Analysis Of the Effectiveness of Material Deployment and Dissemination Intervention Based on SEIR Model and Multi-Layer LSTM Modeling

Lu Liang [1], Mingyuan Liu [2, *] and Ziyi Xiong [2]

[1] School of Information Engineering, Lanzhou Vocational Technical College, Lanzhou, China

[2] Innovation Academy for Precision Measurement Science and Technology, CAS, Wuhan, China

* Corresponding Author Email: lmyszq1017@163.com

Abstract. This study focuses on the correlation between the distribution of household goods and the spread of diseases based on the SEIR infectious disease prediction model and the multilayer LSTM model. By exploring the characteristics of the affected population before and after the implementation of the centralized distribution measure in stages, it was found that centralized distribution significantly reduced the growth rate of the affected population. Based on this, an improved SEIR transmission model incorporating the factors of material distribution is constructed, which verifies the key role of centralized distribution in suppressing the spread of the disease by quantitatively analyzing the intervention effect of material distribution on the transmission process. At the same time, a Multi-Step Multi-Layer LSTM-based material demand forecasting framework is proposed, which realizes the accurate forecasting of material demand by integrating historical data and dynamic influencing factors. The results of the study provide theoretical support and technical means for the optimization of material deployment scheme, which is an important reference value for resource management under public health events.

Keywords: Material Distribution; SEIR Infectious Disease Prediction Model; Multi-Layer LSTM Model.

1. Introduction

In this study, the SEIR infectious disease prediction model and multilayer LSTM model [1] were introduced to investigate the complex association mechanism between household material distribution and disease transmission. Non-essential outbound purchasing behaviors significantly increase the risk of transmission, but the coupling relationship between the spatial and temporal distribution characteristics of material distribution and transmission dynamics has not been systematically revealed [2]. To address this situation, this study proposes to incorporate material distribution into the analytical framework of the diffusion model, and quantitatively assess the intervention effect of centralized distribution measures by constructing an improved SEIR model [3]. The study firstly found that centralized distribution significantly reduced the growth rate of the affected population through phase-by-phase comparative analysis, which verified its prevention and control efficacy. Then, the Multi-Step Multi-Layer LSTM model [4] was introduced to achieve accurate prediction of material demand and provide decision support for dynamic optimization of the distribution scheme. The results of this study not only expand the application boundary of the communication dynamics model [5], but also provide a theoretical basis and technical path for resource allocation under public health events [6].

2. Impact of Large-Scale Movement of Various Types of Living Materials on the Epidemic

This section calls for an analysis of the effects of the effects before and after the implementation of the distribution of vegetable packs in the Conservancy. First, the native infected and asymptomatic infected were combined to total the infected. The number of infected persons was also counted, the growth rate of the number of infected persons was calculated, and the statistics related to vegetable packs in each district on a daily basis during the epidemic in Changchun City were integrated and processed. After that, the specific effects were divided into two stages of discussion before and after the distribution of vegetable packs. Through comparative analysis, it was obtained that the distribution of vegetable packs in Changchun City had an inhibiting effect on the number of infections caused by the epidemic. Finally, the SEIR infectious disease prediction model introduced into the distribution of vegetable packs is established, and it is concluded that the prediction results are mostly fitted with the actual results, which illustrates the effectiveness of the SEIR infectious disease prediction model constructed in this paper.

2.1. Data Visualization and Comparative Analysis

Firstly, the change of infected people from March 4 to May 23 in Changchun City, the amount of change of infected people and the amount of vegetable packages received are visualized in comparison as shown in Fig. 1 below.

