\gamma$: Probability of curing among infected persons.

$\omega$: Probability of an infected person being isolated.

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$\alpha$: Probability of reverting to positive in recovered patients.
$\mu$: Daily emergency supply requirements per exposed person.
K: Collection of infected areas, K={1,2, … , k}.
J: Medical supply point collection, J={1,2, … , j}.
T: The set of a duration of COVID-19, T={1,2, … , t}.
$N_k$(t): Total population in the infected area k at time t.
$S_k$(t): Number of susceptible individuals in the infected area k not quarantined at time t.
$E_k$(t): Number of unquarantined contacts in infected area k at time t.
$I_k$(t): Number of infected persons in infected area k not quarantined at time t.
$SQ_k$(t): Number of susceptible individuals isolated in the infected area k at time t.
$EQ_k$(t): Number of contacts isolated in infected area k at time t.
$IQ_k$(t): Number of infected persons isolated in infected area k at time t.
$R_k$(t): Number of recovered persons in the infected area k at time t.
$D_k$(t): Number of deaths in infected area k at time t.
$d_k$(t): Demand for emergency supplies in the infected area k at time t.

### 4.2.2. Assumptions

1. Natural birth and death rates of the population were not considered. Because these factors usually take a long time to have an impact on the demographic structure, they were not considered.
2. The population is stable in each infected area. In other words, the government is assumed to have taken strong control after the outbreak, and no population movement was considered.
3. The quantity type of emergency medical supplies available was known.
4. Those who are not carrying the virus in the SQ will become part of S after 14 days (14-day medical observation period), and if we assume that 1/14th of the daily SQ return to the susceptible population (S), it will lead to a situation of insufficient demand during the period of increasing infections and rich demand during the period of decreasing infections. Therefore, a treatment of a 10% increase in the demand during the period of increasing infections and a 10% decrease during the period of decreasing infections of the epidemic is later made in the demand forecast.
5. Cured patients were no longer considered infected, except for a certain probability of "re-infection" of their own.

### 4.2.3. Modeling

Under each of the previous assumptions, the behavior of the spread of the outbreak in infected area k at moment t, that is, the change in the number of each population, is given by the following equations:

$$\frac{dS_k(\mathrm{t})}{dt} = -[\sigma\beta + \rho\sigma(1-\beta)]\frac{S_k(\mathrm{t})(I_k(\mathrm{t})+E_k(\mathrm{t}))}{N_k(\mathrm{t})} + q * SQ_k(\mathrm{t}) \tag{5}$$

$$\frac{dE_k(\mathrm{t})}{dt} = \sigma\beta(1-\rho)\frac{S_k(\mathrm{t})(I_k(\mathrm{t})+E_k(\mathrm{t}))}{N_k(\mathrm{t})} - \varepsilon E_k(\mathrm{t}) \tag{6}$$

$$\frac{dI_k(\mathrm{t})}{dt} = \varepsilon E_k(\mathrm{t}) - \omega I_k(\mathrm{t}) \tag{7}$$

$$\frac{dSQ_k(\mathrm{t})}{dt} = \sigma\rho(1-\beta)\frac{S_k(\mathrm{t})(I_k(\mathrm{t})+E_k(\mathrm{t}))}{N_k(\mathrm{t})} - q * SQ_k(\mathrm{t}) \tag{8}$$

$$\frac{dEQ_k(\mathrm{t})}{dt} = \sigma\beta\rho\frac{S_k(\mathrm{t})(I_k(\mathrm{t})+E_k(\mathrm{t}))}{N_k(\mathrm{t})} - \theta * EQ_k(\mathrm{t}) \tag{9}$$

$$\frac{dIQ_k(\mathrm{t})}{dt} = \omega I_k(\mathrm{t}) + \theta * EQ_k(\mathrm{t}) - (\delta + \gamma) * IQ_k(\mathrm{t}) + \alpha R_k(\mathrm{t}) \tag{10}$$

$$\frac{dR_k(\mathrm{t})}{dt} = \gamma * IQ_k(\mathrm{t}) - \alpha R_k(\mathrm{t}) \tag{11}$$

Equation (5) describes the change in the number of unquarantined susceptible persons in infected area k; the number of susceptible individuals is in a constant process of reduction, and part of the exposure to infected persons is isolated into isolated susceptible persons. Undetected infected susceptible persons become non-isolated latent persons, and uninfected susceptible persons in isolation became susceptible again after 14 days of isolation. It is assumed that 1/14th of the SQ quit consuming resources every day, and reverting back to the susceptible will lead to the under-prediction of supplies in the rising infection period and the error phenomenon of rich supplies in the falling infection period; thus, the subsequent supply prediction model will be improved with respect to this point. Equation (6) describes the variation in the number of isolated undetected infection latents. Undetected infection latents come from susceptible individuals who are in contact with infected individuals with a probability ϱ of being detected for isolation and becoming isolated infection latents, and a proportion of those become infected after the incubation period. Equation (7) describes the variation in the number of infected individuals who are not isolated, which comes from the fact that undetected infection latents have a ω probability of being detected and then isolated for treatment. Equation (8) describes the change in the number of isolated susceptibles, where some become isolated infection latents and some return to susceptibility at the end of the isolation period. Equation (9) describes the change in the number of isolated patients referred to the hospital for treatment. Equation (10) describes the change in the number of hospitalized patients, some of whom are cured, and some of whom die. Equation (11) describes the change in the number of recovered patients with an $\alpha$ probability of re-infection after recovery. Because data are usually reported daily during an epidemic, the above system of differential equations was transformed into a system of difference equations as follows:

