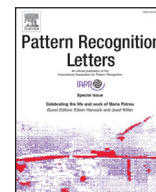




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# Prediction on transmission trajectory of COVID-19 based on particle swarm algorithm



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## ABSTRACT

This study aimed to predict the transmission trajectory of the 2019 Corona Virus Disease (COVID-19). The particle swarm optimization (PSO) algorithm was combined with the traditional susceptible exposed infected recovered (SEIR) infectious disease prediction model to propose a SEIR-PSO prediction model on the COVID-19. In addition, the domestic epidemic data from February 25, 2020 to March 20, 2020 in China were selected as the training set for analysis. The results showed that when the conversion rate, recovery rate, and mortality rate of the SEIR-PSO model were 1/5, 1/15, and 1/13, its predictive effect on the number of people diagnosed with COVID-19 was the closest to the real data; and the SEIR-PSO model showed a mean-square errors (MSE) value of 1304.35 and mean absolute error (MAE) value of 1069.18, showing the best prediction effect compared with the susceptible infectious susceptible (SIS) model and the SEIR model. In contrary to the standard particle swarm optimization (SPSO) and linear weighted particle swarm optimization (LPSO), which were two classical improved PSO algorithms, the reliability and diversity of the SEIR-PSO model were higher. In summary, the SEIR-PSO model showed excellent performance in predicting the time series of COVID-19 epidemic data, and showed reliable application value for the prevention and control of COVID-19 epidemic.

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## 1. Introduction

Since the outbreak of the 2019 Corona Virus Disease (COVID-19) at the end of 2019, it has become a global pandemic [1]. It appeared in early December 2019 in China, reached peak from the end of January to early February 2020, and then was steadily declining. The domestic COVID-19 has been effectively controlled with the concerted efforts of the people across the country. However, it is still spreading around the world. As of May 25, 2021, a total of 16.903 million people have been diagnosed globally, and a total of 3.483 million people have died. There are currently 15.074 million confirmed cases, and it is the severest in the United States, India, and Brazil. For example, the number of confirmed cases in a single day on May 25 was as high as 196,000 in India, and the highest number of new cases in a single day was over 400,000, which directly led to the collapse of the Indian medical system. At present, although several countries have developed a vaccine against COVID-19 virus, the vaccination rate is slow, the vaccination rate is low, so that the herd immunity is far from being achieved, so the new crown epidemic is still not optimistic.

There are two main ways of transmission of COVID-19. One is to spread through the respiratory tract in the form of droplets, and the other is to spread through close contact. At present, the main preventive measure is to wear masks (such as medical surgical masks and n95 masks), to avoid going to crowded places, and to actively carry out the vaccination and so on [2-4]. The main clinical manifestations of COVID-19 are fever, dry cough, fatigue, and diarrhea. Some patients may have no obvious clinical symptoms after being infected [5]. The clinical manifestations of COVID-19 in adults and children are also different. Some adult patients have good disease resistance and less virus in their bodies. After being infected with the COVID-19, their condition is mild, and may be accompanied by mild fever, cough, weakness, and other uncomfortable symptoms, but there may be no signs of pneumonia by lung imaging examination; while some patients with mild symptoms may suddenly deteriorate, with acute dyspnea syndrome, organ failure, etc., and it may lead to death if not treated in time [6,7]. Children infected with COVID-19 have no typical clinical manifestations, and their symptoms are milder than adults; and it may be just a slight malaise, or a mild loss of appetite and nausea in serious case [8].

Reports show that the shortest and longest incubation period of COVID-19 are 0d and 24d, respectively, so the average incubation

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tion period is 5.2d. In addition to patients with COVID-19, asymptomatic infections may also be the source of infection of new coronary pneumonia. To prevent and control the epidemic as soon as possible, the spread prediction of COVID-19 is also very important in addition to avoiding close contact [9,10]. Although the COVID-19 in China has been effectively controlled, confirmed cases from abroad are still in severe form. Therefore, the spread risk assessment of the COVID-19 and the prediction of the spreading law are very important to the prevention and control of the COVID-19.

Based on above introduction and analyzed, a SEIR-PSO hybrid model for the spread of COVID-19 was proposed and applied to predict the number of people diagnosed with COVID-19 in this study, so that the disease could be predicted, prevented, and controlled effectively.

## 2. Methods

### 2.1. Classical model of traditional SEIR disease dynamics

The core issue of epidemiology is the spreading modeling and risk assessment of infectious diseases. The current infectious disease models include statistical models, Agentbased models, cellular automata models, and propagation physical dynamics models [11]. SEIR is a classic transmission physical dynamics model, which can specifically simulate the spread of diseases among different groups. It is different from the traditional classic dynamics model and is added with new exposure mechanism [12], so it is more suitable for the modeling and prediction of COVID-19 virus.

The SEIR model divides the population of the simulated test area into four categories: susceptible population in group S, the latent population in group E, the infectious population in group I, and the removal population in group R. The physical process of the spread of COVID-19 virus is driven by population movement. It is assumed that the following differential equations can be established at different time nodes:

$$\frac{DS(t)}{Dt} = \frac{S(t)}{A} \frac{B}{Z_I} I(t) \quad (1)$$

$$\frac{DE(t)}{Dt} = \frac{S(t)}{A} \frac{B}{Z_I} I(t) + \frac{S(t)}{A + \sum in_{(a,b)}} \times \left( \sum in_{(a,b)} P_{(b,t)} \frac{B}{Z_I} \right) - \frac{E(t)}{T_E} \quad (2)$$

