A Prediction Framework for Turning Period Structures in COVID-19 Epidemic and Its Application to Practical Emergency Risk Management (Postprint)

Authors: Lan DI

Date: 2023-02-01T00:00:00+00:00

Abstract

The aim of this paper is first to establish a general prediction framework for turning (period) term structures in COVID-19 epidemics related to the implementation of emergency risk man#2;agement in practice, which enables reliable estimation of the peak period based on the new concept of "Turning Period" (instead of the traditional focus on "Turning Point") for infectious disease spreading such as the COVID-19 epidemic that appeared early in 2020. Given that emergency risk management necessarily requires rapid implementation of emergency plans, the identification of the Turning Period is a key element of emergency planning, as it needs to provide a timeline for effective actions and solutions to combat a pandemic by reducing unexpected risks as quickly as possible. As an application, the paper also discusses how this "Turning Term (Period) Structure" is used to predict the peak phase of the COVID-19 epidemic in Wuhan from January 2020 to early March 2020. Our study shows that the prediction framework established in this paper is capa#2;ble to provide the trajectory of COVID-19 case dynamics for a few weeks starting from Feb. 10, 2020 to early March 2020, from which we successfully predicted that the turning period of the COVID-19 epi#2;demic in Wuhan would arrive within one week after Feb. 14, 2020, as verified by actual observations in practice. The method established in this paper for the prediction of "Turning Term (Period) Structures", along with the associated criteria for the Turning Term Structure of COVID-19 epidemics, is expected to be a useful and powerful tool for implementing the so-called "dynamic zero-COVID-19 policy" on an ongoing basis in practice.

ChinaRxiv 中X

Full Text

Preamble

Journal of Systems Science and Information
August 2022, Vol. 10, No. 4, pp. 309–337
DOI: 10.21078/JSSI-2022-309-29

A Prediction Framework for Turning Period Structures in COVID-19 Epidemic and Its Application to Practical Emergency Risk Management

Lan Di
School of Artificial Intelligence and Computer Science, Jiangnan University, Wuxi 214122, China
E-mail: dilan@jiangnan.edu.cn

Yudi Gu∗
Center of Information Construct and Management, Jiangnan University, Wuxi 214122, China
E-mail: udy1215@jiangnan.edu.cn

Guoqi Qian
School of Mathematics & Statistics, University of Melbourne, Melbourne VIC 3010, Australia
E-mail: qguoqi@unimelb.edu.au

George Xianzhi Yuan
Business School, East China University of Science and Technology, Shanghai 200237, China;
Business School, Chengdu University, Chengdu 610106, China;
Business School, Sun Yat-sen University, Guangzhou 510275, China
E-mail: george yuan99@yahoo.com

Received December 29, 2021, accepted June 13, 2022
Supported by the National Natural Science Foundation of China (71971031, U1811462)
∗Corresponding author

Abstract

This paper establishes a general prediction framework for turning (period) term structures in COVID-19 epidemic related to the implementation of emergency risk management in practice, enabling reliable estimation of the peak period based on the new concept of "Turning Period" —as opposed to the traditional focus on "Turning Point" —for infectious disease spreading such as the COVID-19 epidemic that emerged in early 2020. Since emergency risk management requires rapid implementation of emergency plans, identification of the Turning Period is a key element in emergency planning as it provides a timeline for effective actions and solutions to combat a pandemic by reducing unexpected risk as quickly as possible. As applications, the paper discusses how this "Turning Term (Period) Structure" can be used to predict the peak phase for the COVID-19 epidemic in Wuhan from January 2020 to early March 2020. Our study shows that the prediction framework established in this paper is capable of providing the trajectory of COVID-19 case dynamics for several weeks starting from February 10, 2020 to early March 2020, from which we successfully predicted that the turning period of the COVID-19 epidemic in Wuhan would arrive within one week after February 14, 2020, as verified by actual observations in practice. The method established in this paper for predicting "Turning Term (Period) Structures" by applying it to the COVID-19 epidemic in China in early 2020 appears timely and accurate, providing adequate time for governments, hospitals, essential industry sectors, and services to meet peak demands and prepare aftermath planning. The associated criteria for the Turning Term Structure of COVID-19 epidemic are expected to be a useful and powerful tool for implementing the so-called "dynamic zero-COVID-19 policy" on an ongoing basis in practice.

Keywords: prediction framework; turning period structure; turning phase; COVID-19 epidemic; emergency risk management; emergency plan; Delta and Gamma; iSEIR; spatio-temporal model; supersaturation phenomenon; multiplex network; dynamic zero-COVID-19 policy

1 Introduction of the Background and Related Literature

Infectious disease epidemics consistently present challenges to human society, threatening human life safety and causing social upheaval and economic losses. In recent years, novel virus outbreaks have increased globally, from SARS-CoV in 2003, H1N1 influenza A in 2009, MERS-CoV in 2012, Ebola in 2015, Zika in 2016, H5N7 avian influenza in 2017, to the current coronavirus infection (COVID-19). These outbreaks have brought great loss to human life, disrupted population movement, and adversely impacted global development.

This study first extends our iSEIR model given by Yuan et al. [**?**] to describe the progression of COVID-19 daily cases in Wuhan, then proposes a new concept called "Turning period" or "Turning Phase," which plays a very important role in assisting better planning for the time frame from the perspective of emergency risk plans, particularly for forward-looking planning in the ongoing battle against the COVID-19 pandemic worldwide since early 2020.

By assessing the performance of our iSEIR model in predicting the timeline of COVID-19 spread in Wuhan since late December 2019, aided by our new concept of "Turning Period Structure (Turning Term)" to predict the control of the epidemic outbreak measured by a reduction in the number of infected people, it shows that our iSEIR model (see Yuan et al. [?] for more details)—an extension of the SEIR model that describes the spread and behavior of infectious diseases for individuals under a probability framework—works well to accurately predict that "the COVID-19 situation in China would peak around middle to late February as early as February 7, 2020." Combined with the case study in this paper, we emphasize that identification of the "Turning (Time) Period" is a key element for successful implementation in supporting emergency plans, as it must provide a timeline for effective actions and solutions to combat a pandemic by reducing unexpected risk as quickly as possible. Our study also indicates that the implementation of the emergency program in practice associated with the "Isolation Control Program" (or "Quarantine Program" in Wuhan, see Begley [?]) since January 23, 2020 by China in Wuhan and other cities and places at the domestic level may provide good experiences for other countries and regions to learn from.