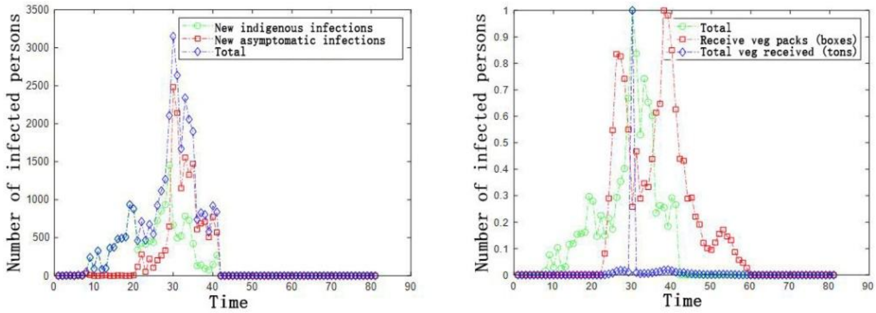

Fig. 1 Comparison between the number of infected persons and the number of vegetable packages received from March 4 to May 23 in Changchun City

By analyzing the time evolution of newly diagnosed cases of COVID-19 in Changchun City, we can find that the overall situation shows four phases: “low incidence period - growth period - slowdown period - end period”. And when Changchun City, before and after the implementation of the distribution of vegetable packages, there are changes in the number of infected people, the specific effect is divided into the distribution of vegetable packages before the distribution of vegetable packages and after the distribution of vegetable packages of two phases to discuss. The cumulative changes in the number of infected people before and after the distribution of vegetable packages are plotted as shown in Fig. 2 below.

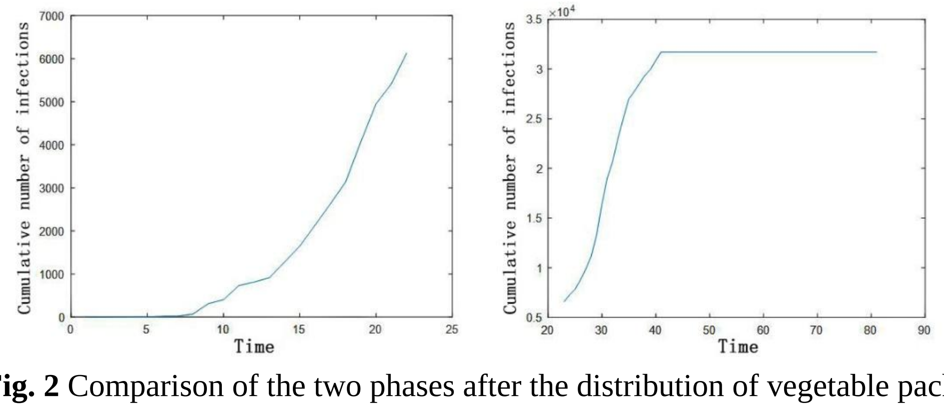

Fig. 2 Comparison of the two phases after the distribution of vegetable packs

From Fig. 2 above, we can see that the cumulative number of infected people before the distribution of vegetable packs changed steeply, indicating that the cumulative number of infected people before the distribution of vegetable packs in Changchun City was always increasing, and the growth rate of the cumulative number of infected people increased because of the slope of the curve became larger. However, after the distribution of vegetable packs, although the number of infected people is still increasing, we can see that the slope of the curve is getting smaller, which indicates that the growth rate is decreasing, so we can think that the distribution of vegetable packs in Changchun city has inhibited the number of infected people caused by the epidemic. In order to further study the specific impact of vegetable package distribution we introduce the infectious disease prediction model.

2.2. Introduction of SEIR Infectious Disease Prediction Model for Vegetable Packet Distribution

2.2.1 Traditional SIR model and kinetic analysis

In the SIR model with asymptomatic infected persons, the total population is divided into 4 states. s, I, $I1$, and R represent the number of susceptible, infected, asymptomatic infected (asymptomatic carriers), and recovered (infected and cured and infected, asymptomatic and self-cured) persons at time t, respectively. The flow chart of disease transmission between these four states is shown in Fig. 3 below.