$$\frac{DI(t)}{Dt} = \frac{E(t)}{T_E} - \frac{I(t)}{T_I} \quad (3)$$

$$\frac{DR(t)}{Dt} = \frac{I(t)}{T_I} \quad (4)$$

In the equations (1) - (4) above,  $S(t)$ ,  $E(t)$ ,  $I(t)$ , and  $R(t)$  represented the number of people in the 4 groups at the moment  $t$ ;  $A$  represented the total population of the 4 groups;  $D$  referred to the differential operator;  $B$  was the basic infection number;  $in_{(a,b)}$  represented the population flow index flowing a spatial unit  $a$  to  $b$  in a certain area;  $P_{(b,t)}$  represents the infection probability of the spatial unit  $b$ ;  $T_E$  meant the length of incubation period, and  $T_I$  was the length of the infection period. If  $P_\alpha$  was to express the probability of a latent person transferring from  $E$  to  $I$ ,  $P_\beta$  was to express the probability of  $S$  being infected by  $I$  and transferred to  $E$ ,  $P_\gamma$  was to express the probability of  $S$  being infected by  $E$  and transferred to  $E$ ,  $P_\chi$  was the probability of  $I$  die, and  $P_\delta$  referred to the probability of  $I$  cured, then the number of susceptible population in group S can be expressed as Eq. (5) below:

$$\frac{DS(t)}{Dt} = -\frac{P_\beta S(t)I(t)}{A} - \frac{P_\gamma S(t)E(t)}{A} \quad (5)$$

The number of latent population in group E could be written as follows:

$$\frac{DS(t)}{Dt} = \frac{P_\beta S(t)I(t)}{A} + \frac{P_\gamma S(t)E(t)}{A} - P_\alpha E(t) \quad (6)$$

The number of infected population in group I could be expressed as Eq. (7):

$$\frac{DI(t)}{Dt} = P_\alpha E(t) - P_\chi I(t) - P_\delta I(t) \quad (7)$$

The number of removal population in group R was calculated as follows:

$$\frac{DR(t)}{Dt} = P_\chi I(t) + P_\delta I(t) \quad (8)$$

The specific structure of SEIR model was given as Fig. 1.

### 2.2. COVID-19 prediction model of based on PSO algorithm

Particle Swarm Optimization (PSO) is a heuristic swarm parallel algorithm proposed by Kennedy et al. in the 1990s. In this study, it was assumed that in a multi-dimensional search space, a particle swarm  $L$  with  $z$  particles was initialized, then the position information of the particles in the  $L$  can be expressed by the following equation:

$$L = (L_1, L_2, L_3, \dots, L_z) \quad (9)$$

In the particle swarm  $L$ , the position of each particle corresponded to a  $n$ -dimensional vector, and the position information of the  $m^{th}$  particle in the  $n$ -dimensional space can be expressed by the Eq. (10) below:

$$L_m = (L_{m1}, L_{m2}, L_{m3}, \dots, L_{mn})^T \quad (10)$$

Similarly, the velocity of each particle corresponded to a  $n$ -dimensional vector, and the velocity of the  $m^{th}$  particle in the  $n$ -dimensional space can be expressed as follows:

$$V_m = (V_{m1}, V_{m2}, V_{m3}, \dots, V_{mn})^T \quad (11)$$

In the PSO algorithm, each particle has to be performed with the iterative optimization to approach the position of the global optimal solution, during which, the historical best position ( $pbest_m$ ) and the swarm best position ( $gbest_m$ ) that each particle passed can be expressed by the following equations:

$$pbest_m = (pbest_{m1}, pbest_{m2}, pbest_{m3}, \dots, pbest_{mn})^T \quad (12)$$

$$gbest_g = (gbest_{g1}, gbest_{g2}, gbest_{g3}, \dots, gbest_{gn})^T \quad (13)$$

The iterative equations for velocity and position of particle  $m$  at time  $t+1$  in this algorithm can be expressed by the following equations:

$$V_{mn}(t+1) = V_{mn}(t) + \omega_1 \rho_1 [pbest_{mn}(t) - L_{mn}(t)] + \omega_2 \rho_2 [gbest_{gn}(t) - L_{mn}(t)] \quad (14)$$

$$L_{mn}(t+1) = L_{mn}(t) + V_{mn}(t+1) \quad (15)$$

In the above equations,  $V_{mn}(t+1)$  referred to the  $n^{th}$  dimensional velocity of the  $m^{th}$  particle at time  $t+1$ ;  $\omega_1$  and  $\omega_2$  represented the cognitive factor and social factor, respectively;  $\rho_1$  and  $\rho_2$  were random numbers that obeyed the normal distribution, with the value range of [0,1];  $gbest_{gn}(t)$  referred to the best location of any particle in the  $n$ -dimensional at time  $t$ ; and  $L_{mn}(t+1)$  represented the position of  $m^{th}$  particle in the  $n$ -dimensional space at time  $t+1$ .

The PSO algorithm essentially co-evolves through mutual cooperation and information sharing among individual particles. It includes two processes: random search and information transmission. In information transmission, the neighborhood topology of the particle swarm plays the most direct and effective role. However, it is easy for the particle swarm to quickly gather in the local optimal solution due to the high propagation rate of shared information. The PSO algorithm contains two topological structures.

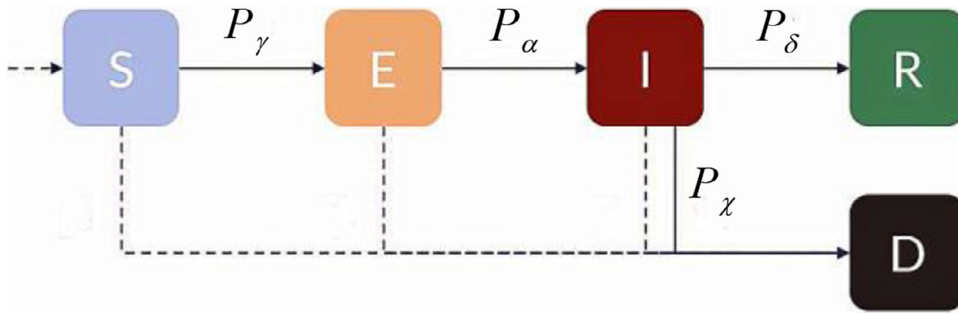


Fig. 1. Schematic diagram of SEIR model.