Over the past century, the traditional model called "SEIR" (denoting infectious disease dynamics as susceptible-exposed-infectious-resistant) and its various deterministic versions have been introduced and become very popular for analyzing and predicting epidemic development (see Liu et al. [?], Murray [?], Wu et al. [?, ?], Prem et al. [?], Li et al. [?], Lin et al. [?], Kuniya [?], Roosa et al. [?] and references therein). The SEIR model tracks the flows of people between four states: the susceptible state variable "S," the exposed variable "E," the infected variable "I," and the resistant variable "R." Each variable represents the number of people in those groups. Taking COVID-19 as an example, assuming the average number of exposed cases generated by one infected person of COVID-19, this number could be regarded as the so-called "basic reproduction number" (which is indeed the expected number of cases directly generated by one case in a population where all individuals are susceptible to infection). The study of the basic reproduction number, related features for globally stable endemic and disease-free equilibria, and thresholds has always been mainstream for both academic researchers and practitioners in the subject of epidemic disease spread behavior and related social issues.

On the other hand, a great deal of effort has been devoted to studying the process and evolution of the limits of the Basic Reproduction Number and similar thresholds in predicting global dynamics of epidemics. In particular, since the occurrence of COVID-19 in late December 2019 in Wuhan, studies on impacts such as how serious the infectious disease outbreak is to society and predictions of how many people would become infected have attracted a large number of scholars, with reports by Cao et al. [?, ?], Cowling and Leung [?], Hermanowicz [?], Li et al. [?], Guan et al. [?] and references therein.

Moreover, modeling the situation of COVID-19 and effects of different containment strategies in China with dynamic differential equations and parameter estimation has also received considerable attention from numerous scholars (see Gu et al. [?], Hu et al. [?], Zhao et al. [?], Yan et al. [?], Wang et al. [?], Tang et al. [?], Huang et al. [?], Cui and Hu [?], Huang et al. [?], Ross [?], Jia et al. [?]

and related references). We also note that Jia et al. [?] discussed population flow based on spatio-temporal distribution due to COVID-19 in China as early as 2020, and Yuan et al. [?] also provided some initial study for the prediction of peak period using the new concept of Turning Phase for the COVID-19 epidemic in China with data from January 2020 to February 2020.

In particular, Professor Murray [?] led his IHME COVID-19 health service utilization forecasting team to work on estimates of predicted health service utilization and deaths due to COVID-19 by day for the next four months for each state in the US. Their objective was to determine the extent and timing of deaths and excess demand for hospital services due to COVID-19 in the US (also see the study of Kuniya [?] on Japan, Murray [?] on USA, Wu et al. [?, ?], Prem et al. [?] on China).

It appears that almost all of these studies still follow the approach of paying attention mainly to modeling or forecasting the behavior of epidemic spread directly related to those infected who also become infectious—that is, the variable "I" of the SEIR model—but not much useful study has paid attention to establishing a general framework for the prediction of the critical turning period for the spread of pandemic diseases (e.g., the outbreak of COVID-19 epidemic and related issues in practice) in general.

The objective of this paper is to fill this gap, as we believe it is crucial to study the general dynamics of COVID-19 outbreaks in each country or region, which faces the simple expectation of finding in which time period the battle with COVID-19 will be under control. Given that for any infectious disease, it should be accepted that in general it is impossible to find or identify the exact turning time point (the so-called "critical point") for a pandemic associated with various dynamics and uncertainty. However, by using a new idea of thinking about a "time period" (which is a period of time interval) instead of an exact time point to identify the possible main change in epidemic dynamic behavior using indicators such as the "number of infectious people" (denoted by I) being significantly reduced, plus the "population of the exposed" (denoted by E) also being under control to reach a certain limited level below, then in this way it becomes possible for us to identify and define different phases and stages for the mechanics of infectious disease spreading with support from useful tools such as the iSEIR model we introduced in [?] with quantitative analysis.

The goal of this paper is to establish a general framework of the turning term (period) structure for COVID-19 epidemic related to the implementation of emergency risk management in practice, which allows us to conduct reliable prediction for the "turning period" (not the traditional way focusing mainly on "turning point") for case studies such as the COVID-19 epidemic in China in early 2020. Given that emergency risk management is always associated with the implementation of an emergency plan, the identification of the Turning Time Period is key to emergency planning as it provides a timeline for effective actions and solutions to combat a pandemic by reducing unexpected risk as quickly as possible. We also discuss how this "turning term (period) structure" is used to predict the peak phase for the COVID-19 epidemic in Wuhan from January 2020 to early March 2020. Indeed, based on observed available daily data of COVID-19 in Wuhan from January 23, 2020 to February 10, 2020 as input, the framework established in this paper is capable of providing the trajectory of COVID-19 case dynamics for several weeks starting from February 10, 2020 to early March 2020, from which we successfully predicted that the turning period of the COVID-19 epidemic in Wuhan would arrive within one week after February 14, 2020, as verified by true observations in practice.

The method established in this paper for predicting the turning term structure for the COVID-19 epidemic in China in early 2020 appears timely and accurate, providing adequate time for governments, hospitals, essential industry sectors, and services to meet peak demands and prepare aftermath planning. The associated criteria for the Turning Term Structure of COVID-19 epidemic are expected to be a useful tool for implementing the so-called "dynamic zero-COVID-19 policy" on an ongoing basis in practice.

This paper consists of five sections as follows. Section 1 provides background for the current study. Section 2 explains the challenges faced by the emergency mechanism of epidemic prevention and control of infectious diseases globally today and describes what our iSEIR dynamic model with multiplex networks looks like as a tool to help us establish the framework for predicting turning periods (for epidemics such as COVID-19) for emergency risk management in practice, which is discussed in Section 3. In Section 3, we introduce the key new concept called "Turning Period (Phase)" based on our iSEIR model for emergency implementation response in an epidemic infectious disease that occurred in Wuhan in early 2020. Section 4 presents our case study showing our prediction for the "Peak Period" of COVID-19 in Wuhan, China from January 2020 to February 2020. Section 5 summarizes what we learned from the implementation of risk management in dealing with COVID-19 in Wuhan, China in early 2020, and discusses how the framework established in this paper for predicting turning term (phase) structure for COVID-19 epidemic infectious disease appears timely and accurate, providing adequate time for governments, hospitals, essential industry sectors, and services to meet peak demands and prepare aftermath planning. The associated criteria for the turning term structure (for epidemics such as COVID-19 and related ones) are expected to be a useful tool for implementing the so-called "dynamic zero-COVID-19 policy" with ongoing support in practice.