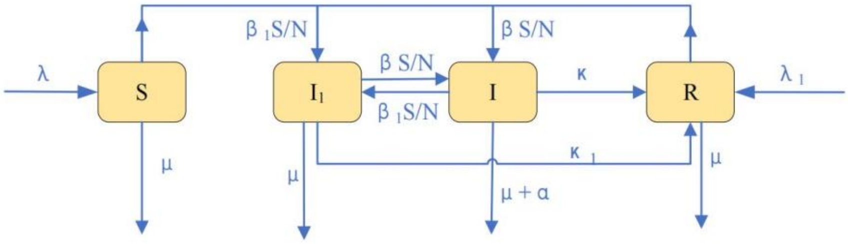

Fig. 3 Disease Transmission Flowchart

First, infected person I and asymptomatic carrier $I1$ infect uninfected person S with a chance of β to become infected with disease and a chance of β_1 to become asymptomatically infected. The recovery rate for infected person I is K and the rate of return to normal for asymptomatic carriers is K_1. The natural rate of increase for susceptible persons is λ. The natural rate of increase is 8 for susceptible persons and λ_1 for asymptomatic carriers. The mortality rate of uninfected, asymptomatic carriers and recovered persons is μ, and the mortality rate of infected persons is $\alpha+\lambda$. All of these parameters are positive.

Based on the above assumptions, the expression of the model is as follows:

Denote the total population as N:

$$N = S + I + I_1 + R \tag{1}$$

Based on the above assumptions, the expression of the model is as follows:

$$\begin{cases} \dfrac{dS}{dt} = \lambda - \dfrac{(\beta-\beta_1)S(I+I_1)}{N} - \mu S \\ \dfrac{dI}{dt} = \dfrac{\beta S(I+I_1)}{N} - (\alpha+\kappa+\mu)I \\ \dfrac{dI_1}{dt} = \dfrac{\beta_1 S(I+I_1)}{N} - \kappa_1 I_1 - \mu I_1 \\ \dfrac{dR}{dt} = \lambda_1 + \kappa I + \kappa_1 I_1 - \mu R \end{cases} \tag{2}$$

2.2.2 SEIR infectious disease prediction model

Reflecting on the fact that the epidemic in many cities could not be effectively controlled in a short period of time, it is very likely that there is a correlation between the development of the epidemic and the distribution of living materials, and that many people can easily come into contact with other infected or latent persons in the process of going out to purchase materials, thus leading to their becoming latent persons and then spreading them to other susceptible people, leading to the repeated spread of the epidemic virus and the large-scale spread of the epidemic. Therefore, combining the characteristics of the incubation period of the new coronary pneumonia outbreak, the SEIR model was selected from a number of infectious disease models to categorize the population involved in the spread of the outbreak into susceptible (S), which refers to those who are not infected with the disease but have a relatively low level of immunity, which makes them easy to be contacted and infected, and latent (E), which refers to those who have already been infected by the virus but have not yet developed symptoms of infection; Infected (I), people who are already infected and can be transmitted to other susceptible people; Removed (R), people who have recovered from, recovered from, or died from the disease.

2.2.3 Parameters

(1) Total population of Changchun City in nine regions

The total population of the nine regions in Changchun City is 3.22 million.

(2) Transmission coefficient $\beta : \beta = nb$, where n is the average number of infected or latent persons with the ability to transmit the disease that may be transmitted to other persons by contact with susceptible persons per day; and b is the probability of transmission by a single contact, which can be based on references. $b = 0.015$ The transmission coefficient reflects the intensity of disease transmission, which is the probability of transmission by a single contact. The transmission coefficient reflects the intensity of disease transmission, β with larger coefficients representing the greater likelihood that a population will be infected by contact with an infected or incubated person.

(3) α indicates the probability that a latent person becomes infected. According to the statistical conclusions drawn by the National Health and Wellness Commission, the average incubation period of the New Crown Pneumonia Virus is about 10 days, so $\alpha = 1/10$ can be taken.