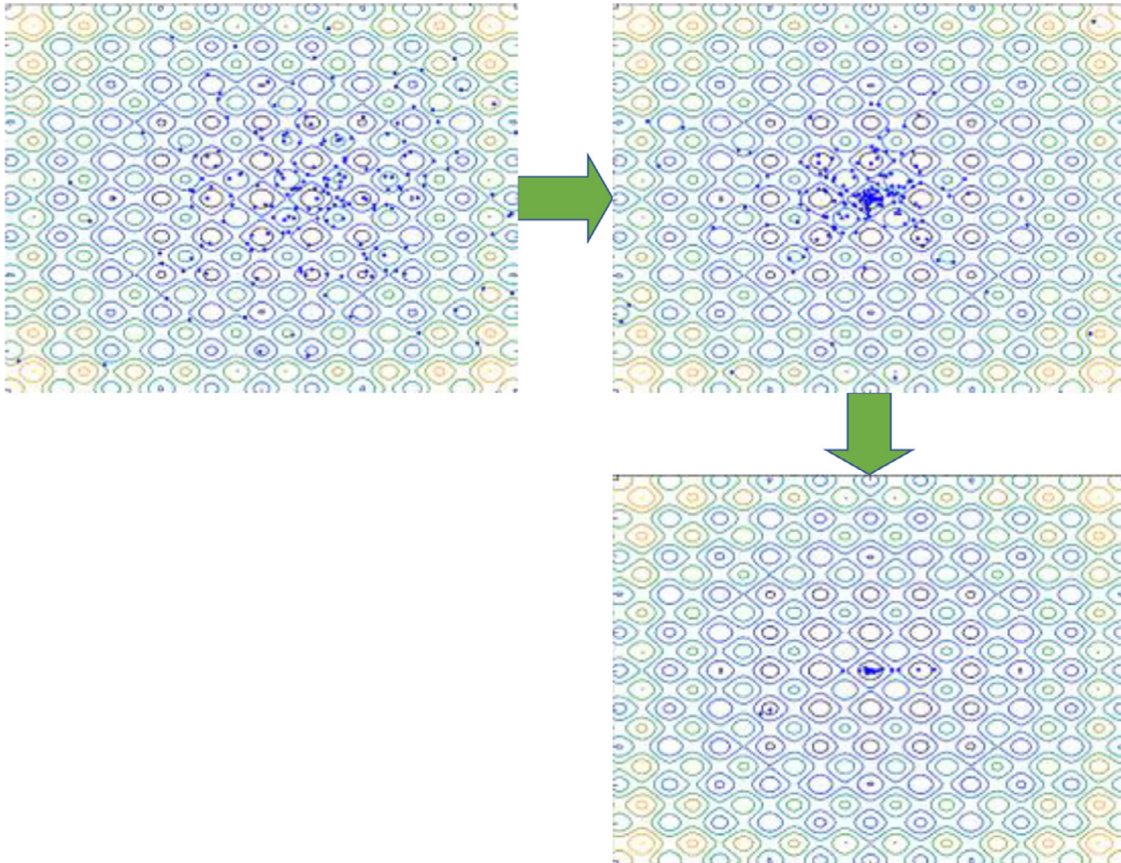


Fig. 2. Optimal process of PSO.

The topological structure of the particles in the iterative process is called static network topology. During the iterative process, the particles can dynamically adjust the neighborhood network according to factors such as population density or their own location, which is called dynamic network topology. However, both network structures are based on fully coupled networks. Therefore, the computational defects of the traditional PSO algorithm can be improved by suppressing the information dissemination rate of the PSO algorithm and ensuring the diversity of the population during dissemination. The specific process can be observed in Fig. 2.

In order to more accurately extract the data information in the PSO model, the SEIR model and the traditional PSO model were adopted to perform linear regression modeling, and the SEIR-PSO hybrid model was proposed, which reduced the information transmission rate of the traditional PSO algorithm. It was believed in this study that there was a linear correlation between the SEIR model and the PSO model, so a multivariate linear equation can be constructed, and the predicted value of the SEIR-PSO model calcu-

lated by linear regression can be expressed as follows:

$$\hat{f} = Hx + c \tag{16}$$

In the above Eq. (16),  $\hat{f}$  represented the prediction result of the SEIR-PSO model;  $H$  referred to the coefficient matrix;  $x$  represented the model independent variables, and  $c$  was the bias unit. To ensure the  $\hat{f}$  was more closer to the true value  $f$ , the following loss function was defined in this study to solve the optimal parameters:

$$Y = \frac{1}{n} \sum_{i=1}^n (\hat{f}_i - f_i)^2 \tag{17}$$

When the  $H$  and  $c$  under minimized loss function were required, the optimization function can be converted to Eq. (18) below:

$$(\hat{H}, \hat{c}) = \arg \min_{(H,c)} \sum_{i=1}^n (Hx_i + c - f_i)^2 \tag{18}$$



When the SEIR-PSO model was trained, the least squares method can be used to optimize the parameters. When the SEIR-PSO algorithm was used for calculation, the introduction of the SEIR model slowed down the spread of information and enhanced the wide-area search capability. Each iteration of the SEIR-PSO algorithm reduced the diameter of the topological network structure contained in the PSO, enhanced the local exploration capability of the algorithm, gradually accelerated the convergence rate, and finally converged to the global optimal solution.