---

2 The Challenges of the Emergency Mechanism for Epidemic Prevention in Practice

The key idea of the "SEIR Epidemic Model" can be traced back to Dr. Ronald Ross, who received the Nobel Prize for Physiology or Medicine in 1902 for his work on malaria, which laid the foundation for combatting epidemic diseases (see [?]). In 1927, Kermack and McKendrick formulated a simple deterministic model called SIR to describe the dynamic mechanism for directly transmitted viral or bacterial agents in a closed population (see [?]). Since then, scholars have contributed to and advanced this field. A significant milestone in the study of epidemics was the publication of "The Mathematical Theory of Infectious Diseases" in 1957 by Bailey (see [?]). Among these, the famous SEIR model, a core subject in epidemiology (see [?]), as mentioned above, forms the basis for describing the mechanism of infectious disease spread and has been used in numerous research projects and applications. In the SEIR model, the "S" state refers to the susceptible group (or ignorants) who are susceptible to disease but have not yet been infected; the "E" state refers to the exposed group who are infected but not yet infectious (or lurkers); the "I" state refers to those infected who also become infectious; and the "R" state refers to those who have recovered from infection (through treatment or natural recovery) who may or may no longer be infectious, or those who have passed away.

2.1 Key Issues of the Emergency Mechanism for Epidemic Prevention in Practice

Infectious diseases have always been a major challenge to human society, threatening human life safety and causing social upheaval and economic losses. Every scenario of an epidemic outbreak due to a novel infectious disease carries a similar set of challenges: the unknown nature of the new pathogen/strain, a lack of immediate effective treatment and vaccine, and an ill-prepared public health infrastructure to accommodate the surge in potential patients and need for testing. Public health policies that could alleviate and help prevent the impact and scale of an outbreak require significant and massive governmental and societal implementation of emergency planning and intervention strategies. At present, we want to focus the objective of this paper toward three key issues in approaching these outbreaks:

1. How do we establish a spatiotemporal model for infectious disease outbreaks to describe the mechanics of disease spread?
2. How do we conduct numerical simulation and develop risk prediction indicators to perform numerical simulation based on real scenes, which can be used to provide an outlook and planning schedule associated with a key period known as the "Turning Phase" during disease spread?
3. How do we carry out effective predictive analysis of infectious disease epidemics on an ongoing basis to cooperate with dynamic management, support public health emergency plans/services, and support community responses by establishing a coherent big data method for data fusion from different sources with different structures?

[Figure 1: see original paper]

In combatting these outbreaks, the immediate implementation of an emergency response mechanism delays an epidemic' s peak, which affords us more time to control the epidemic by reducing the number of infections in a concentrated period. Thus, a successful emergency plan lengthens the "Turning Phase" (or "Turning Time Period," see [?]), as shown by Figure 1 for the time interval "Between T0 and T1." Effective ways of flattening the curve include intervention actions such as distancing or isolation programs (e.g., see quarantine program and related issues discussed in [?], [?] and related references).

Thus, a major challenge faced by current responses to epidemic prevention and infectious disease control is finding a way to predict the critical time period "Turning Period (Phase)"–or "Turning Term"–when implementing an emergency plan. Knowing this timeline is critical to combat the outbreak of an epidemic or infectious disease.

In this section, we discuss the framework for the "Turning Phase" under the "iSEIR" model introduced by Yuan et al. [?], which was used to predict the "Turning Phase" for the COVID-19 epidemic from January 2020 to early March 2020 in China using only data from February 10, 2020. Here we first give a brief introduction to the iSEIR model, which stands for "individual Susceptible-Exposed-Infective-Removed."

2.2 Framework of the iSEIR Dynamic Model with Multiplex Networks

For the convenience of our discussion, we provide an introduction to the general framework of our iSEIR model, which was introduced in [?] with more details and numerical simulations linked to applications. In one word, our iSEIR model operates under a probability perspective for each individual with the name "individual Susceptible-Exposed-Infective-Removed (iSEIR)," which is an extension of the classic SEIR model. The iSEIR model allows us to conduct simulations from the individual levels located on the nodes of different community networks by incorporating uncertainty with probability to conduct random simulation in the corresponding multiplex network.

2.2.1 The Classical SEIR Model For the SEIR model, we use $S(t)$, $E(t)$, $I(t)$, and $R(t)$ to represent the proportion of the population being in state S, E, I, and R at time t, respectively. In the present case, the system of ODEs describing the dynamics of an SEIR epidemic model has the following form:

$$\begin{cases} \frac{dS}{dt} = -\mu(k)SE, \\ \frac{dE}{dt} = \mu(k)SE - \beta EI, \\ \frac{dI}{dt} = \beta EI - \lambda I, \\ \frac{dR}{dt} = \lambda I, \end{cases}$$

where μ is the rate at which an exposed individual becomes infective, λ is the recovery rate, and with normalization condition (each variable is in percentage change) $S(t)+E(t)+I(t)+R(t) = 1$ for $t > 0$ (e.g., the case where the population considered remains at a certain amount).

The above deterministic SEIR model and its generalizations have received considerable attention from various researchers. Indeed, the SEIR model represents the spread of an epidemic more accurately than the corresponding SIR model that does not account for the latent period. The SEIR model has a slower growth rate, since after pathogen invasion, susceptible individuals must pass through the exposed class before they can contribute to the transmission process, as shown by Figure 2A below:

[Figure 2: see original paper]

2.2.2 Framework of iSEIR Dynamic Systems with Multiplex Networks
Based on the previous discussion, the iSEIR model (see Figure 2B below for illustration) is an extension of the SEIR model but presented in a different expression, which is in component form as follows in Equation (3):

$$\begin{cases} \frac{dS}{dt} = A - S(t)E(t)\sum_{i,j} p_{ij} - S(t)\sum_i \varepsilon_i, \\ \frac{dE}{dt} = S(t)E(t)\sum_{i,j} p_{ij} - E(t)I(t)\sum_{j,k} q_{jk} - E(t)\sum_j \alpha_j, \\ \frac{dI}{dt} = E(t)I(t)\sum_{j,k} q_{jk} - I(t)\sum_k \lambda_k, \\ \frac{dR}{dt} = S(t)\sum_i \varepsilon_i + E(t)\sum_j \alpha_j + I(t)\sum_k \lambda_k, \end{cases}$$

where parameters in the system are illustrated as follows: A is the growth rate of new arrivals; μ denotes the transfer probability from $S(t)$ to $E(t)$; p_{ij} denotes the connection probability of the i-th sample in $S(t)$ to the j-th sample in $E(t)$ (equals 1 if connected, 0 otherwise); ε_i denotes the transfer probability from $S(t)$ to $R(t)$, which is the removal probability; β_j denotes the transfer probability from $E(t)$ to $I(t)$; q_{jk} denotes the connection probability of the j-th sample in $E(t)$ to the k-th sample in $I(t)$ (equals 1 if connected, 0 otherwise); α_j denotes the transfer probability from $E(t)$ to $R(t)$; and λ_k denotes the transfer probability from $I(t)$ to $R(t)$. The proposed iSEIR model is shown in Figure 2B (iSEIR model illustration):

[Figure 2: see original paper]

To make system (3) concise and easy to analyze, we use the following notations: $\varepsilon = \sum_i \varepsilon_i$, $\alpha = \sum_j \alpha_j$, $\lambda = \sum_k \lambda_k$, $\mu p = \sum_{i,j} p_{ij}$, and $\beta q = \sum_{j,k} q_{jk}$.

