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Self-correcting error-based prediction model for the COVID-19 pandemic and analysis of economic impacts

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ABSTRACT
In order to improve the prediction accuracy of COVID-19 and strengthen the economic management and control, a self-correcting intelligent pandemic prediction model is proposed. The research shows that: (1) The pandemic, as a major social factor, has a great impact on the consumption expenditure level of various industries, and directly affects the public consumption expenditure level in different periods for example the spend_all in California decreased by 37.7%; (2) The economic losses caused by the increasingly serious pandemic period far less than the economic losses caused by the panic in the early stage of the pandemic, and the reason is the government’s strong guarantee policies stimulate economic recovery. For example, the spend_all in California has increased from -37.7% to about -18%; (3) The proposed model improves the prediction accuracy of economic trend, and the government can make prediction according to the early warning economic prediction, which provides reference for the economic management control at the micro level of enterprises and the macro level of the nation; (4) The dual strategies of self correcting prediction and pandemic control realize the overall design of real-time control and performance optimization of economic process, and provide reference for the overall recovery of the economy.

1. Introduction
Since the beginning of 2020, the worldwide outbreak pandemic of Corona Virus Disease 2019 (COVID-19) has caused a tremendous economic and social upheaval (Ali et al., 2020), with a vast majority of industries hit hard and resulted in plummeting revenues of the small and medium-sized enterprises. Due to the long incubation period and asymptomatic nature of COVID-19 in super-transmitters, it has led to a rapid spread of the virus across the globe (Li et al., 2020). By the end of October 2020, there were 33,842,281 confirmed cases worldwide, including 101,064 deaths (From WHO website statistics). Decision-makers around the world have being tried recovering the society and economy by enacting different policies and regulations, such as asking the people to get quarantined at their home (BMuhammad & Sheereen, 2020), increasing the back payment of relief (Xie, 2020), accelerating the process of vaccine development (Shafl et al., 2020). Meanwhile, in the control of the pandemic, many companies were affected severely by the environmental crisis (Motl, 2020). The uncertainty of the spread of the pandemic, to some extent, has led to poor government decisions, which can have disastrous consequences for the country’s society and economy (Hernandez-Matamoros et al., 2020). To resolve social problems caused by this pandemic and reduce the impact on the social and economic development (Berger et al., 2020), regional governments need make forecasts based on the trend of the pandemic. Therefore, the establishment of a model, which can effectively predict the economic data, is based on the development trend of the pandemic. The model can help the government valuate the current policy effects and provide a reference basis for the formulation of further policies.

In the literature, there are some research results on pandemic analysis and forecasting methods. There are two main types of mainstream analysis and forecasting methods. The first uses a statistical and mathematical modeling for analysis, and the second method uses a more advanced computer fitting forecasting method. Among the most representative methods in the first type category is the ARIMA (Auto Regressive Integrated Moving Average) model developed by Andres

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Hernandez-Matamoros (Hernandez-Matamoros et al., 2020) that used a polynomial function to compose parameters, such as the population of the country and the number of infected cases to predict the pandemic data. In the study by Zhou et al., a combination of geographic information system (GIS) and data analysis (Zhou et al., 2020) were used to predict the geographical pandemic. Among the second type of method, the representative one is the one adopted by Chanjuan Sun (Sun & Zhai, 2020). The study introduces two new indicators in the popular Wells-Riley model, based on a perfect mix, for predicting the probability of airborne virus-related infections - the underlying causes of maintaining adequate social distance and spatial ventilation. In addition, Abdelrahman E. E. Eltouhy et al. further developed an algorithm based on the nonlinear auto-regressive exogenous input (NARX) neural network (Eltouky et al., 2020), which incorporated the historical data of patients with COVID-19 and public factors such as population, median age index, and public and private healthcare expenditures to obtain a higher accuracy. There are also lots of up-to-date international research on Covid-19 and sustainable development such as data-driven models like the representative one is the one adopted by Chanjuan Sun (Sun et al., 2020), web site (2020), Li et al., 2020, Lilliecrap et al., 2015, Ahmed et al., 2021, Loey et al., 2021, Xing et al., 2020, Aslan et al., 2021, Panahi et al., 2021), and built social environmental factors (Gautam, 2021), living environment matters (A et al., 2020), video surveillance (Ghosh et al., 2020), artificial intelligence (Shorufuzaman et al., 2021), machine learning (Pham et al., 2020, Turkoglu, 2021, Cao et al., 2020, Cao & Ren, 2018, Milojivic-Dupont & Creutzig, 2021, Pourhomayoun & Shakibi, 2021, Arvind et al., 2021, Choudrie et al., 2021), and etc (Rahmani & Mirmahaleh, 2021, Ss et al., 2020, Tang et al., 2019; Tang, Zhang, & Lin, 2020; Jianguo Wang, 2021; Jianguo Wang, Cao, & Yu, 2021; Junqi Wang, Huang, Feng, & Cao, 2021; Xu, Luo, Chuck, & Cao, 2020; Zhang, Tang, Yang, & Zha, 2020; Kaffenberger, 2020). Among these studies, deep learning has become one of the mainstream methods of studying COVID-19, which is considered as a promising direction with prospect and application.