### 2.3. Evaluation method of SEIR-PSO model

The Mean-Square Errors (MSE), Mean Absolute Error (MAE), Reliability, and Diversity were adopted to evaluate the calculation performance of the SEIR-PSO algorithm model. MSE reflected the deviation between the predicted value of the model and the true value, and the function expression was as follows:

$$MSE = \sqrt{\frac{\sum_{i=1}^n (\hat{f}_i - f_i)^2}{n}} \quad (19)$$

In the equation above,  $\hat{f}_i$  represented the predicted value of the SEIR-PSO model on the  $i^{\text{th}}$  day, and  $f_i$  referred to the true value on the  $i^{\text{th}}$  day.

The MAE value reflects the actual situation of the error of the predicted value of the algorithm, and its function expression was given as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{f}_i - f_i| \quad (20)$$

Reliability reflects the ratio of the number of experiments that the algorithm reaches the preset conditions to the total number of times, and its function expression could be written as equation below:

$$Reliability = \frac{r}{R} \times 100\% \quad (21)$$

In the above Eq. (21),  $r$  represented the number of trials for the algorithm in this study to meet the accuracy requirements, and  $R$  represented the total number of experiments.

The level of Diversity reflects the computational performance of the algorithm. The decrease of Diversity will cause the PSO algorithm to fall into a local optimal solution. The function expression was as follows:

$$Diversity = \frac{\sum_{i=1}^{\mathfrak{N}} \|x_i - x'\|_2}{\mathfrak{N} \times l} \quad (22)$$

In the Eq. (22),  $\mathfrak{N}$  represented the size of the particle swarm;  $x$  was a convergent feasible solution of the algorithm, and  $l$  referred to the distance between the two most distant points in the search space of the SEIR-PSO algorithm.

### 2.4. Statistical analysis

The SPSS22.0 software was adopted to perform statistical analysis on the data of this study. Counting data were expressed in% and tested with  $\chi^2$ . The two independent samples were tested using  $t$ .  $P < 0.05$  indicated that the difference was statistically significant.

## 3. The experimental results

### 3.1. Predicted results on the number of people infected with COVID-19

Since the domestic epidemic situation has stabilized, the domestic epidemic data from February 25, 2020 to March 20, 2020

were selected as the training set in this study, and the SEIR-PSO model was adopted to predict the number of people diagnosed within 24 days. The prediction results were shown in Fig. 3. The prediction result of the SIS (susceptible infectious susceptible) model was higher than the real data, the prediction result of the SEIR (susceptible exposed infectious recovered) model was closer to the real data, and the prediction result of the SEIR-PSO model proposed in this study was more similar to the real data. However, it was found in this study that the prediction results of the three models suffered from some deviations compared with the real data. The number of confirmed infected people was small, and the fluctuation of various external factors would cause the real data to change, but it was impossible for the algorithm to take into account external interference factors.

### 3.2. Impacts of SEIR-PSO model parameters on the prediction results

Affected by many aspects, the accuracy of SEIR-PSO algorithm in this study was not high enough in predicting the number of confirmed cases. Therefore, the model parameters were revised to predict the spread of COVID-19 and analyze the effects of different parameters on the prediction results. It is known that main parameters that affect the prediction results of the SEIR-PSO algorithm are  $P_\alpha$ ,  $P_\beta$ ,  $P_\gamma$ ,  $P_\chi$ , and  $P_\delta$ . In the above 5 parameters,  $P_\alpha$ ,  $P_\beta$ , and  $P_\gamma$  represented the infection rates, so only  $P_\alpha$  was analyzed only here.  $P_\delta$  was the recovery rate of the infected persons, and  $P_\chi$  referred to the mortality rate of the infected persons. The quantitative analysis was performed based on the COVID-19 prediction curve and the weighted error to analyze the impacts of conversion rate  $P_\alpha$  from  $E$  to  $I$  on the prediction results. Fig. 4 illustrated the prediction effects when  $P_\alpha$  was in different values. The results showed that when the conversion rate was 1/5, the weighted error of the SEIR-PSO algorithm was 1723.16, which had the best predictive effect on COVID-19.

The recovery rate  $P_\delta$  was changed to analyze the difference caused by the SEIR-PSO model to the prediction results. When different values were taken, the prediction effect was shown in Fig. 5. From the initial data (February 25) to March 2, the prediction trend of the data was different. For different values of  $P_\delta$ , the SEIR-PSO algorithm was assigned different weights. The results revealed that when the recovery rate  $P_\delta$  was 1/15, the weighted error calculated by the SEIR-PSO algorithm was 1746.25, showing the best predictive effect on COVID-19. In addition, it was found that as time increased, the larger the  $P_\delta$  value, the better the prediction effect.

The mortality rate  $P_\chi$  was changed to analyze the difference caused by the SEIR-PSO model to the prediction results. When different values were taken, the prediction effect was shown in Fig. 6. The results showed that when the mortality rate  $P_\chi$  was 1/13, the weighted error calculated by the SEIR-PSO algorithm was 1819.24, which had the better predictive effect on COVID-19 than that at other value.

### 3.3. Comparisons on evaluation results of three different models

The SEIR-PSO algorithm proposed in this study was compared with the SIS and SEIR models based on the domestic epidemic data from February 25, 2020 to March 20, 2020 for training. The  $P_\alpha$ ,  $P_\beta$ , and  $P_\chi$  values of SEIR-PSO algorithm were set as 1/5, 1/15, and 1/13, respectively. The prediction results of different algorithms were shown in Fig. 7. The results revealed that the training effect of the SIS model was poor, because it paid too much attention to the fitting of each training data, which led to overfitting during training; the SEIR model included more input variables, but less training data during model training, there was also an overfitting. However, the SEIR algorithm took into account the transi-