As our iSEIR model is based on the framework of multiplex networks for the community population, we first give a brief description of the notations used in reference [**?**]. By supposing the population S related to the COVID-19 epidemic consists of N individuals S_j, $j = 1, 2, \cdots, N$ (namely $S := \{S_j, j = 1, 2, \cdots, N\}$), and also supposing these N individuals are distributed over M continuous domains U_i, $i = 1, 2, \cdots, M$, where a domain may refer to a residential district or a network, we can conduct simulation based on a probability perspective for each individual using iSEIR in a population multiplex network by following five steps.

Step 1: We first allow the transition from state S to state R directly with probability ε per unit time (the same below) by following equation:

$$\begin{cases} \frac{dS}{dt} = A - \mu SE - \varepsilon S, \\ \frac{dE}{dt} = \mu SE - \beta EI - \alpha E, \\ \frac{dI}{dt} = \beta EI - \lambda I, \\ \frac{dR}{dt} = \varepsilon S + \alpha E + \lambda I, \end{cases}$$

where A is the growth rate or new arrivals; ε is the probability of a susceptible person being directly transformed into an immune person by means of, e.g., isolation; μ is the rate of a susceptible being exposed; β is the rate of an exposed person becoming infectious; and λ is the rate of an infectious person entering an immune state. Figure 3B below provides a visual presentation of (5). Note that there is no direct transition between S and I in (5) as illustrated by Figure 2B.

Step 2: Each individual in the network at time t is identified by its state and position in that state group.

Step 3: We establish an adjacency matrix to describe the influence effects between individuals.

Step 4: Computing the probabilities of transitions between states involves considering two aspects (the K-adjacency method): (4.1) The distances between uninfected individuals and their neighborhoods of infected individuals within; (4.2) The number of infected individuals.

Step 5: The full specification of the model is given by combining steps 1 to 4 together with an individual-level representation of (5) illustrated in Figure 3B below.

These five steps help us run simulations to observe the so-called "Supersaturation Phenomenon" under the probability perspective of all individuals by applying the iSEIR model, which helps us identify the "Turning Phase," critical for any emergency plan to successfully respond to pandemic outbreaks under emergency conditions in practice. Thus, the iSEIR model will be used as a tool to discuss how we can establish the framework for predicting the critical "Turning Phase"for emergency implementation response in an epidemic infectious disease outbreak described in the next section.

---

3 Framework for the Critical "Turning Phase" in Emergency Response Implementation

In this section, we discuss the framework for predicting the "Turning Term" using our iSEIR Model introduced in [**?**], which was used to successfully predict the Turning Phase for the COVID-19 epidemic from January 2020 to early

March 2020 in China using only data from February 10, 2020. As previously discussed, in the battle for epidemic prevention and control of infectious disease outbreaks, it is crucial to implement effective prevention measures in the early stages. Furthermore, identifying the beginning and ending points of the time interval that forms the "Turning Time Period" lets us know how long to expect to implement emergency protocols to effectively flatten the curve. It is possible to make this predictive analysis of the "Turning Time Period" using the iSEIR model through the "Supersaturation Phenomenon" elaborated below (see [?]).

3.1 The Concept of "Turning Time Period" for Emergency Risk Management

As discussed in the beginning, not much attention has been paid to studying the critical "Turning Period" for the spread of pandemic diseases, and past experience in history also tells us that in general it is impossible to conduct reliable prediction of the so-called exact turning point (time) for any infectious disease spread by humans due to various dynamics and associated uncertainty that are always beyond our control for timely emergency risk management planning. Thus, the key goal of this paper is to establish a framework for predicting the "Turning Period" (instead of "Turning Point") by borrowing key risk indicators called "Delta" and "Gamma" accepted and used by financial risk management (see [?]) in the financial industry in practice. In this way, it becomes possible for us to implement reliable prediction under the support of the new concept "Turning Time Period (Turning Period)" to support emergency risk management planning by identifying upper and lower limits for damage testing, or the loss with a given confidence level as a standard or criterion. The associated indicators then allow us to identify different phases and stages of infectious disease spreading through the iSEIR model, which we elaborate in Part A and Part B below. Through this approach, it is possible to calculate the critical time period of the "Turning Time Phase (Turning Phase)" for preparation of emergency risk management planning in practice.

Part A: Identifying Different Time Phases of Epidemics

We propose identification of three general phases (time periods) for the emergency response of epidemic infectious disease spread paired with medical response actions, as elaborated below and illustrated by Figure 3A.

1) **The First Phase:** The initial starting stage corresponds to the initial occurrence and preparation for a possible emergency plan for a new infectious disease which may or may not transform into a new epidemic.

2) **The Second Phase:** For our consideration, this is the most important phase—the so-called "First Half-Time Phase,"otherwise known as the "Turning Phase" (or "Turning Period")—which starts with the beginning of a possible outbreak and includes the delayed epidemic peak by implementation of emergency planning to control disease spread. The First Half-Time phase involves Delta and Gamma indicators (elaborated more in Part B

below) to measure the daily change in the number of new patients (i.e., the indicator "Delta") and the rate of daily change in the number of new patients (i.e., the indicator "Gamma"). As shown by Figure 3A below (see also Figure 1 above), the time interval from T_0 to T_1 is our "Turning Phase (Turning Period)," and also marks the end of the "First Half-Time Phase" to achieve control of epidemic infectious disease spreading.

3) **The Third Phase:** During this stage, the infectious disease spreading enters the so-called "Second Half-Time Phase," meaning the peak for the epidemic has passed and the rate of spreading is under better control. This is measured by a continuously decreasing rate of new infections per day, and ultimately leads to any but not exclusively of the following scenarios: (a) the disease completely disappears; (b) an effective vaccine/treatment is introduced; (c) the strain could also disappear and reappear cyclically in seasons, or for other reasons.