Analyzing the literatures, we found that all of the above mentioned algorithms have certain weaknesses in common: first, the model requires a large amount of data to input in advance, relies heavily on prior data and cannot achieve effective prediction for pandemics without historical data records. Second, the economic factors are not considered. Only the infection rate and mortality rate of the pandemic are simply predicted, and the prediction result is relatively single, which does not have a significant reference significance and practical value for the formulation of a social-economic recovery policy.

Based on the above problems, this study was expected to determine the relationship between the pandemic trends and the social-economic development. A smart pandemic forecasting model named LDPPG was constructed, based on theses data using the LSTM (Long Short-Term Memory) (Peng et al., 2021, Peng et al., 2016, Deng et al., 2019) and the DDGP (Deep Deterministic Policy Gradient) algorithms. The model combined the pandemic and economic data over a time to adjust the prediction parameters dynamically and make reasonable predictions of the social-economic trends, based on daily updated pandemic statistics as the main reference indicators, to help the decision-makers assess the benefits of the current decisions and reference for next decisions. Our study made improvements in the following aspects: first, The innovation of this study is that the proposed model combines the DDPG model with LSTM model. We improved the these two models to suit COVID-19’s prediction. Our model draw lessons from the correction ability of DDGP’s reinforcement learning to improve the accuracy of the prediction model, which updates the slope of existing data to make it approach the trend of real data locally. Then it updates the LSTM network, so as to reduce the error and improve the prediction accuracy. The experimental results shows that the prediction ability and correction ability of the network are improved. Second, the economic data and pandemic development data were integrated and analyzed initially. Subsequently, the data were tracked quickly when the factors changed rapidly with the neural network’s excellent fitting ability. This can provide the policy benefit analysis for the decision-makers. Third, in the real-time updating of the disease prediction scenarios, the output strength of the prediction data was adjusted in real time using the latest data and accelerated the network update function. As a result, the data could be automatically corrected in a short time compared with the rapidly changing and irregular data.

2. Materials and methods

This Section will start with how to obtain and process the data, and discuss the construction of the proposed model and the prediction of the data including the error calculation and network optimization.

2.1. Collected data

Due to the differences and comprehensiveness of the data statistics in different places, we selected the US states preliminary screening, where pandemic and economic statistics data could be easily acquired and recognized by Johns Hopkins University Centre for Systems Science and Engineering (JHU CSH) and the Oxford COVID-19 Government Response Tracker (OxCGRT) . We identified several states with the most representative pandemic characteristics occurring in the US as the study subjects, namely, California, New York, Texas, Washington, Iowa, and Florida. California, New York, Texas, Washington, Iowa, and Florida, and the source of the data were the daily pandemic data of each state from January 2020. The data included the number of deaths, confirmed diagnoses, new confirmed diagnoses, and new deaths. Table 1 shows the data types and descriptions of pandemic statistics. For economic data, credit/debit card spending levels by the industry were selected, which broadly reflected the socio-economic status of society (Blecker, 1989). The contents of the socio-economic data collected in the above states are shown in Table 1 and Table 2.

2.2. Summarized data

After the statistics of the collected data, the summary data are got. Fig. 1 and Fig. 2 indicate that the consumer spending levels in California, New York, Texas, Washington, Iowa, and Florida states showed a strong correlation with the development of the pandemic, exhibiting different trends during the various periods of the pandemic development. During the beginning of the pandemic, even before it spread to the U.S., public panic led to a sharp decrease in spending levels and a sharp drop in income for most SMEs. However, after the decline bottomed out, the consumer spending and economic indicators gradually rebounded due to fear of the pandemic situation.