$$S_k(\mathrm{t+1}) = S_k(\mathrm{t}) - [\sigma\beta + \rho\sigma(1-\beta)]\frac{S_k(\mathrm{t})(I_k(\mathrm{t})+E_k(\mathrm{t}))}{N_k(\mathrm{t})} + q * SQ_k(\mathrm{t}) \tag{12}$$

$$E_k(\mathrm{t}+1) = E_k(\mathrm{t}) + \sigma\beta(1-\rho)\frac{S_k(\mathrm{t})(I_k(\mathrm{t})+E_k(\mathrm{t}))}{N_k(\mathrm{t})} - \varepsilon E_k(\mathrm{t}) \tag{13}$$

$$I_k(\mathrm{t}+1) = I_k(\mathrm{t}) + \varepsilon E_k(\mathrm{t}) - \omega I_k(\mathrm{t}) \tag{14}$$

$$SQ_k(\mathrm{t+1}) = SQ_k(\mathrm{t}) + \sigma\rho(1-\beta)\frac{S_k(\mathrm{t})(I_k(\mathrm{t})+E_k(\mathrm{t}))}{N_k(\mathrm{t})} - q * SQ_k(\mathrm{t}) \tag{15}$$

$$EQ_k(\mathrm{t+1}) = EQ_k(\mathrm{t}) + \sigma\beta\rho\frac{S_k(\mathrm{t})(I_k(\mathrm{t})+E_k(\mathrm{t}))}{N_k(\mathrm{t})} - \theta * EQ_k(\mathrm{t}) \tag{16}$$

$$IQ_k(\mathrm{t+1}) = IQ_k(\mathrm{t}) + \omega I_k(\mathrm{t}) + \theta * EQ_k(\mathrm{t}) - (\delta + \gamma) * IQ_k(\mathrm{t}) + \alpha R_k(\mathrm{t}) \tag{17}$$

$$R_k(\mathrm{t}+1) = R_k(\mathrm{t}) + \gamma * IQ_k(\mathrm{t}) - \alpha R_k(\mathrm{t}) \tag{18}$$

Given the initial values of $S_k(0)$, $E_k(0)$, $I_k(0)$, $SQ_k(0)$, $EQ_k(0)$, $IQ_k(0)$, $R_k(0)$, et cetera, the number of susceptible persons, contacts, infected persons, recovered persons, and dead persons in the infected area k can be predicted by the above formula.

4.2.4. Model Elaboration

Epidemics of different scales have always coexisted with us. In addition to large-scale infectious diseases, such as smallpox and novel coronavirus pneumonia, a variety of infectious diseases can also emerge after natural disasters including floods and earthquakes. It is the first priority of prevention of post-disaster infectious diseases, but, once infectious diseases occur, accurate prediction of medical supplies needs is important for their scale control and prevention and its effectiveness, for avoiding secondary harm to people in disaster areas.The improved SEIR model above, although designed for the novel coronavirus pneumonia, does not differ significantly from and limit to the common infectious disease. When making predictions for other infectious diseases, changes can be made to fit the situation, e.g. the case of lifelong immune infectious diseases the R to IQ recurrent positive route

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can be removed. The number of people in need of supplies is easy to predict from the model for subsequent distribution. It has implications for the control of infectious diseases in life.

*4.3. Emergency Material Requirements Model*

4.3.1. Safety Stock Model

After predicting the number of people in isolation of infection latents and isolation of infection, the demand for emergency supplies is predicted by combining the knowledge related to inventory management (Guo and Zhou 2011). Safety stock is a business logistics concept that provides a buffer stock for uncertainties in the supply and demand of materials. Companies use safety stocks to ensure that production activities are not affected by uncertainties, and there are no production stoppages. The concept has great similarity to emergency supply stockpiles; the difference is that emergency supplies should meet the demand as much as possible, and the requirement for controlling the cost is not very high. The safety-stock model and its applicability are explained below. Uncertainty in customer demand, unstable production processes, variable distribution cycles, and high or low service levels are important factors that affect safety stock, which is modeled differently depending on whether customer demand and lead time vary randomly. Equation (19) is the classical model for safety stock.

$$SS = z\sqrt{\sigma_d^2(\bar{L}) + \sigma_L^2\left(\bar{d}\right)^2} \tag{19}$$

In Equation (19), SS represents safety stock, $\bar{L}$ represents mean lead time, $\bar{d}$ represents average daily demand, z represents the service level coefficient, $\sigma_d$ is the standard deviation of demand d, and $\sigma_L$ is the standard deviation of lead time. Equation (19) indicates that the safety stock is equal to the service-level factor multiplied by the standard deviation of demand during the replenishment cycle. From the above description, we can see that the safety stock model is designed to address demand uncertainty, supply uncertainty, and availability requirements, which match well with the demand forecasting for emergency supplies in this study. Therefore, based on the above idea of the safety stock model, the following briefly describes the demand forecasting model used in this study.