Of the three phases listed above, the most important time period to identify is the beginning and ending time points of the "First-Half Phase" (known as the "Turning Period"). This phase is crucial to controlling the outbreak and spread of an epidemic infectious disease after the first case occurrence. Thus, being able to identify the "First Half-Phase" is essential for reliable prediction of the "Turning Period" (or "Turning Phase"), as the ending time point of the Turning Period will allow us to predict when the outbreak of the infectious disease is under control at the level we may set (incorporating ability and capability in practice).

The next challenge is how to identify or predict this Turning Period. To determine the Turning Period, we look to the occurrence of the so-called "Supersaturation Phenomenon" (elaborated below) based on our iSEIR model (see [**?**], [**?**] and also the report by [**?**]) by running simulations for the four control variables $S(t)$, $E(t)$, $I(t)$, and $R(t)$ in the iSEIR model (see [**?**]). These variables are functions of time t under the probability framework of individuals involved in the epidemic disease' s spread. Our prediction can be achieved once we observe the so-called "supersaturation phenomenon" —the moment where the future value range of T_1 observes both $E(t)$ and $I(t)$ decreasing, as shown by Figure 3B.

We determine this by simulating an iSEIR model that incorporates data from the initial daily disease spread (further explained in Part B below) (see also Figure 3B for both $E(t)$ and $I(t)$ decreasing at time t in the future).

[Figure 3: see original paper]

Part B: Prediction of the Turning Period by iSEIR Model with Delta and Gamma Indicators

When COVID-19 first emerged, we suggested using Delta and Gamma indicators to measure the daily change of new patients and the change rate of the daily change for new patients. These variables allowed us to identify the beginning point of the time interval for the Turning Period within China. For example, to identify the starting point T_0 of the Turning Period, the level we considered for Delta was set as "no greater than 10% daily," and Gamma as "no larger than 1% daily" as criteria to establish the framework for the "Dynamic Zero-COVID-19 Policy" in practice (see more discussion in Section 5 below).

Next, to predict the future ending time point T_1 of the Turning Period, which measures when the epidemic disease spread is under control, we run numerical simulations based on the iSEIR model as shown in Figure 3B. Note that T_1 is determined to be the time point from which both variables $E(t)$ and $I(t)$ start to drop (see the illustration given by both Figure 3B and Figure 3A).

The combination of Part A and Part B allowed us to reliably predict the Turning Period of COVID-19 since its first case in Wuhan (China) in late December 2019. Using only the available data released by the Domestic Health Commission of China from February 10, 2020, we correctly assessed that "COVID-19 would peak around middle to late February, and enter the Second Half Period around February 20, 2020" (see the report given by [**?**], and also confirmed by WHO' s report [**?**]).

To further understand our predictive simulation, we briefly describe the new idea of our iSEIR model and the related "Supersaturation Phenomenon" in the next section.

3.2 iSEIR Model as a Tool for "Supersaturation Phenomenon"

It is well known that almost all key models such as SEIR and related mathematical tools that exist to model the mechanics of epidemic disease spread are established under deterministic frameworks which assume that all individual behaviors and patterns are uniform (i.e., all behaviors of individuals are homogeneous), but this is not true as each individual' s behavior of infecting or being infected is different. To better describe the dynamics of "spreading behavior" in multiplex networks at an individual level, to community and then to population levels, we introduced the so-called "iSEIR model (individual Susceptible-Exposed-Infective-Removed)" which operates under a probability perspective for each individual (see reference [**?**]) around two years ago as an extension of the classic SEIR model. This "iSEIR" model allows us to conduct simulations from the individual level located on the nodes of different community networks by incorporating uncertainty with probability to conduct random scenario studies considering the corresponding multiplex networks. The behavior distribution of S, E, I, and R can also be numerically simulated from the iSEIR model with properly specified parameter values on population scales (in percentage change), population density, and transfer rates to produce simulation results such as those given by Figure 3B above.

Actually, the example of simulation results given by Figure 3B based on the iSEIR model suggests that the intensity and extensiveness of disease spread can be lowered by external intervention under a so-called "supersaturation phenomenon" (please see Theorem 3.3 below for its mathematical discussion with details). This phenomenon occurs when at some point in the future (denoted by T_1) both variables "$E(t)$" and "$I(t)$" drop in value and do not increase anymore, as shown around the x-axis value when time t is approximately 1500 units in Figure 3B. Indeed, at the time when $t = 1500$, both variables "$E(t)$" and "$I(t)$" reach the state called the "supersaturation phenomenon." Thus, the "supersaturation phenomenon" in the iSEIR model allows us to predict the turning period for the outbreak of epidemic disease spread in application. Indeed, as discussed by Yuan et al. [**?**], since the first three equations in system (5) do not contain the variable $R(t)$, we can conclude that the dynamics in (5) can be completely represented at the population level by the first three equations below (6):

$$\begin{cases} \frac{dS}{dt} = A - \mu p S(t) - \varepsilon S(t), \\ \frac{dE}{dt} = \mu p S(t)E(t) - \beta q E(t)I(t) - \alpha E(t), \\ \frac{dI}{dt} = \beta q E(t)I(t) - \lambda I(t). \end{cases}$$

Now based on propagation dynamics theory, we know that the behavior of the entire infectious disease spreading system depends on a certain propagation threshold parameter R_0, called the basic reproduction number. In particular, R_0 impacts the equilibrium distribution of disease spreading states. Specifically: (1) When $R_0 \leq 1$, the virus spread will eventually disappear; and (2) When $R_0 > 1$, the disease spreading will achieve an equilibrium distribution. These properties will be confirmed by Theorem 3.3 below in this section.

Denoted by $x := (E, I, S)^T$, then the model system (6) can be expressed as $\frac{dx}{dt} := F(x) - V(x)$, where

$$F(x) = \begin{pmatrix} \mu p S E \\ \beta q E I \\ 0 \end{pmatrix}, \quad V(x) = \begin{pmatrix} \beta q E I + \alpha E \\ -\beta q E I + \lambda I \\ -A + \mu p S E + \varepsilon S \end{pmatrix}.$$

By defining $G := FV^{-1}$, the available spectral radius (i.e., the basic reproduction number R_0) can be found from van den Driessche and Watmough [**?**] to be:

$$R_0 := \rho(A) = \frac{(\beta q)(\mu p)}{(\beta q + \alpha)\lambda}.$$

A plausible initial setting is needed for studying disease spreading dynamics. For this we assume there is only one spreader at the beginning, and the initial setting for disease spreading is given by $S(0) = \frac{N-1}{N}$, $E(0) = \frac{1}{2N}$, $I(0) = \frac{1}{2N}$, $R(0) = 0$.

Next we provide two lemmas taken from Zhao et al. [**?**].