As Fig. 1 indicates, the growth of the pandemic in the New York State rose rapidly after 61 days, and the main reason for this analysis is that New York is the state with the largest incoming population and the highest mobility of people, which exacerbates the extent of

| Table 1 | Relevant pandemic data |
|-----------------|------------------------|
| **Statistical item** | **Explanation** |
| case_count | Confirmed COVID-19 cases per 100,000 people |
| death_count | Confirmed COVID-19 deaths per 100,000 people |
| new_case_count | New confirmed COVID-19 cases |
| new_death_count | New confirmed COVID-19 deaths |

1 Thomas Hale, Noam Angrist, Rafael Goldszmidt, Beatriz Kira, Anna Petherick, Toby Phillips, Samuel Webster, Emily Cameron-Blake, Laura Hallas, Saptarshi Majumdar, and Helen Tarlow.(2021). “A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker)”.
performance such as the accommodation and food, arts and entertainment, consumer spending sharply declined, and the spread of the pandemic followed by a halt in all types of business and activities, consumer spending fell extremely fast. However, in the recent 121-day mark, the pandemic slowed down significantly, due to executive orders such as mandatory masks and curfews issued in the New York State. Other states, such as California and Florida showed a spike in the number of infections, because the effective control measures were not implemented. On day 31, there was a short-lived rise in the consumer spending, as the pandemic panic led to a mad rush for food in all regions, and increased demand for food meant increased consumption. With a rapid spread of the pandemic followed by a halt in all types of business and community activities, consumer spending sharply declined, and the year-over-year level of consumer spending fell extremely fast.

### 2.3. Data pre-processing

The collected database included data reflecting the development of the pandemic, such as the number of deaths, number of confirmed cases, number of new confirmed cases and number of new deaths in each state of the United States. It also included data reflecting the economic performance such as the accommodation and food, arts and entertainment, storage logistics and clothing accessories, health care and social assistance, warehouse and transportation industry, and the average credit/debit card spending level of low, middle and high income people. Due to the large geographic variation in the number of confirmed diagnoses, all input data were normalized and input into the neural network, and then a reverse normalization step was performed. In this network, the Z-score standardization was used, using the Equation (1).

$$ z = \frac{x - \mu}{\sigma} $$

where $\mu$ is the mean of all sample sizes and $\sigma$ is the standard deviation of all sample data.

In addition, the discrepancies in the published data and the data did not change for more than five days. It was combined to strengthen the network’s sensitivity in the changing trends.

#### 2.4. The network construction

Our study focused on the learning of the existing pandemic data by building a LSTM neural network. In the learning process, every 5-day data for each region included the number of diagnoses, deaths, cures and the consumption expenditure data of each industry in Table 2, which were combined into a set of data and fed into the neural network for learning the trend. We replaced the traditional LSTM’s front convolution layer with a basic fully connected layer to enhance the fitting ability of the data, and used multiple LSTM-connected layers in the network for fitting the data, which is a definable Dropout layer in the middle to prevent over-fitting. Finally, we used the Adam activation function in the output layer to activate the data. To improve the fitting ability of local data, we designed a deep reinforcement learning retraining the data tracking algorithm.

#### 2.4.1. Trend Forecasting Network

The LSTM network is a modified version of the recurrent neural network (RNN) (Sh et al., 2020, Peng et al., 2021), and designed specifically to solve the long-term dependence problem in general RNN networks. The basic component of the LSTM network is storage blocks, specifically to solve the long-term dependence problem in general RNN networks. The basic component of the LSTM network is storage blocks, with the help of an activation function (Sigmoid or tanh), and the output has a value between 0 and 1. Since the output information only must pass positive values to the next Gates, it was sufficient to use the Sigmoid activation function, followed by the tanh function to scale the values between [-1, 1]. These three gates and cell states of the LSTM are represented by the following Equation (2) to (5). The LSTM cellular...
The deterministic policy is one, in which the action is performed by a single-step reward value returned by the environment after the state $s_t$ interact with the environment to generate the next state $s_{t+1}$ and $R_t$ is the reward value of the next state. The reward value of the next state $R_t$ is only related to the current state $s_t$ and the next action $a_{t+1}$. For the action-value function of the critic network output, a part was used to calculate the mean square error shown with Equation (9), which was used to update the Actor section of the network as shown in Equation (10).