4.3.2. Symbol Description

EQ(t): The number of infection latents, this part is that of the isolated infection latents, because the infection latents who are not found isolated do not need medical supplies for the time being; IQ(t): Number of inpatients; J={$j|j = 1,2,\dots,J$}: Types of emergency supplies; N(t): Number of health care workers in the area; t=1,2,,…,t: Time series, a point in time of the epidemic is selected as 1 and thereafter timed with a fixed time period; $N_j$: The average demand for j across all personnel; $E_j$: the demand of infection latents criteria for category j materials; $I_j$: Criteria for inpatient demand for category j supplies; $A_j$: The existing material inventory of material in category j; z: Service Level Factor. This factor can vary with the type of emergency supplies, For example, the value of medical supplies used to save lives can be set higher, while non-medicinal supplies such as food can be lowered appropriately. When the z value is 1.65, it means that the desired demand satisfaction rate is 95%; L: The average delivery time for emergency supplies, the value can be adjusted according to the epidemic situation, when the epidemic is serious, the average period of shortage of supplies is short; $\sigma'_{jd}$: Standard deviation of demand history; M(t): Number of new patients on day t.

4.3.3. Mathematical Models

The demand forecasting model constructed based on the above theory can be expressed by Equations (20)–(23).

$$D_j'(\mathrm{t}) = \begin{cases} z \times \sigma'_{jd} \times \sqrt{L} + \sigma_d, & j \in Food\ supplies\ ; \\ MAX\{z \times \sigma'_{jd} \times \sqrt{L} + \sigma_d - A_j | 0\}, & j \in Medical\ supplies\ ; \end{cases} \tag{20}$$

$$\sigma'_{jd} = \sqrt{\frac{\sum_{t}^{t-7}[\sigma_d - \overline{\sigma_d}]^2}{7}} \tag{21}$$

$$\sigma_d = \begin{cases} N_j \times (N(t) + \mathrm{EQ(t)} + \mathrm{IQ(t)}), & j \in Food\ supplies\ ; \\ \mathrm{EQ(t)} \times E_j + \mathrm{IQ(t)} \times I_j, & j \in Medical\ supplies\ ; \end{cases} \tag{22}$$

$$\overline{\sigma_d} = \frac{\sum_{t}^{t-7} \sigma_d}{7} \tag{23}$$

$$D_j\ (\mathrm{t}) = \begin{cases} D_j'(\mathrm{t}) \times (1 + 10\%), & \mathrm{M(t)} \leq \mathrm{M}\ (\mathrm{t}+1)\ ; \\ D_j'(\mathrm{t}) \times (1 - 10\%), & \mathrm{M(t)} > \mathrm{M}\ (\mathrm{t}+1)\ ; \end{cases} \tag{24}$$

Equation (20) is the demand forecasting formula. Equations (21)–(23) are the explanatory equations for each variable. The first Equation (20) is the demand forecast for food supplies, and the second is the demand forecast for medical supplies, in which medical supplies are ventilators, belong to non-consumable medical supplies, so the past inventory is considered. Equation (24) implies that since assumption (4) will generate an error, it will lead to the under-prediction of supplies during the period of increasing infections and the over-estimation of supplies during the period of decreasing infections. A treatment of a 10% increase in demand during the period of increasing infections and a 10% decrease in demand during the period of decreasing infections is made. Because real material demand data are not available, to verify the feasibility of this model, a traditional method, that is, the number of people multiplied by the average demand, is used to predict the demand, and the two results are compared to verify the feasibility of the model.

$$D_j\ (\mathrm{t}) = \begin{cases} N_j \times\ (N(t) + \mathrm{EQ(t)} + \mathrm{IQ(t)})\ , & j \in Food\ supplies\ ; \\ MAX\{(\mathrm{EQ(t)} \times E_j + \mathrm{IQ(t)} \times I_j) - A_j | 0\}, & j \in Medical\ supplies\ ; \end{cases} \tag{25}$$

## 5. Results and Discussion

### *5.1. Case Description and Parameter Assignment Test*

Since December 2019, several cases of pneumonia of unknown origin have been identified in some hospitals in Wuhan, Hubei Province, and confirmed to be respiratory infections caused by COVID-19. A full-blown outbreak occurred at the end of January 2020, with the city of Wuhan closing on January 23, and increase in number of confirmed cases and deaths. The case background for this article was referred from the top medical journals “Journal of the American Medical Association”, “Association of Public Health Interventions with the Epidemiology of the COVID-19 Outbreak in Wuhan, China” (Pan et al. 2020). In the third of the five different epidemic phases delineated in the article, the epidemic was in full swing and the government took a series of mandatory measures such as prevention and control, but there was a serious lack of medical resources. However, this was the initial stage of the epidemic, and the situation was so urgent that there were not enough human and material resources to conduct in-depth tracking of the number of sick people. To obtain real data for comparison, the infection data of Hubei Province on February 22, 2020, were used as a starting point to estimate the demand for medical supplies and food for the next 16 days in Hubei Province, including medical personnel. Specific material requirements are listed in Table 1.