Lemma 3.1 For $\nu > 1$, the equation $R = 1 - e^{-\nu R}$ has two solutions: $R = 0$ and a nontrivial solution $0 < R < 1$.

Proof: This is Theorem 1 of Zhao et al. [?], which completes the proof.

Lemma 3.2 For the equation $R = 1 - e^{-\varepsilon R}$, where $\varepsilon = \frac{\lambda+\alpha}{\alpha}$, we have that for a fixed α, R increases as λ increases. Similarly, given a fixed λ, R decreases as α increases.

Proof: This is Theorem 2 of Zhao et al. [?], which completes the proof.

In the following we aim to establish a general theoretical result for the final removal proportion, to be presented in Theorem 3.3, for virus spreading that follows the iSEIR model. Here the final removal proportion in virus spreading dynamics is defined as $R := \text{final}\{R(t)\} = \lim_{t\to\infty} R(t) = R(\infty)$, which can be used to measure the level of virus influence in practice.

When the dynamics of infectious disease spreading following the iSEIR model eventually achieves equilibrium, it is reasonable to assume that $A \approx 0$, ε is close to 0, $I \approx E$ (i.e., the proportion of infected lurkers is nearly zero), and the network size N is sufficiently large. With these assumptions, we have the following key result.

Theorem 3.3 Let $\nu = \frac{\mu p}{\alpha+\lambda}$. Then when $\mu p > \alpha+\lambda$, the equation $R = 1-e^{-\nu R}$ has two solutions: Zero and a nontrivial solution R, where $0 < R < 1$.

Proof: Based on the system of Equations (5) and (6), we have

$$\frac{dR}{dt} = \varepsilon S + \alpha E + \lambda I = A - \mu p S E - \varepsilon S.$$

By using the assumption that $A \approx 0$, and Equation (10), we have

$$\varepsilon S + \alpha E + \lambda I = -\mu p S E - \varepsilon S \frac{dS}{dt}.$$

Now integrating both sides of Equation (11) from the initial time to the stationary time and noting that ε is close to 0, it follows that

$$\int_0^\infty (\varepsilon S + \alpha E + \lambda I) dt = \int_0^\infty -\mu p S E \frac{dS}{dt} dt,$$

then we have that

$$R(\infty) - R(0) = \int_0^\infty (\alpha E + \lambda I) dt = -\int_0^\infty \mu p S E \frac{dS}{S} = -\frac{\alpha E + \lambda I}{\mu p S E}[\ln(S(\infty)) - \ln(S(0))].$$

Noting that $S(0) = \frac{N-1}{N} \approx 1$ (as $N \to \infty$), $R(0) = 0$, $S(\infty) = 1 - R(\infty) = 1 - R$, and $R(\infty) = R$, it follows that

$$R = -\frac{\alpha E + \lambda I}{\mu p S E} \ln(1 - R),$$

which means that

$$\frac{\alpha + \lambda(I/E)}{\mu p S} = -\frac{\ln(1 - R)}{R}.$$

By Equation (15) it follows that $\frac{\alpha+\lambda(I/E)}{\mu p S} = 1 - R$, and thus we obtain the following transcendental equation:

$$R = 1 - e^{-\frac{\mu p}{\alpha+\lambda(I/E)} R},$$

and by the assumption that $I \approx E$, it follows that

$$R = 1 - e^{-\frac{\mu p}{\alpha+\lambda} R}.$$

Now by applying Lemma 3.1 above, let $\nu := \frac{\mu p}{\alpha+\lambda}$. We have $\nu > 1$, which implies that the conclusion is true, completing the proof.

Remark 3.4 Theorem 3.3 gives an equation that must be satisfied by the steady-state removal proportion R for the dynamics of infectious disease spreading following the iSEIR model. This result provides guidance for conducting numerical simulations for the prediction of "Turning Period" (for preparation of emergency risk management in practice when dealing with events such as the COVID-19 epidemic), which will be discussed in Section 4 below, where the supersaturation phenomenon can be observed in the dynamics of infectious disease spreading if "lurkers do not exist" in the community network for the population, such as under the implementation of the "Lockdown and Isolation Control Program" in Wuhan, China from January 23, 2020 to early March 2020 in dealing with the COVID-19 epidemic (see reference [?]).

---

4 Prediction of the "Peak Period" for COVID-19 in Wuhan from Late January to Early February 2020

The methodology outlined above is what we expect when modeling epidemic diseases, including COVID-19 which has become a global pandemic since the epidemic in Wuhan in late December 2019. Taking into account the performance of intervention controls (i.e., the Quarantine program in Wuhan, Hubei province, see [?]) implemented since January 23, 2020 at the domestic level by the Chinese government, we predicted the "Peak Time Period" of COVID-19 in China using our iSEIR model (see [?, ?], [?], and [?]) in two separate reports on February 6, 2020 and February 10, 2020 (see also [?]).

Following the discussion above, first and foremost, we truly believe that the "Turning Period" (or "Turning Phase") for COVID-19 is not a single time point but a period of time interval associated with at least two indicators called "Delta" and "Gamma," which are key measurements used in risk management practice in the financial industry.

4.1 Using Delta and Gamma to Identify the Starting Date of the "Turning Period" of COVID-19 in China as February 1, 2020

Based on the concepts of "Delta" and "Gamma" —Greek letters used in financial risk management, where "Delta"describes the daily change of both "E"and "I,"and "Gamma"accounts for the speed of daily change for the number of new confirmed patients for both "E"and "I"—we plan to predict the "Turning Phase"for COVID-19 in China, but first need to identify the "Starting Point"of COVID-19's Turning Period. Indeed, using daily information from January 23, 2020 to February 6, 2020, we first observed that "Delta" and "Gamma" were below approximately 20% and approximately 2% daily, respectively, "for 5 consecutive days since February 1, 2020," which led us to conclude that "February 1, 2020" heralds the start toward the situation peaking, combined with explanation supported by simulation results based on the iSEIR model given by Figure 4 below (see also Figures 5, 6, and 7 below). Thus we have the following conclusion (see also the report in [?] with more details).

[Figure 4: see original paper]

Conclusion A: The date of February 1, 2020 was the beginning time of the COVID-19 epidemic in China (including Wuhan, Hubei); namely, the starting date for the "Turning Period" of China' s COVID-19 epidemic (see also the report given by [?] released on February 7, 2020). This is also verified by the official daily data released by the National Health Commission (NHC) of China on February 28, 2020 (see reports given by [?], [?], [?], and [?]).