$$L = \frac{1}{N} \sum_i (y_i - Q(s_i, a_i|\theta))^2$$

$$\nabla_{\theta} L | \theta \approx \frac{1}{N} \sum_{i=1}^{N} \nabla Q(s_i, a_i|\theta) \left. \nabla_{\theta} \mu(s_i|\theta') \right|_{\theta'}$$

In the above equations, firstly, we define the sample number of the batch descent gradient as $N$. Secondly, $Q(s, a|\theta_Q)$ and $\nabla Q(s, a|\theta_Q)$ are the critic network $Q$ with an output of $Q$ and its gradient, $\mu(s|\theta_H)$ and $\nabla \mu(s|\theta_H)$ are the actor network $u$ with an output of $u$ and its gradient, respectively. $L$ represents function that update critic by minimizing the loss. $\nabla \theta|_{\theta'}$ is the update of the actor policy using the sampled gradient descent.
network is responsible for playing back the next state sampled in the pool based on experience \( s_{t+1} \) and select the optimal next action \( a_t \). \( N \) samples were sampled in the empirical set \( R \) for calculating the Q value of the current state, which will be replicated periodically into the neural network updates with the soft renewal coefficient, \( \tau \).

\[
\theta_t' \leftarrow \tau \theta_t' + (1-\tau)\theta_t^*
\]

(11)

When a neural network is required to output action, the current state \( s_t \) is made as an input into the Actor target network to derive the output after selecting the action with the largest reward, \( at \) corresponds to a variable within a predefined range with Equation (12).

\[
a_t = \mu(s_t|\theta^*) + N_t
\]

(12)

Simultaneously, to improve the prospective of action selection, the output action was guaranteed to have a certain randomness by adding random noise \( N_t \), which was dynamically added or removed as needed in the actual application.

The DDPG module (Fig. 4) dynamically adjusted the input data according to the error size and updated the training LSTM network. When the prediction was made again, the error was calculated according to the comparison with the real statistics, and the Actor-Critic network parameters were updated. The cycle was continued until the error was sufficiently small and the LSTM could predict according to the new law and then the new data were the output.

2.5. Data self-correction model

According to the published COVID-19 data, the pandemic development and the growth pattern of the number of infections in many regions did not fit the specific model, compared with the total credit/debit card spending. Furthermore, there was no pattern in the growth rate for the time being, so a new method was needed to make the prediction model closer to the real value. This part actually updates the LSTM network by updating the slope of the existing data image to locally approximate the real data trend, thus achieving the goal of reducing the error.

The DDPG algorithm was set to increase or decrease in steps of \( X \) each time, i.e., the normalized data increase or decrease by \( X \) each round, depending on the positive or negative error, and the data increase or decrease proportionally each time, and the calculation method depends on the selected increase or decrease function, and the basic primary function is chosen to process the data twice for experimentation.

Activation was performed at the end of the network using the tanh activation function, which is devised in Equation (13).

\[
\tanh x = \frac{\sinh x}{\cosh x} = \frac{e^x - e^{-x}}{e^x + e^{-x}}
\]

(13)

The tanh activation converges faster than sigmoid. Besides, it can control the amplitude of the value and keep the amplitude of the data unchanged in the deep network.

For each round after updating the data, the new data got by the last calculation, were re-fed to the long and short-term memory artificial neural network to retrain, repredict and recompute of the error. They were scaled up and fed into the deterministic policy gradient algorithm as a reward. The cycle was continued until the output of the long and short-term memory network was close to the new data.

To illustrate the data self-correction process, Fig. 5 and Fig. 6 are given, respectively.

The number of confirmed patients (yellow line), the number of confirmed patients learned by the neural network (red line) and the number of confirmed patients predicted from the learned data (gray line) are shown in Fig. 5. It can be seen that the number of confirmed cases increased rapidly in the later period, and the prediction by the neural network according to the trend of earlier data deviated significantly from the real data due to the slow growth of the number of confirmed cases in the earlier period.