**Table 1.** Material types and demand specifications Unit: per person per day.

| | Mouthpiece | Ventilator | Food |
|---|---|---|---|
| IQ | 6 | 0.2 | a |
| EQ | 6 | 0 | a |
| Medical staff | 6 | 0 | a |

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In the above table, the unit demand for masks was based on the review of information that masks are changed every four hours. Thus, we estimated six masks per person per day, and information obtained through a press conference of the Hubei Provincial Health and Wellness Commission, estimates that there are 170,000 frontline medical personnel in Hubei. Among inpatients, only critically ill patients required ventilators, the ratio of which was calculated in this study, as 0.2. Food intake was calculated assuming that each person needed a unit amount of food.

*5.2. EQ and IQ Numerical Prediction and Error Analysis*

This study validated the model by comparing the predicted data for the subsequent 30-day period in Hubei Province from February 22, with the real data from the 16th to be calculated. The demand forecast model was then used to predict the demand for these 16 days. Because of the different parameter situations in different periods, the following variables and parameters were selected based on the epidemic situation in Hubei reported at that stage (the number of confirmed cases, contacts, cures, and deaths were obtained from the Wuhan Health and Wellness Commission; data on the number of hospitalized patients were obtained through the bulletin; and isolated incubators were obtained through equation (24), which was referenced in the literature (Zou and Liang 2020)).The initial values of the variables are shown in Table 2, and the parameters were assigned as shown in Table 3.

$$E_n = (I_{n+5} + IQ_{n+5} + R_{n+5} + D_{n+5}) - (I_n + IQ_n + R_n + D_n) \tag{26}$$

**Table 2.** Initial settings of the improved SEIR infectious disease dynamic model.

| Variables | I(0) | IQ(0) | S(0) | SQ(0) | E(0) | EQ(0) |
|---|---|---|---|---|---|---|
| value | 46439 | 40127 | 59170000 | 61181 | 1623 | 1346 (Estimated) |
| Description of the values | Official Data | Official data, number of people treated in hospital | Obtained from the total population minus the number of cured deaths | Official data, number of people under medical observation | Number of cured deaths on Feb. 26 minus the number on Feb. 22 | Number of people under medical observation multiplied by the proportion of incubators |

Note: Since the bed data were not updated after February 25, this study assumed that the total number of beds remained unchanged after February 25 to estimate the number of hospitalizations.

**Table 3.** Assignment of parameters to the improved SEIR infectious disease dynamics model.

| parameter | $\beta$ | $\sigma$ | ρ | ε |
|---|---|---|---|---|
| value | 2.05*10^(-9) | 0.448 | 1*10^(-6) | 1/7 |
| parameter | δ | ω | γ | α |
| value | 0.0402 | 0.13 | 0.1769 | 0.122 |

Note: The meanings of the parameters are given in previous symbolic descriptions, and the values of β and ϱ refer to data in the literature (Cao et al. 2020).

The improved infectious disease dynamic model and parameters were tested using MATLAB R2016a. The predicted values of EQ and IQ obtained after several experiments and adjustment of parameters are shown in Figs. 3 and 4.