Indeed, from Table 1 below, we see that Delta and Gamma are within or below approximately 20% and approximately 2% respectively for 5 consecutive days since February 1, 2020. This also confirms the conclusion that February 1, 2020 is the starting date for the Turning Period of the COVID-19 epidemic.

4.2 Prediction of the Second Half-Time Phase after the "Turning Period"for COVID-19 in China: From Mid-February to Late February 2020

Using the concept of Turning Phase and application of the iSEIR model on February 10, 2020, based on three weeks of available daily data (from January 23, 2020 to February 10, 2020) released by the NHC of China, our simulation successfully modeled the future pattern of official data released almost three weeks later, with explanation of results by Figure 4 (see also Figures 5, 6, and 7 below), as shown by Conclusion B below (see also reports from [?] and [?], and inputs data and parameters for the iSEIR model given by Tables 5-7 incorporating official data provided by NHC as of February 10, 2020).

Conclusion B: We have:

First, the date of February 1, 2020 was the initial starting point for the turning point of the COVID-19 epidemic situation in China. Combined with simulation analysis from our internal iSEIR model considering the current situation and the "isolation control program" currently implemented in China, the time interval for controlling the COVID-19 outbreak should be in the period from "mid-February 2020 to before the end of February 2020" (see also reports given by [**?**] and [**?**] and numerical results in Figure 4 and Tables 2-3), with the following findings: (1) The number of infectious and asymptomatic individuals ("E") (in % change) (for China and Hubei) will reach a peak in about 2 days (February 12, 2020), and then after about 7 days (February 17, 2020), the rate of increase will decrease to less than 10%; (2) The daily increase in the number of infected and symptomatic individuals ("I") (for China and Hubei) shows a steady downward trend, and the rate will decrease to within 10% after about 14 days (February 24, 2020); and (3) The proportion of people recovering from infection ("R") (for China and Hubei) will return to more than 80% after about 17 days (February 27, 2020).

Second, we earmarked the second half of February 2020 (around February 20, 2020) as the time period when the peak would occur, as shown by our simulation results on February 10, 2020 (later confirmed by data released by the NHC of China). Our conclusion that "the number of infectious and asymptomatic (E) (in % change) will reach a peak in about 2 days (February 12, 2020)" was confirmed by the NHC report:

The above results conform very well to the actually observed data from the National Health Commission (NHC) of China. Specifically, the daily official data show that February 11, 2020 is the peak time with its Delta value achieving 5.4% daily, the highest value from February 1, 2020 through February 25, 2020. This corroborates our prediction that around February 12, 2020 achieves the outbreak peak based on our iSEIR model. The true daily official data of NHC indeed shows that February 11, 2020 was the peak time with its Delta value (the daily change for the number of close contacts with patients) at 5.4% daily, the highest value in the date range from February 1 through February 25, 2020. This corroborates our prediction of around February 12, 2020 as the peak time based on our iSEIR model.

4.3 The Concept of "Turning Period" Works in Supporting Prediction for the COVID-19 Epidemic in Early 2000

Based on the study and discussion above, it appears that the iSEIR model is able to predict the peak time period for infectious disease spreading of the COVID-19 epidemic with an approximate interval encompassing a larger time period. Based on our work on this issue, we strongly believe that the traditional concept "Turning Point" is not an accurate term to use for predicting dynamic mechanics of infectious disease spreading, but the new concept "Turning Period" should work to describe the behavioral mechanics of infectious disease spreading in practice.

The true data also shows that our prediction for "The second half-time phase after the Turning Period in February 2020" is also confirmed (backed) by the World Health Organization (WHO), whose own data shows that Chinese cases of COVID-19 levelled off sometime during the week of February 14, 2020, as WHO Director-General Tedros Adhanom Ghebreyesus stated in a press conference on February 24, 2020 that the epidemic in China "has been declining steadily" on average since February 2, 2020 (see reports given by [?]).

By conducting "follow-up analysis" to determine the accuracy of our iSEIR model using official data from February 11, 2020 to February 21, 2020, we have the following major findings (see also reports by [?] and [?]): (1) Since February 17, 2020, the "Delta" for the number of close contacts has declined rapidly to 2.4% as of February 23, 2020, and 2.9% as of February 22, 2020 (with one jump to 5.4% as of February 20, 2020) (Table 3 below); (2) Since February 17, 2020, the death rate has remained around the level of 3% (Table 4 below); (3) Since February 17, 2020, the "Delta" of the number of infected people has also declined to around the range from 2% to 4% (Table 5 below).

In addition, as February 17, 2020 and February 18, 2020 had the highest number of confirmed cases in China (Table 5), and Hubei, respectively, it confirms that "we have reason to believe that the inflection point emerged on February 17, 2020 and February 18, 2020, thus this fact validated the prediction we made on February 7, 2020" (see more from reports given by [?], [?], [?], and [?]).

4.4 Overview of Prediction Based on the iSEIR Model

Here we review the results based on our iSEIR model from February 10, 2020 by presenting the original report' s results in two parts.

4.4.1 Outlook Report for COVID-19 as of February 10, 2020 (see [?] and [?]) Based on our iSEIR model and data from China' s novel COVID-19 epidemic released as of February 10, 2020 (see also reports by [?] and [?]), we reach the following three conclusions I, II, and III (corresponding inputs for simulations by applying the iSEIR model are given by Tables 5-6 incorporating official data released by NHC of China on February 10, 2020).

I) COVID-19 at the Domestic Level of China: We have that: (1) At the domestic level, the change in number of close contacts (E) reached a peak in about 2 days (around February 12, 2020), and then after about 7 days (i.e., around February 17, 2020), the number of close contacts began a stable average downward trend of less than 3% (see also Table 3); (2) At the domestic level, the daily decrease in the number of infected people (I) also shows a steady downward trend as of that date, and is within about 10% after approximately

14 days (February 24, 2020); and (3) At the domestic level, the proportion of people recovering from infection (R) will quickly return to around 90% after about 17 days (around February 27, 2020).

[Figure 5: see original paper]

II) COVID-19 at the Level of Hubei Province: Using 144,279 close contacts, 31,728 confirmed infections, and 3.07% mortality as core input parameters as of February 10, 2020, our simulation analysis results show (as above, the vertical Y-axis represents one unit of standardization (from 0 to 1) and the horizontal X-axis represents time whereby one unit is "10 minutes," that is, one day is "144 units"): (1) In Hubei Province, the number of close contacts (E) peaks after about 2 days (around February 12, 2020), and then steadily declines with a change of less than 4% after about 6 days (around February 16, 2020); (2) In Hubei Province, the daily decrease in the number of infected people (I) also shows a steady downward trend, reaching a peak in about 7 days (February 17, 2020), and then decreasing at a rate of around 7%; and (3) In Hubei Province, the proportion of people recovering from infection (R) quickly recovers to around 90% after about 17 days (around February 27, 2020).