The slope of the curve and trend of the new data predicted by the algorithm after correction are shown in Fig. 6 using blue and green lines, respectively. Fig. 5 shows that the error was significant in the case of large variations in the number of diagnoses. In Fig. 5, the self-correcting algorithm calculates the slope of the data and the associated error (blue line) based on the latest data and corrected data, generally updates the neural network, so that the predicted data are closer to the true data.

Meanwhile, the sum of absolute error will be used to evaluate the quality of the model. In Equation 14, \( yi \) is the real data and \( y_{mi} \) is the

![Fig. 4. The architecture of LDPG model](image-url)
predict data the of model.

\[ \text{Error} = \sum_{i=1}^{n} \text{abs}(y_i - y_{\text{mean}}) \]  

(14)

2.6. Error calculation and network optimization

There are two common loss functions, cross entropy and mean square error in the neural networks. The loss function can correctly assess the strengths and weaknesses of the network and can further optimize the network. In this prediction algorithm, the mean square error (MSE) was used to optimize the network. The expression of the mean square error is given by Equation (15) where \( y_i \) is the target value, and \( y_{\text{ip}} \) is the mean of the \( y_i \).

\[ \text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - y_{\text{ip}})^2 \]  

(15)

3. Results and analysis

Initially, the daily characteristics of the changes in credit/debit card spending based on the industry were analyzed according to the North American Industry Classification (NAICS). Also, the changes in the number of outbreak-related deaths, confirmed cases, new confirmed cases, and new deaths were taken into consideration. Subsequently, the impact of the relevant pandemic data on the various industries was analyzed. Based on the self-correcting model, the industry total savings/debit card spending data were simulated and predicted by combining with the pandemic data (Table 1), and the relevant economic parameters as shown in Table 2. The predicted model parameters were then compared with the actual data to prove that the self-correcting model could accurately predict the trend of industry total savings/debit card spending, by combining the pandemic data. Finally, with the economic parameters obtained from the forecasts, a strategy to accelerate economic recovery was proposed.

3.1. COVID-19 data

According to the statistical outbreak data of each state, no corresponding confirmed diagnosis data were published before January 20th, and the earliest data were counted after January 20th. Therefore, the charts related to the pandemic data were based on January 30th as the starting date.

3.1.1. Confirmed cases

According to the daily updated data of the number of confirmed cases in California (Fig. 7), the quorum of the confirmed cases began to increase exponentially on day 63, but after day 205, the upward trend of the confirmed cases began to slowly decline.

3.1.2. New confirmed cases

According to Fig. 7, the number of new confirmed cases increased significantly between day 49 and day 67 per day, rising from 68 to 1162; while after day 67, the number of new confirmed cases per day began to rise exponentially and exhibited a maxima on day 180 with 12,162. Subsequently, the number of new confirmed cases per day began to decline from day 200 and the disease leveled off, keeping the number of new confirmed cases at about 3800.

The analysis shows that the number of new confirmed cases peaked from the date of counting to 185th day, and then declined with the issuance of travel restrictions and public gatherings restrictions in each state. However, there was an increase on day 211, followed by a rapid decline, which was analyzed to be due to the increase in the number of people being tested and the limited testing capacity.

3.1.3. Deaths and New deaths

According to Fig. 8, the number of deaths was relatively low at the beginning of the pandemic. However, from the 60th day, the total number of deaths in the pandemic started to rise linearly, without any trend of slowing down. Simultaneously, it fluctuates wildly after the
The rapid increase in the number of deaths was mainly due to two factors: one was the lack of timely and effective treatment of the infected population, and the other was the presence of a large elderly population in the U.S. society, which was less resistant and less affordable. Therefore, most of the infected elderly people died, because they did not receive timely treatment. Therefore, the number of deaths in the statistics showed an increasing trend.

3.2. Analysis of socio-economic factors

Based on Fig. 2, it can be seen that there was some similarity in the trend of the change in the credit/debit card spending levels (Fig. 9) across industries in the states, where they were located. Therefore, California was selected as a representative in the analysis. The first 80% of the state statistics were used as the model-learning data and the last 20% was used to compare with the prediction.

According to California’s daily spending level data by industry, the debit/savings card spending level in the retail sector and food industry began to rise sharply from 0.0509 to 0.946 between day 29 and day 49. However, on day 49, consumer spending in almost all sectors except the food industry started to fall sharply, with the debit/savings card consumer spending in the retail sector and the food distribution industry dropping to 0.149 from day 49 to day 63 (a decrease of 79.7%). Alternatively, the spending level parameter kept floating around 0.18 after day 63. The trend of change in the savings/debit card spending in other sectors was similar, started to fall sharply on day 49, and gradually increased after day 63.