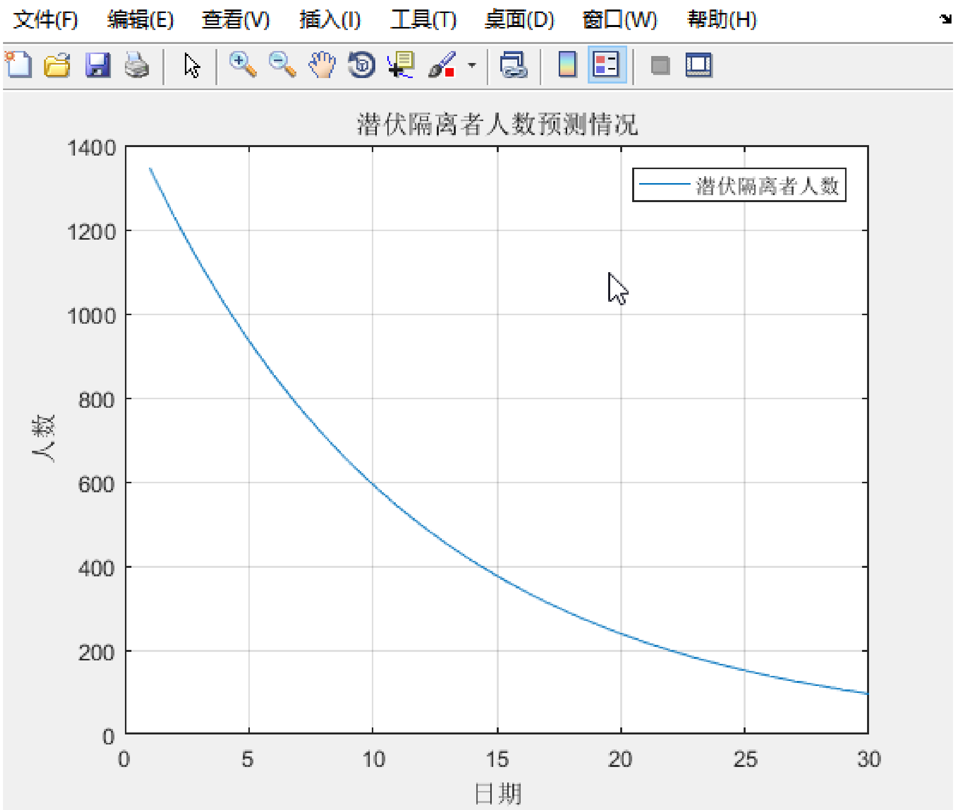


**Figure 3.** EQ predictor values.

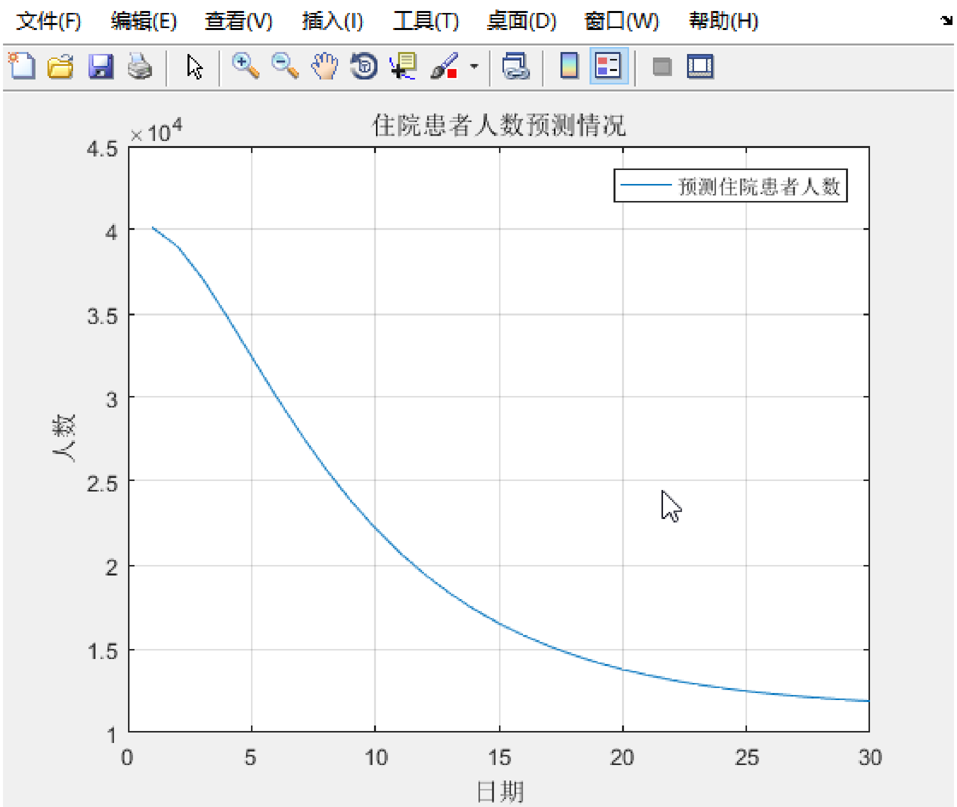


**Figure 4.** IQ predictor values.

The model results indicate that the predicted values of EQ and IQ were in line with the real data trend. Tables 4 and 5 show the predicted values of EQ and IQ during February 22 to March 8. Tables 6 and 7 show the true values of EQ and IQ during this time.

**Table 4.** Predicted values for isolated infection latents (EQ).

| Date | 2.22 | 2. 23 | 2.24 | 2.25 | 2.26 | 2.27 | 2.28 | 2.29 |
|---|---|---|---|---|---|---|---|---|
| projected number | 1346 | 1229 | 1122 | 1025 | 936 | 854 | 780 | 712 |
| Date | 3.1 | 3.2 | 3.3 | 3.4 | 3.5 | 3.6 | 3.7 | 3.8 |
| projected number | 650 | 594 | 542 | 495 | 452 | 413 | 377 | 344 |

**Table 5.** Inpatient (IQ) predictive values.

| Date | 2.22 | 2. 23 | 2.24 | 2.25 | 2.26 | 2.27 | 2.28 | 2.29 |
|---|---|---|---|---|---|---|---|---|
| projected number | 40127 | 39028 | 37134 | 34849 | 32434 | 30053 | 27800 | 25728 |
| Date | 3.1 | 3.2 | 3.3 | 3.4 | 3.5 | 3.6 | 3.7 | 3.8 |
| projected number | 23857 | 22191 | 20723 | 19439 | 18321 | 17352 | 16515 | 15792 |

**Table 6.** True values of isolated infection latents (EQ).

| Date | 2.22 | 2. 23 | 2.24 | 2.25 | 2.26 | 2.27 | 2.28 | 2.29 |
|---|---|---|---|---|---|---|---|---|
| Number | 1346 | 1289 | 1176 | 1088 | 1019 | 949 | 865 | 787 |
| Date | 3.1 | 3.2 | 3.3 | 3.4 | 3.5 | 3.6 | 3.7 | 3.8 |
| Number | 707 | 625 | 556 | 502 | 463 | 403 | 343 | 291 |

**Table 7.** Inpatient (IQ) true values.

| Date | 2.22 | 2. 23 | 2.24 | 2.25 | 2.26 | 2.27 | 2.28 | 2.29 |
|---|---|---|---|---|---|---|---|---|
| Number | 40127 | 39073 | 37896 | 36242 | 34978 | 32878 | 31064 | 28912 |
| Date | 3.1 | 3.2 | 3.3 | 3.4 | 3.5 | 3.6 | 3.7 | 3.8 |
| Number | 26901 | 25050 | 23039 | 20765 | 19758 | 18518 | 17078 | 15826 |