(4) γ denotes the probability that an infected person recovers through cure, which can be taken as $\gamma = 0.94$.

2.2.4 Modeling

The initials of the above four categories are used to represent the number of such populations, i.e., S is the susceptible, E is the latent, I is the infected, and R is the emigrated. The number of the four categories of populations will change dynamically with time and the development of the epidemic, and thus can be expressed by the following ordinary differential equation:

$$\frac{dS}{dt} = -\beta_1 \frac{SI}{N} - \beta_2 \frac{SE}{N} \tag{3}$$

$$\frac{dE}{dt} = \beta_1 \frac{SI}{N} + \beta_2 \frac{SE}{N} - \alpha E \tag{4}$$

$$\frac{dI}{dt} = \alpha E - \gamma I \tag{5}$$

$$\frac{dR}{dt} = \gamma I \tag{6}$$

$$N = S + E + I + R \tag{7}$$

After that, this paper solves the above infectious disease prediction model by MATLAB.

2.3. Results of the Model

In order to make the results more accurate, the prediction results of the infectious model of SI, SIS, SIR, and SEIR are plotted in python as shown in Fig. 4 below, using the population of Changchun as the basic data (the vertical axis is the proportion of the population, and the horizontal axis is the time).

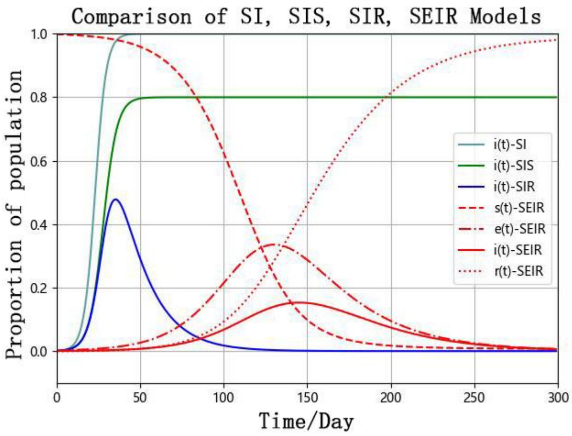

Fig. 4 Comparison of infection model prediction results

As shown in Fig. 4 above, only SEIR's infection model predicts a smaller proportion of infected population in the early stage, although the number of infected people is higher, the total population of Changchun is 3.22 million, so the proportion of infected population is smaller, comparing the proportion of infected population in the prediction results of the infection models of SI, SIS, and SIR is greater than 0.5, and the proportion of infected population in the prediction results of the infection model of SEIR is less than 0.3. This is in line with the Changchun's epidemic trend, proving that SEIR's infectious disease model can more effectively describe the trend of the new crown epidemic in Changchun.

The comparative image of the data from March 25 to April 13 is plotted as shown in Fig. 5 below.

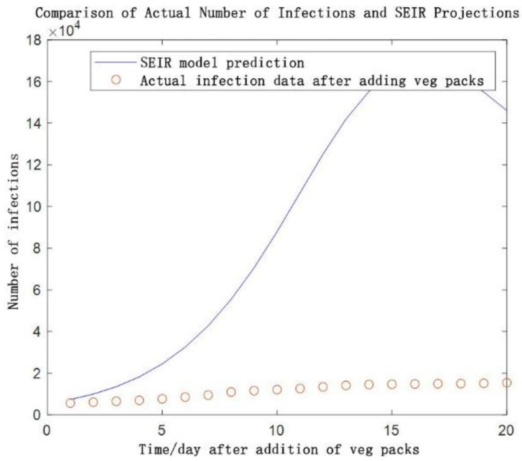

Fig. 5 Comparison between the predicted data and the actual infection data after the addition of vegetable packs

From Fig. 5 above, it can be seen that the number of infected people predicted by the SEIR model is more than twice as much as the actual number of infected people after the addition of the vegetable packs, which shows that the epidemic has been obviously controlled after the vegetable packs appeared. From this, we can get the following conclusion: the number of infected people in Changchun City increased rapidly before the implementation of vegetable packages, and the number of infected people increased slowly after the implementation of vegetable packages, and eventually did not increase, which played a positive role in stopping the epidemic.