On day 29, much of the rapid growth in the food industry marketing comes from the fact that the population was panicking about the rapid development of the pandemic (Fig. 7, shows the rapid growth in the number of confirmed cases) and fears that the state was running low on daily food stocks, which led to the hoarding of large amounts of food. The level of food spending began to decline after the subsequent food rush, and continued to level off as the government relief and other assistance efforts began. On the other hand, people spending on public services and social gatherings, such as arts and entertainment, significantly declined. Most of these events were held in public places, such as concerts, movies and rallies, and people were more concerned about stocking up on food and protecting themselves, when the pandemic was approaching. However, most of the media and government attention were focused on the state of the pandemic in China and other representative countries, and the demand for the social events sharply decreased. These factors combined to create a sharp downward trend in all sectors, except for the retail food industry-level.

3.3. Prediction

The discussion in the previous sections analyzed the impact of development in the pandemic on the level of credit/savings card consumption expenditures in each sector. The pandemic data and the related economic policies were the main factors influencing the level of consumption expenditure in each sector, while the level of people’s consumption in different sectors (Fig. 9) impacted the level of credit/savings card consumption expenditure in the society to some extent. During the pandemic, self-correcting forecasts of credit/savings card consumption expenditure levels were made during the pandemic period compared to the same period before January 31, to enable a rapid economic recovery and sustained social stability. By predicting the trend of the overall credit/savings card consumption expenditure level in the industry, it provided a reference to the government, which enabled the government to make the next economic recovery measures in advance, and then gave reference data for the policy evaluation and risk warning.

Through the study of the U.S. data, we selected the most representative states such as California, Florida, Iowa, and Texas, within the U.S. for prediction of change of credit/savings card consumer spending levels. Therefore, the trend of the selected state credit/savings card consumer spending level with the pandemic data revealed the trend of most U.S. states, and demonstrated to some extent the usefulness of the self-correcting model for the economic analysis of the U.S. in general by analysis and forecasting of these selected states.

From Fig. 10, it can be found that since the trend of savings/debit
the main factor influencing the change in savings/debit card consumption expenditure, and other related economic parameters (Table 2) were secondary factors. The analysis of the changes in the pandemic data and the trends in debit/debit card consumption expenditure and related parameters by industry revealed that when the number of confirmed cases and the number of new confirmed cases per day first started to rise significantly, the debit/debit card consumption expenditure in all industries, except the food industry showed a sharp decline, and the overall debit/debit card consumption expenditure level in the industry decreased. To stimulate short-term economic recovery and maintain growth for a long time, in March 2020, the U.S. government enacted a policy to support small and micro companies and passed an economic bailout bill worth up to $2.2 trillion to help create new businesses. The government also passed an economic bailout bill worth $2 trillion to help create jobs through the maintenance of a large number of small- and medium-sized enterprises. All of these are to stimulate economic growth by abolishing the licensing system and stimulating the reemployment of the unemployed.

(2) In this study, we found that in response to the rapid decline in the economy, the U.S. passed an economic bailout bill to stop the decline in the economic indicators such as savings/debit card consumer spending. After the policy was enacted, the economy began showing a rebound. Simultaneously, the level of savings/debit card spending and related economic parameters continued to rebound, unaffected by the rise in the number of confirmed cases and deaths, although that the pandemic data were still showing a rapid rise at the time. After the government started to adopt relevant economic policies, the impact of the pandemic on business and social consumption started to diminish. Along with the economic recovery, the trend of the pandemic exhibited a gradual decrease.

(3) The spend_all is the sum of credit/debit card expenditure levels of various industries, and its change trend is somehow similar to other economic indicators, which is the most representative. Fig. 12 shows the prediction error of spend_all for four states of U.S. For California, Florida and Iowa, the absolute prediction error with LSTM method are 0.35, 2.56, 0.45, respectively. However, the error of LDDPG is 0.01, 0.04, 0.02, respectively. The experimental results are satisfactory. The predicted error of Texas is more regular variation, so the prediction data is obtained using the traditional LSTM algorithm with little error. On the contrast, the data among the remaining states with large fluctuations in the data variation, and the prediction spend-all errors using the traditional LSTM do not meet the expectations, and the errors are reduced significantly by the proposed self-correcting model.