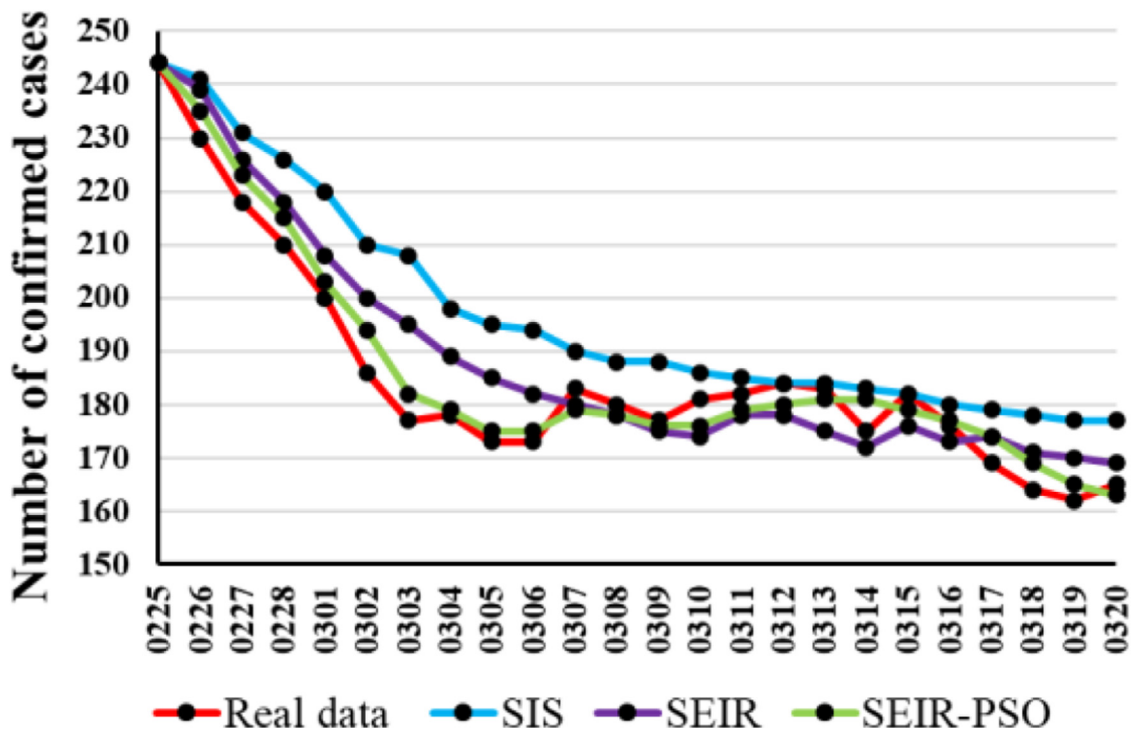


Fig. 3. Comparison on the number of confirmed people based on different prediction methods.

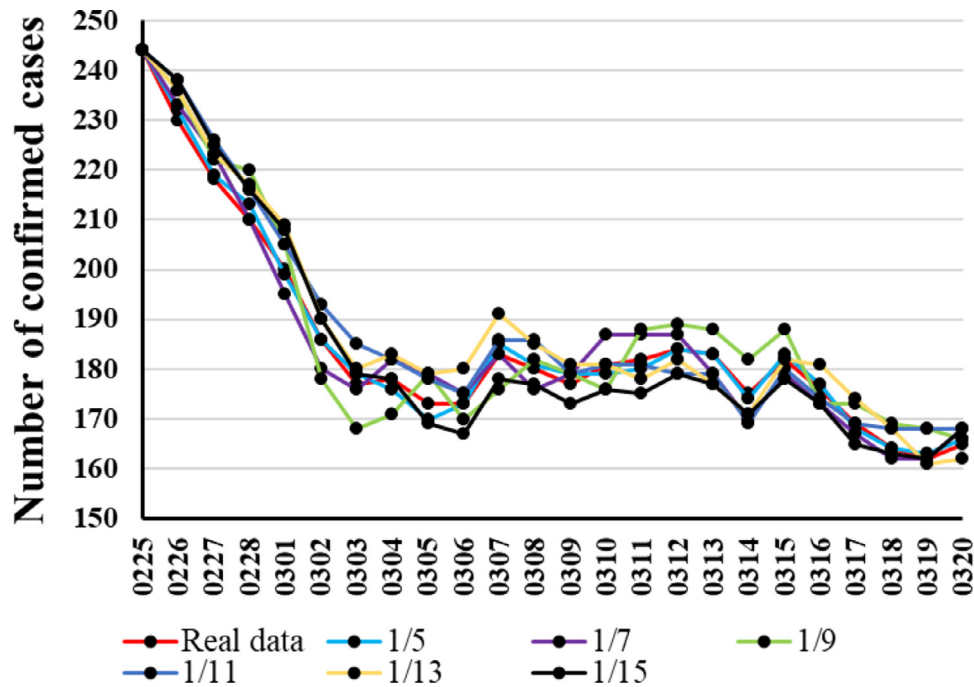


Fig. 4. Impacts conversion rate  $P_{\alpha}$  on prediction results of SEIR-PSO model (a: difference in prediction results of diagnosed people at different conversion rates; and b: comparison on weighted errors at initial value of conversion rate  $P_{\alpha}$ ).

tion among different states, so the training result was better than that of the SIS model. In addition, the SEIR-PSO algorithm prediction results showed that the MSE value was 1304.35 and the MAE value was 1069.18, which were much higher than the those of the SIS model (876.9 and 661.29) and the SEIR model (1002.31 and 845.44), and the differences were statistically obvious ( $P < 0.05$ ).