3. Scientific Distribution of Living Materials

In this paper, through the establishment of multi-Step based multi-layer LSTM deep learning time series model, the vegetable package supply program from April 10 to April 15 is predicted to be compared with the real program, and then the adjustment of the program is carried out. The specific process is as follows:

Firstly, the docking situation (including the number of vegetable packages, the total amount of vegetables, and the issued quantity) and the self-picked situation (self-picked vegetable packages, the total amount of self-picked vegetables, and the issued quantity) of nine districts in Changchun City from March 26 to April 9 are counted, after which the LSTM network structure is constructed, and the trained prediction values are used instead of the base values so that the later prediction data can be realized as continuous prediction. Extrinsic factors that may affect the vegetable package supply scheme are collected, and a multilayer LSTM model trained in the same way is constructed, after which the data obtained from mutation prediction is used for sequence replacement. Finally, by solving the model, the vegetable package supply scheme from April 10 to April 15 is derived and adjusted for comparison.

3.1. Establishment of Multi-Step Based Multi-Layer LSTM Time Series Prediction Models

Select the short-term information in the time series that can be learned in depth, construct a deep neural network that conforms to its change pattern, and further identify it as a Long Short-Term Memory neural network (LSTM).

Establish the Multi-Step based multi-layer LSTM deep learning time series model, firstly, adjust the time unit, due to the long prediction time, choose the recursive strategy, and at the same time, analyze the role of the influence of the other factors during this period of time as the input factor in the network, and then combined with the improved particle swarm algorithm to accelerate the speed of the model computation.

LSTM is an improved network formed by adding long and short-term memory units to the hidden layer of the recurrent neural network, including forgetting gates, input gates, and output gates, which is used to control the use of historical information, and its network structure is shown in Fig. 6.

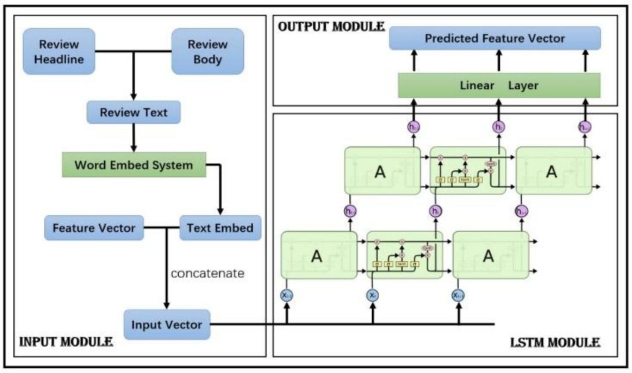

Fig. 6 Improved LSTM network structure

In the above Fig. 6, s_{t-1} is the long-term state input, h_{t-1} is the short-term state input, $f(t)$ is the output of the forgetting gate, which transmits part of the time series discarded or deleted at the previous moment; after entering the short-term state, 4 input gate structures are set up, of which $i(t)$, $g(t)$ and $w(t)$ are mutation prediction and $x(t)$ is the ordinary sequence prediction, and the corresponding excitation function is tanh.

When entering the long-term state, the deep neural network prediction, when the error tolerance is satisfied, the next step is to replace the short-term sequence, output the prediction information h_t, while the short-term state information of the previous moment h_{t-1} through the forgetting gate and the long-term state information s_{t-1} combined, constituting the current long-term state information of the LSTM s_t; when the error tolerance is not satisfied, the feedback signals are passed to the two ends, and in the training phase to pass the error function, and thus the LSTM network predicts again.