The above correlation data analysis revealed the state of the pandemic development. However, the most important influencing factor showed different trends of correlation with the economic situation in different time periods. The economic development statistics of several representative states showed that the national government could
contain the damage and impact of the pandemic on the economy timely by taking the right economic recovery measures at the right time. The economic recovery was accelerated to some extent, by adjusting the relevant economic recovery policies. After the proposal of the U.S. economic stimulus policy in March and April, no further policies were introduced to stimulate the economic recovery. This resulted in the level of savings/debit card spending in various industries in a negative state, despite the recovery, and it was not possible to achieve a positive year-on-year consumer spending in a short period. Therefore, the use of computer models combined with pandemic data to forecast economic trends can provide an effective reference for the policy makers to discuss the economic recovery proposals, and achieve a rapid economic recovery through accurate policy updates. The prediction data of proposed model was analyzed and reported that the number of confirmed cases and deaths of the epidemic played a significant role in influencing the level of per capita consumption, resulting in a negative growth rate of less than zero for all consumptions except food consumption. Investigating the association between post-social composition and the number of COVID-19 cases/deaths in the European region, Srikanta Sanmigrahi et al. (Sanmigrahi et al., 2020) executed several spatial regression models in order to explain the spatially non-stationary distribution of COVID cases/deaths and to examine the spatial dependence between observations, and found a strong positive correlation between income/total population on the number of confirmed COVID-19 cases/deaths. In addition, Md Arafatur Rahman et al. (Rahman, 2020) developed a dynamic clustering framework to help stakeholders as well as users to infer good strategies in Malaysia, which was shown to improve 60% in reducing economic losses and 20% in military unit utilization. The comparison with related studies shows that income, expenditure, and social infrastructure are mutually influenced by COVID-19, and its rules are applied in most countries globally, thus also demonstrating that the COVID-19 case/death counts can be used to predict economic trends through self-correcting prediction models, which can inform global policy makers to develop realistic economic policies.

There are several limitation of this study. This study considers the number of infections and deaths of the epidemic as the main factors affecting the economy to predict the trend of various consumption levels, but the model has some limitations for areas with high population mobility. Meanwhile, this study considers the impact of the number of diagnosed cases and deaths on economic consumption, which has limitations in some areas where epidemic data collection is difficult.

5. Conclusion

To analyze and predict the socio-economic impact of the pandemic, this study used the COVID-19 pandemic statistics of the representative states in the United States as the main impact factor. We also combined with the data on the level of consumer spending in each state industry. A self-correcting model was constructed to track the changes in the future trend of consumer spending in each industry by adding daily data. The following conclusions were drawn from the study:

- The level of consumer spending in various sectors was substantially correlated with the development of the pandemic. Since March 1, the pace of the pandemic has accelerated and the panic prompts people to hoard food, which caused the level of consumer spending on credit/savings cards in the food sector has increased 94.7%. After that, the level of consumer spending in other entertainment and public service sectors dropped sharply. Although, it had a certain growth after enacting and enforcing some policies to simulate economic growth, the level of all consumer spending were less than 0, which means the profitability of enterprises was still lower than the profit value of the same period. The pandemic have a significant impact on the production of many affiliated companies and bringing most SMEs to the brink of bankruptcy.

- The proposed LDDPG model with the economy data can predict pandemic data more accurately. The traditional approaches (e.g., using specific mathematical models or geographic analysis, etc.) did not incorporate economic influencing factors to adjust according to the daily updated data. They are not possible to add other influencing factors (e.g., unemployment rate, consumption level of various industries, and the number of new deaths per day) timely for comprehensive data analysis. Therefore, this self-correcting model can provide an effective reference for the decision-makers, and dynamically update the prediction parameters with the daily update of the pandemic. As a result, the government and decision-makers can determine the degree of impact on the pandemic and on the economy and design strategies to be enacted in advance.

As a sudden pandemic, COVID-19 prediction has the characteristics of less training data, but higher demand for prediction accuracy. The model improves the prediction ability and correction ability of the network. The proposed model is also a general one. If the train data is population or electric load, then the model can be applied to society management or power system.

Declaration of Competing Interest

The authors report no declarations of interest.

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