Reliability and Diversity were adopted to analyze the SEIR-PSO algorithm proposed in this study, and two classical improved PSOs:

standard particle swarm optimization (SPSO) and linear weighted particle swarm optimization (LPSO) were introduced for analysis. As illustrated in Fig. 8, the Reliabilities of the SEIR-PSO, SPSO, and LPSO algorithms were  $5.63E-61$ ,  $16.1255$ , and  $1.21E-18$ , respectively. It can be seen that the stability of the experimental results of the SEIR-PSO algorithm was much better than that of the SPSO algorithm and the LPSO algorithm, and the difference was statistically obvious ( $P < 0.05$ ), which indicated that the SEIR-PSO algorithm

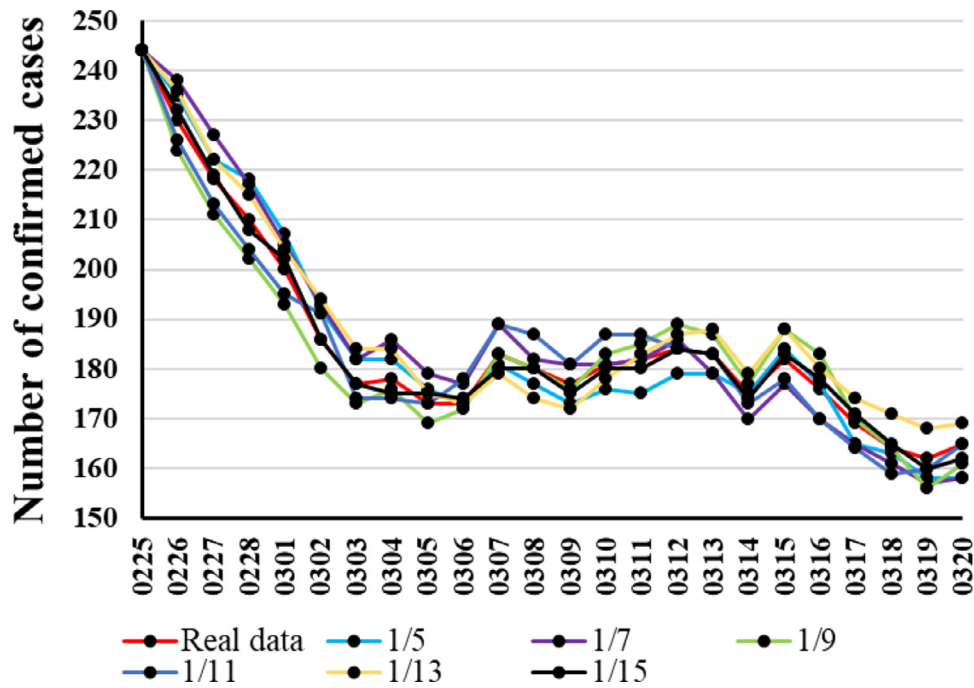


Fig. 5. Impacts recovery rate  $P_\delta$  on prediction results of SEIR-PSO model (a: difference in prediction results of diagnosed people at different recovery rates; and b: comparison on weighted errors at initial value of recovery rate  $P_\delta$ ).

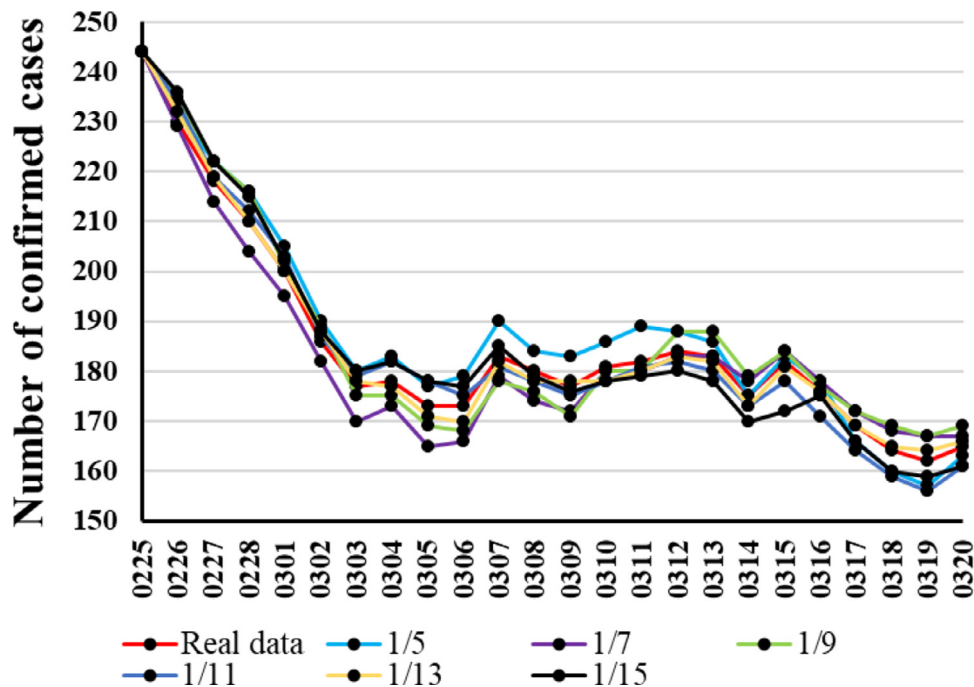


Fig. 6. Impacts mortality rate  $P_\chi$  on prediction results of SEIR- PSO model (a: difference in prediction results of diagnosed people at different mortality rates; and b: comparison on weighted errors at initial value of mortality rate  $P_\chi$ ).

had a slower information transmission rate, wider search range, and longer time. Thus, it can continuously and steadily converge to the global optimal solution, so the calculation results output by the SEIR-PSO algorithm were more stable and reliable. The algorithm diversity analysis revealed that when the improved PSO was optimized, the diversity level of the SEIR-PSO algorithm proposed in this study was higher than that of the SPSO algorithm and the LPSO algorithm, and the decrease was slower with the increase of

the number of iterations. It suggested that the SEIR-PSO algorithm had better search capabilities and a higher probability of obtaining the global optimal solution. As the number of iterations increased, the diversity of SPSO calculations decayed rapidly, causing the SPSO algorithm to fall into a local optimum in the multi-peak solution space. The LPSO algorithm also showed an insignificant convergence trend, resulting in slow propagation rate and too higher randomness of particle search in the information transmis-