Considering the prominent influence of the external environment on the transportation of vegetable packages, multiple activation functions are set when constructing the input gate of the LSTM network for the prediction of the mutation amount, which makes the final model closer to the complex actual situation.

Assuming that the hidden layer weight coefficients and bias terms of the input gate are $U_i, b_i, U_g, b_g, U_w, b_w$ The hidden layer weight coefficients and bias terms of the output layer are W_o, U_o, b_o, the forward algorithmic process used by LSTM to make predictions is:

(1) Oblivious gate calculation equation

$$f(t) = \sigma(U_f h_{t-1} + b_f) \tag{8}$$

(2) Input gate calculation formula

$$i(t) = \sigma(U_i h_{t-1} + b_i) \tag{9}$$

$$g(t) = \sigma(U_g h_{t-1} + b_g) \tag{10}$$

$$w(t) = \sigma(U_w h_{t-1} + b_w) \tag{11}$$

$$x(t) = \tanh(U_x h_{t-1} + b_x) \tag{12}$$

$$x(t) = \tanh(U_x h_{t-1} + b_x) \tag{13}$$

(3) Output Gate Calculation Equation

$$h_t = \tanh(s_{t-1}) + i(t) + g(t) + w(t) + x(t) \tag{14}$$

where the input sigmoid function and the output tanh function are obtained by derivation respectively:

$$\begin{cases} \sigma(z) = y = \dfrac{1}{1+e^{-z}}; \sigma'(z) = y(1-y) \\ \tanh(z) = y = \dfrac{e^z - e^{-z}}{e^z + e^{-z}}; \tanh'(z) = 1 - y^2 \end{cases} \tag{15}$$

Finally, after a complete LSTM calculation, the output value 2 is the target prediction value.

3.2. Results of the Model

The comparison results are visualized as shown in Fig. 7 below.

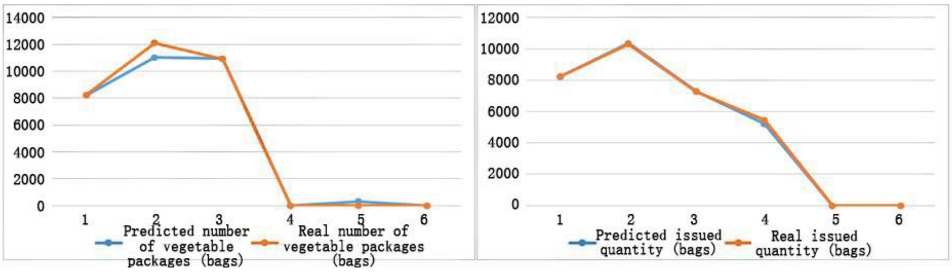

Fig. 7 Comparison of partial prediction results with real results

From Fig. 7, it is known that the multi-Step based multi-layer LSTM time series prediction model established in this paper predicts the results accurately.

4. Conclusion

This study systematically reveals the complex interaction between the distribution of household goods and communication dynamics by constructing a multidimensional analytical framework. The results show that the centralized distribution model significantly reduces the growth rate of the affected population by reducing non-essential outings, and its intervention effect is quantitatively verified in the improved SEIR model. The model breaks through the limitations of the traditional communication model, and effectively portrays the coupling mechanism between resource allocation and the communication process through the introduction of material distribution variables. At the application level, the multi-Step multilayer LSTM-based material demand prediction model shows high prediction accuracy, and its ability to dynamically integrate historical data and external disturbances provides technical support for the scientific formulation of distribution programs. It is found that accurate matching of material supply and demand can be realized through predictive data-driven resource scheduling, thus reducing the risk of dissemination while safeguarding people's needs. The innovation of this study lies in the interdisciplinary integration of the material distribution system with the communication dynamics model, which breaks through the limitations of single-field research. The results of this study not only provide an analytical paradigm for similar public health events, but also provide theoretical support for the construction of an intelligent prevention and control system.

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