Next, the fit and error of the predicted values were analyzed. The predicted data of the isolated latents and hospitalized patients were fitted to the real data obtained from the query information, and the results are shown in Figs. 5 and 6. The goodness-of-fit value for the predicted value of EQ was 0.988013, and the goodness-of-fit value for the predicted value of IQ was 0.979685. It can be seen that the model fits well. The average relative error of the calculated EQ prediction values was 6.4%, and the average relative error value of IQ prediction values was 6.225%. The prediction accuracy was high, and the relative error distribution is shown in Figs. 7 and 8.

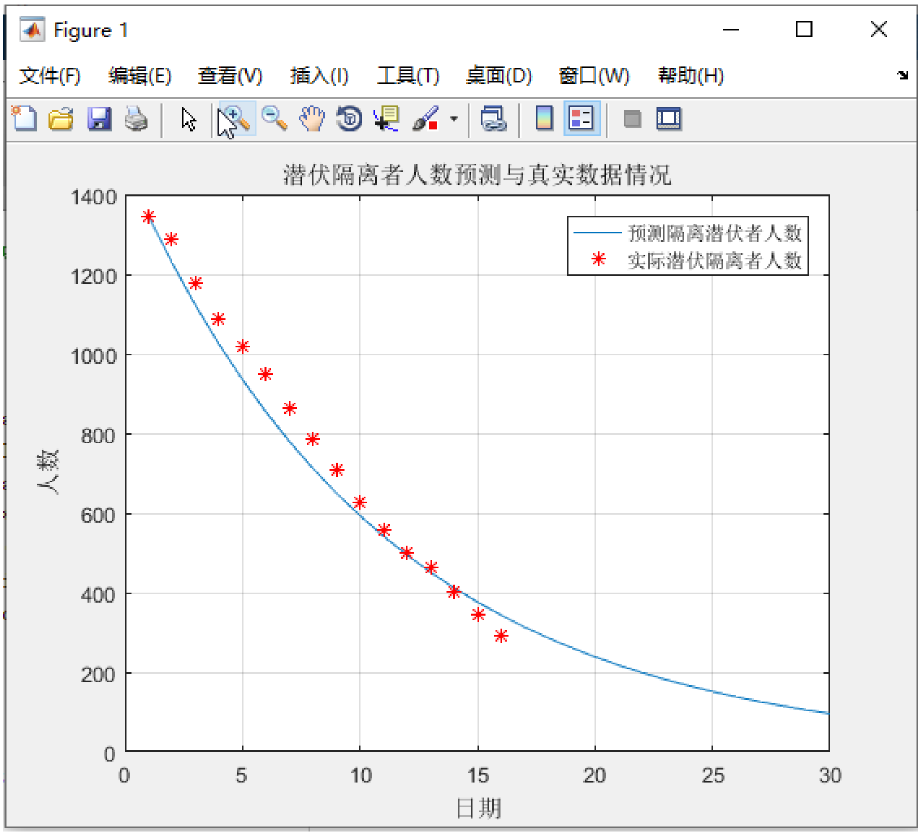


**Figure 5.** Comparison of the predicted and actual number of EQ.

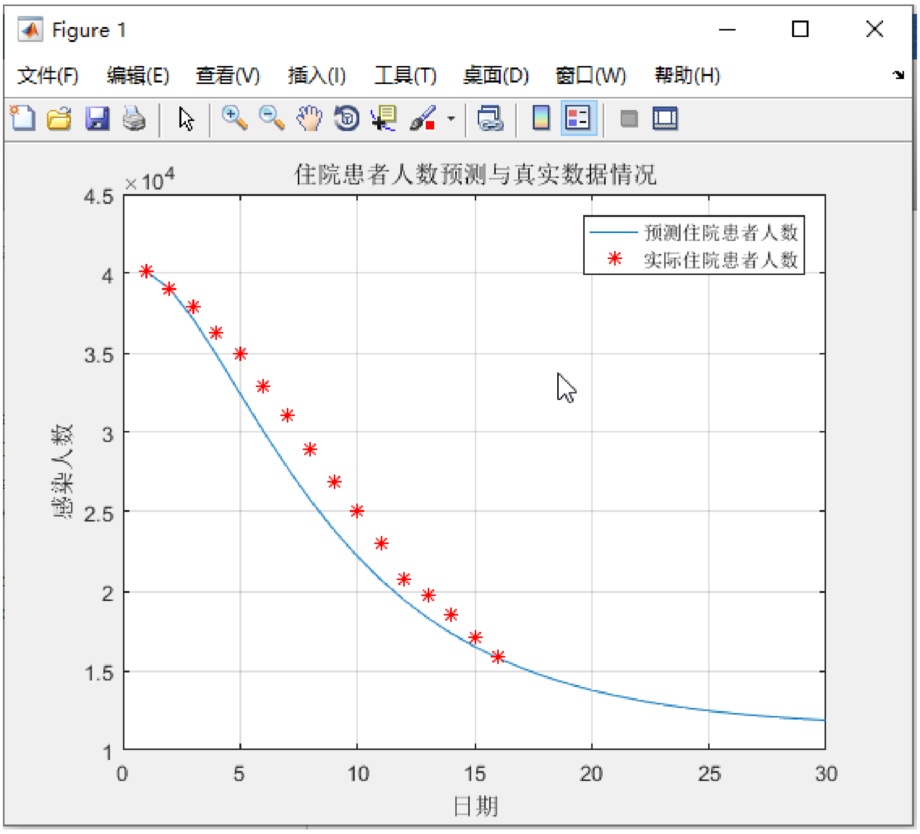


**Figure 6.** Comparison of the predicted and actual number of IQ.

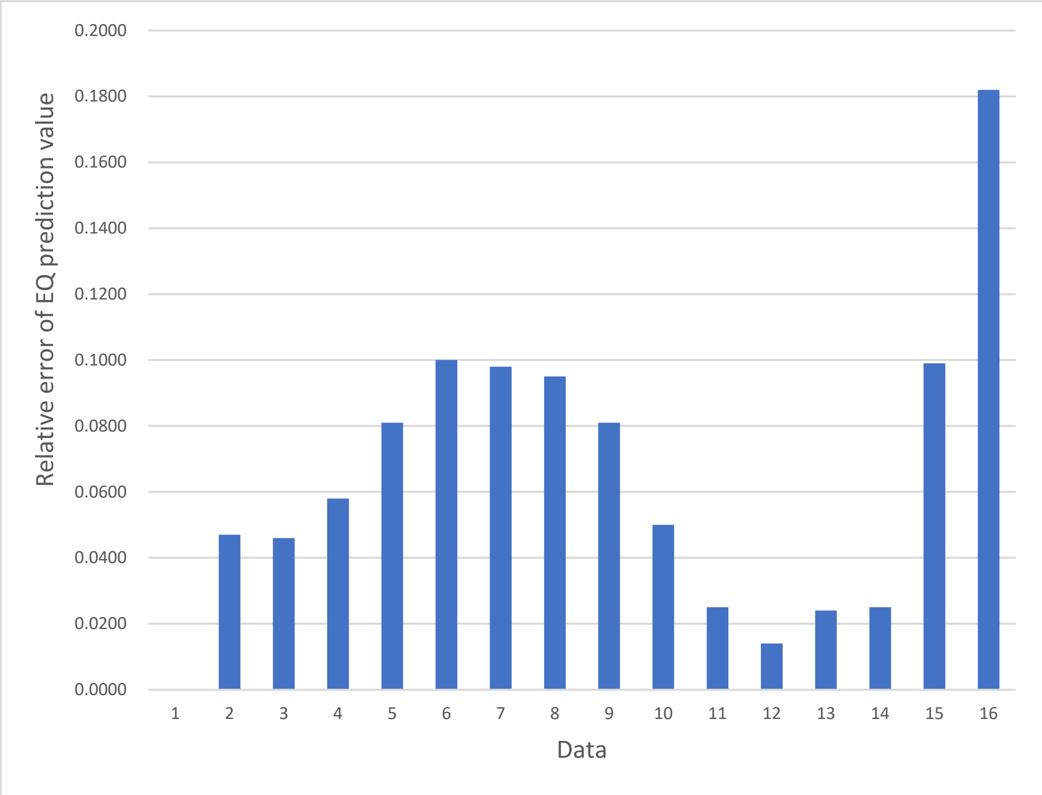


**Figure 7.** Relative error of the EQ prediction value.

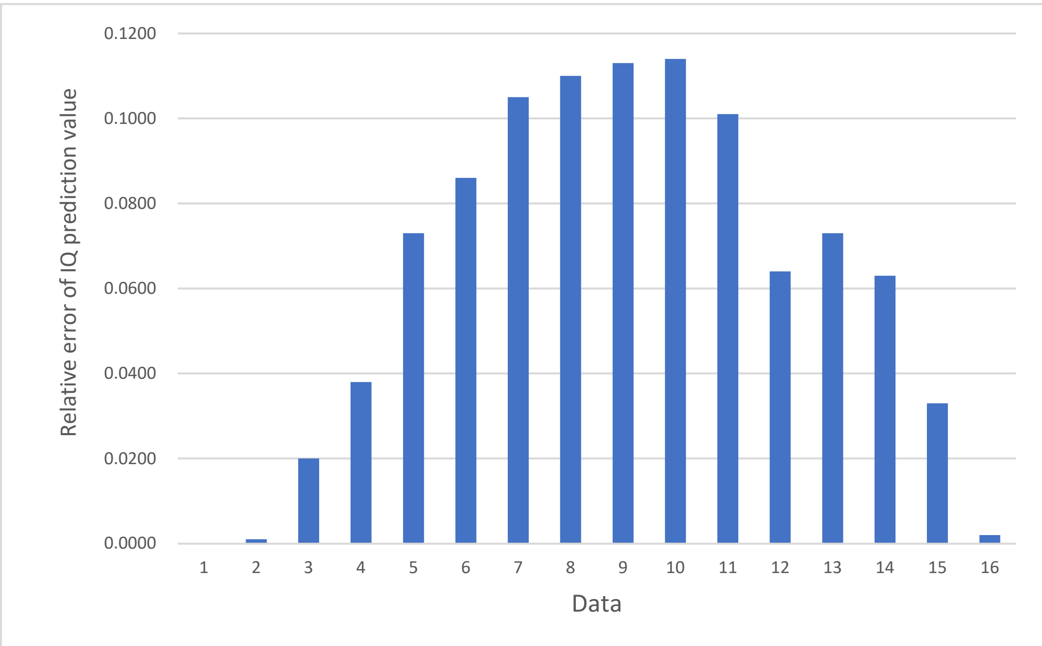


**Figure 8.** Relative error of the IQ prediction value.

*5.3. Demand Forecast*

The data was incorporated into the demand forecasting model, and the urgency of the epidemic decreased at this point, depending on the case context. The number of new confirmed cases decreased, that is, $M(t) > M(t+1)$, and the availability factor z was set to 1.28 for food items and 1.65 for medical items. The average delivery period of the emergency supplies was assumed to be 4d. The predicted demand obtained by solving for 1day as a timing unit is listed in the following Table. (Since the original volume of the ventilator cannot be checked, the first day of the estimated volume was taken as the standard here.)

**Table 8.** Projected demand for various types of emergency supplies (safety stock theory).

| **Data** | **2.22** | **2．23** | **2.24** | **2.25** | **2.26** | **2.27** | **2.28** | **2.29** |
|---|---|---|---|---|---|---|---|---|