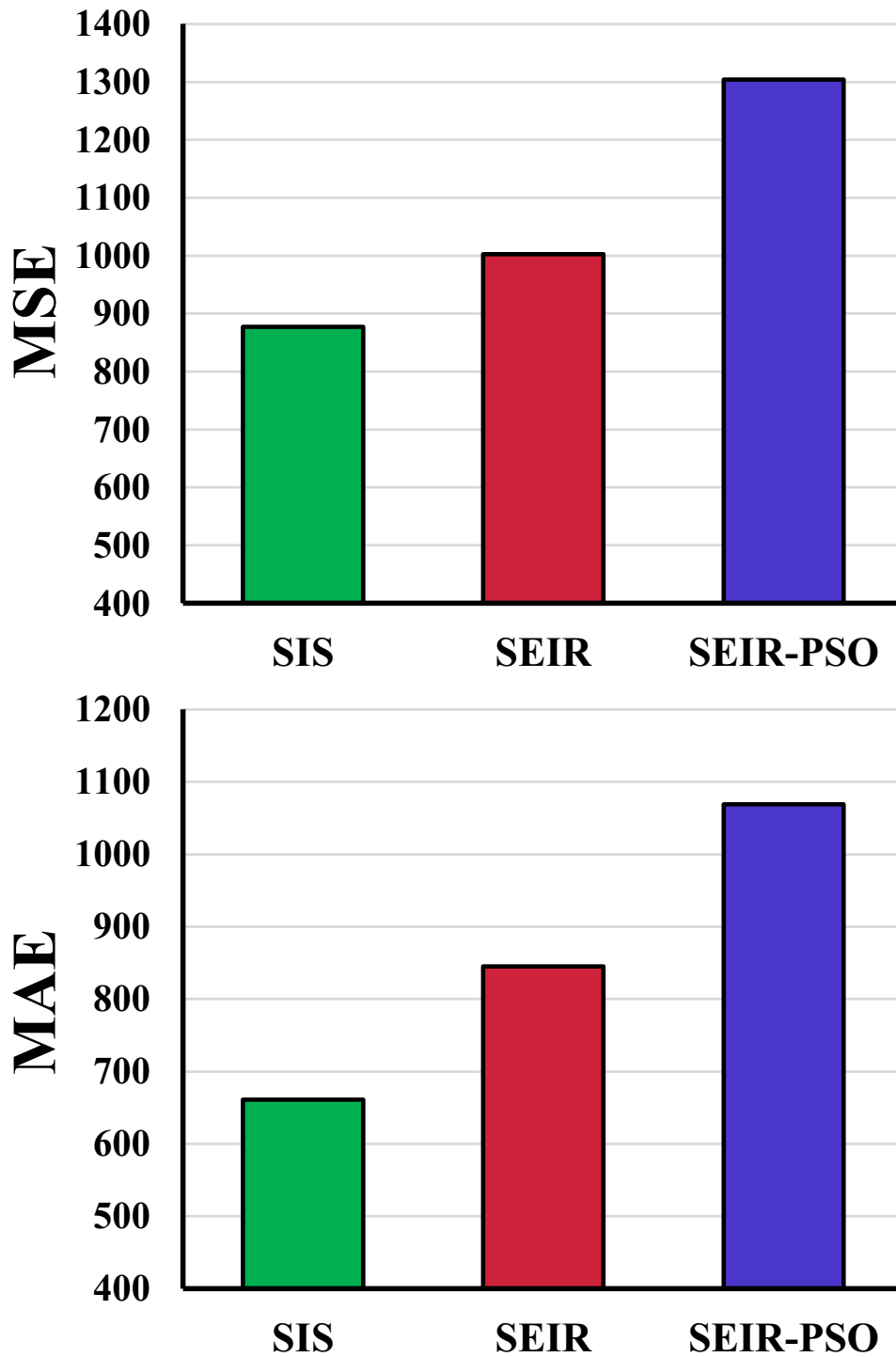


Fig. 7. Comparison on results of different prediction models.

sion process, which also made the LPSO algorithm unable to obtain the global optimal value.

#### 4. Discussion

Since December 2019, the COVID-19 has spread worldwide, with a case fatality rate of 2.1%. COVID-19 shares up to 75% homology with SARS but is not the same as SARS. Studies have found that COVID-19 belongs to a new type of  $\beta$ -coronavirus, and its

genome sequence consists of approximately 29kb with 10 genes, which can effectively encode 10 proteins [13,14]. At present, the mechanism of infection invasion is not clear. Some studies speculate that the possible mechanism is that COVID-19 can combine with angiotensin-converting enzyme 2 on human cells to cause human infection, thereby inducing the body's excessive immune response and causing multiple organ damage [15,16]. There is currently no specific medicine for the treatment of COVID-19, and the prevention and control of the epidemic still relies on nucleic acid



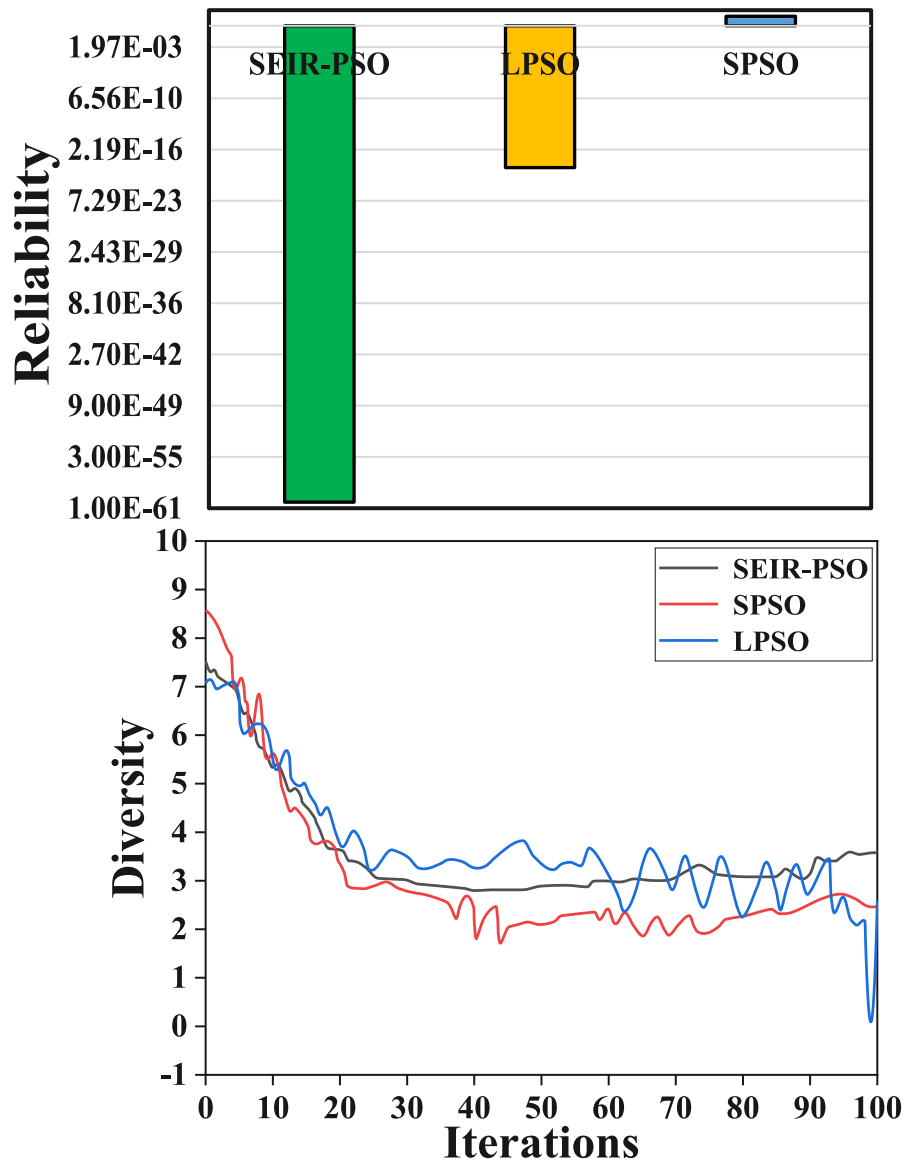


Fig. 8. Reliability and Diversity comparison based on different algorithms.

testing and vaccination [17]. The vaccination rate in China is relatively high, but the population base is large, resulting in a low vaccination rate. Therefore, predicting the development trend of COVID-19 is still an important task.

The transmission trajectory prediction of COVID-19 is to construct an accurate disease prediction model with less data. In this study, the PSO algorithm was combined with the traditional SEIR infectious disease prediction model to propose a SEIR-PSO COVID-19 prediction mode. The proposed model inherited the excellent spatial local search capabilities of the traditional PSO algorithm, and integrated the autocorrelation of infectious disease prediction of the SEIR model. It was believed in this study that the prediction results of the SEIR-PSO model were related to five parameters, which could be divided into three categories: conversion rate, recovery rate, and mortality rate. In this study, the domestic infection data of the COVID-19 for a total of 24 days from February to March 2020 were selected for prediction. It was found that the SEIR-PSO model proposed in this study could predict the number of confirmed persons infected with COVID-19, but the predictive accuracy was not enough. Therefore, the prediction results were reevaluated by changing the parameters of the SEIR-PSO algorithm

and analyzing the prediction effect and weighted error under different parameter values. It was found that when the conversion rate was  $1/5$ , the recovery rate was  $1/15$ , and the mortality rate was  $1/13$ , the SEIR-PSO algorithm had the smallest weighted error value and had the highest predictive effect on COVID-19. In addition, the algorithm proposed in this study was compared with the other two infectious disease prediction models and found that both the SIS model and the SEIR model suffered overfitting during model training, but the SEIR model had a better prediction effect than the SIS model. The reason might be that the SEIR model took into account the transition among different states, and the SEIR-PSO algorithm had the common advantages of the PSO algorithm and the SEIR prediction model. The prediction results showed that the MSE value of the SEIR-PSO algorithm was 1304.35, and the MAE value was 1069.18, so the SEIR-PSO algorithm had the best prediction effect. Two classic improved PSO algorithms (SPSO and LPSO) were introduced in this study for comparative analysis to verify the calculation effect of the SEIR-PSO algorithm. The results suggested that compared with the SPSO algorithm and the LPSO algorithm, the SEIR-PSO algorithm was more reliable, and its diversity decreased slowly with the increase of the number of iterations.

This indicated that the SEIR-PSO algorithm limited the propagation rate of the traditional PSO algorithm by introducing the SEIR model, so it had better search capabilities and could continuously and stably converge to the global optimal solution, with more reliable output calculation results.

## 5. Conclusion

A SEIR-PSO hybrid model for the spread of COVID-19 was proposed and applied to predict the number of people diagnosed with COVID-19 in this study. The results showed that when the conversion rate was 1/5, the recovery rate was 1/15, and the mortality rate was 1/13, the prediction result of the SEIR-PSO model was closest to the real result, showing excellent prediction performance and reliable application value for the prevention and control of the COVID-19. However, when the SEIR-PSO model proposed in this study was adopted to make predictions, it was necessary to assume that the cured cases had obtained permanent immunity, and the data set selected when training the SEIR-PSO model was shorter and the sample size was small. The parameters have to be readjusted in predicting the number of people diagnosed for a longer time. These limitations have to be solved in future work. In summary, the proposed SEIR-PSO model could predict the transmission trajectory of COVID-19 accurately, which was conducive to preventing and controlling the COVID-19, showing great significance in clinic.

## Declaration of Competing Interest

The authors declared that they have no conflicts of interest to this work.

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