| Mask | 1166190 | 1158081 | 1154169 | 1153250 | 1150410 | 1145338 | 1143390 | 1140342 |
| Respirato r | 8056 | 7769 | 7624 | 7588 | 7495 | 7326 | 7263 | 7173 |
| Food | 193459a | 192165a | 191255a | 190656a | 189783a | 188630a | 187909a | 187083a |
| Data | 3.1 | 3.2 | 3.3 | 3.4 | 3.5 | 3.6 | 3.7 | 3.8 |
| Mask | 1115306 | 1105184 | 1093649 | 1081756 | 1070166 | 1059280 | 1049302 | 1040304 |
| Respirato r | 6984 | 6657 | 6258 | 5832 | 5409 | 5007 | 4636 | 4300 |
| Food | 185884a | 184197a | 182274a | 180292a | 178361a | 176546a | 174883a | 173384a |

The projected data in Table 8 shows that, the supplies demand also decreases as the number of patients decrease. The demand for respirator is listed for clarity, but the actual demand for them is declining, and the subsequent demand would become zero because the original stock would be sufficient to meet the demand with a decline in the number of patients. Next, the result data derived from the demand forecasting model is compared with the number of people times unit demand method to verify the feasibility of the model in this study.

**Table 9.** Forecasted values of demand for various types of emergency supplies (traditional method).

| Data | 2.22 | 2.23 | 2.24 | 2.25 | 2.26 | 2.27 | 2.28 | 2.29 |
|---|---|---|---|---|---|---|---|---|
| Mask | 1268838 | 1261542 | 1249536 | 1235244 | 1220220 | 1205442 | 1191480 | 1178640 |
| Respirator | 8025 | 7806 | 7427 | 6970 | 6487 | 6011 | 5560 | 5146 |
| Food | 211473a | 210257a | 208256a | 205874a | 203370a | 200907a | 198580a | 196440a |
| Data | 3.1 | 3.2 | 3.3 | 3.4 | 3.5 | 3.6 | 3.7 | 3.8 |
| Mask | 1167042 | 1156710 | 1147590 | 1139604 | 1132638 | 1126590 | 1121352 | 1116816 |
| Respirator | 4771 | 4438 | 4145 | 3888 | 3664 | 3470 | 3303 | 3158 |
| Food | 194507a | 192785a | 191265a | 189934a | 188773a | 187765a | 186892a | 186136a |

The data in Tables 8 and 9 are compared and analyzed, and the difference between the two sets of data is small, indicating that the demand forecasting model of this study is in line with reality. The main difference between the two sets of data is that the number of mask ventilators in Table 8 is higher compared to Table 9, and the food is lower. This is due to the setting of availability coefficients, which can be set differently for different stage characteristics. Compared with the direct method of using the number of people multiplied by the unit demand, the demand prediction model of this study is designed to be flexible and consistent with the actual data, and can be designed according to the severity of the epidemic and different kinds of supplies.

## 6. Conclusions

This study addressed the uncertainty of demand during an epidemic period by combining an improved infectious disease dynamics model with estimation of demand after the epidemic, drawing on the safety stock theory. This method can predict the demand for different epidemic areas and different epidemic stages after the epidemic, which lays a foundation for the subsequent dispatch and distribution of emergency supplies and provides a direction for relief work, and has a certain reference value. However, there are some shortcomings in the demand forecasting model: (1) The forecasted demand is the amount of supplies needed for the medical sites in the area, and the demand of all people in the area is not taken into account. (2) The probability of a susceptible person becoming an isolated susceptible person and the probability parameter of a latent person becoming an isolated latent person are approximated to be the same, which can lead to errors. (3) The validation method of the demand prediction model is inadequate. In the next study, we will further classify and predict all persons in the prediction area, and further optimize the selection of model parameters and the model validation method.

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