[Figure 6: see original paper]

III) COVID-19 at the Level of Wuhan City: Using 83,917 close contacts (estimated), 18,454 confirmed infections, and 4.05% mortality rate as key input parameters as of February 10, 2020, combined with the current intervention situation in Wuhan, our simulation analysis results show (as above, the vertical Y-axis represents one unit of standardization (from 0 to 1) and the horizontal X-axis represents time whereby one unit is "10 minutes," that is, one day is "144 units"):

[Figure 7: see original paper]

(1) In the city of Wuhan, after about 4 days, the daily variation of the number of close contacts (E) is in a stable downward range of about 4%; (2) In the city of Wuhan, the daily decrease in the number of infected people (I) is also a steady downward trend, reaching a peak in about 4 days, and then decreasing at a rate of around 4%; and (3) In the city of Wuhan, the proportion of people (R) recovering from infection quickly recovers to close to 90% after about 17 days (around February 27, 2020).

4.4.2 Entering into the Second Half of the COVID-19 Epidemic on February 20, 2020 On February 16, 2020, the reports we released (see [**?**] and [**?**]) stated that "Once the peak has been identified, a different approach has to be taken with regard to city management, economic development, and epidemic control measures." This is actually in line with the Chinese leader' s address on February 23, 2020, where he stressed that the country needs to resume production and normal life. Since the COVID-19 virus could be spread asymptomatically, being able to model its trend is crucial to timeline projections.

Also, Dr. Bruce Aylward, an epidemiologist who led a 25-member team from WHO to conduct a 9-day field study trip to Beijing, Guangdong, Sichuan, and Hubei, shared this viewpoint. "They are using big data, artificial intelligence in places," Dr. Aylward said, "It' s a technology-powered and science-driven agile response at a phenomenal scale" (see [?], [?], [?], and also the report in [?]).

---

5 Lessons Learned from Prevention of the COVID-19 Epidemic in China since Early 2020

Our predictions based on the iSEIR model on February 6, 2020 were validated by the official data released by the NHC on COVID-19. The numbers for China and its six regions (including Hubei Province and Hubei' s five cities: Wuhan, Xiaogan, Suizhou, Huanggang, and Huangshi) were as follows: 76,936 confirmed patients at the domestic level of China as of February 22 (with 64,084 confirmed cases from Hubei province) and 12,852 in other provinces, 628,517 people with close contacts (with patients), and a 3.17% mortality rate of confirmed infected cases. Our conclusions, originally published on February 16, 2020, are as follows (see [?], [?], [?], and [?]) in two parts.

The First Part: We have that (1) February 1, 2020 is the starting point for the formation of the epidemic' s Turning (Inflection) Point which will form around mid-February (see [?] for the concept and definition of "Turning (Inflection) Point" formation and establishment of supporting standard indicators); and (2) We reported that the COVID-19 epidemic in China has reached controllable measures in our February 16, 2020 report, and that we are now entering the second half of the struggle against COVID-19 in China (see [?], [?], [?]).

The Second Part: There appear similar development trends in Hubei province, as well as in Wuhan, Xiaogan, Suizhou, Huanggang, and Huangshi (with reference to the figure below): (1) The number of close contacts (represented by "E") begins to decline rapidly after about February 16, 2020, then in a short period of time, the number of close contacts follows a stable downward change of less than 10%; and (2) The daily variation of new confirmed infected cases (represented by "I") is also in a stable downward variation. In a very short time (no more than 3 to 10 days), the number of daily changes for infected people is within the range of 10% (but higher than the overall average).

Using the official data for the COVID-19 epidemic released as of February 21, 2020 by the NHC of China, the four tables (Tables 3-6) show the daily changes in the number of close contacts, the number of infections, and the death rate of confirmed patients in five cities (Wuhan, Xiaogan, Suizhou, Huanggang, and Huangshi). The official data confirms the predictive analysis reports we made on February 6, 2020 and February 10, 2020, and we have the following findings: (1) Since February 17, 2020, the daily variation of close contacts in all seven simulated areas has declined rapidly to 4% (the domestic average change is lower than that in Hubei province); (2) Since February 17, 2020, the death rate of confirmed patients in China has remained within 3%, but the death rate of confirmed patients in Hubei Province is slightly higher than that in China, remaining at about 3.5%; and (3) Since February 17, 2020, the daily variation of the number of infected people in all seven simulated areas has also declined to within 4% (the daily variation of Wuhan is slightly higher than that of the whole country, but that of Xiaogan, Suizhou, Huanggang, and Huangshi remains within 2%).

(a) Based on the number of existing confirmed cases, we determined the inflection time around February 17, 2020. Using the iSEIR model on February 11, 2020, we predicted that February 17, 2020 and February 18, 2020 would have the highest number of existing confirmed cases in China and Hubei Province, respectively. Today (as of February 22, 2020 for the data used in the original reports given by [?], [?], [?], and [?]), the number of existing confirmed cases and the highest confirmed cases in China and Hubei Province have been reduced by more than 5,700 and 5,000 respectively. Considering the three-day screening in Hubei Province from February 17, 2020 to February 19, 2020, we have reason to believe that the true Turning (Inflection) Point based on the number of existing confirmed cases emerged at approximately February 17, 2020.

(b) Through comprehensive analysis of Hubei province, we determine the inflection time period around between February 17, 2020 and February 19, 2020. The data set combined with the previous conclusion leads us to believe that COVID-19 infection in China (including Wuhan, Hubei) has been fully controlled since mid-February 2020, with February 18, 2020 as the most precise date (we arrive at February 18, 2020 as after February 17, 2020, the daily change of confirmed patients is less than 1% in negative numbers).

In summary, we believe that the iSEIR model is a reliable predictor for the Turning Period of the struggle against COVID-19 through introducing concepts of "Turning Phase" and "Supersaturation Phenomenon." This model accounts for intervention policies and methods such as isolation control programs (e.g., quarantine) such as those implemented in February 2020 in China (see [?] and [?]). Beyond using our iSEIR model for COVID-19 in China from late December to early March 2020, we hope the prediction framework established in this paper can be further used to study outbreaks worldwide.

When we incorporate the public official data released by the Chinese government since January 23, 2020, our iSEIR simulation allowed us to conclude that: The date of February 1, 2020 is the starting point for the formation of the turning point of the COVID-19 epidemic situation in China. Considering the intervention efforts implemented at the state level, the time period for controlling the COVID-19 epidemic should be around mid-February 2020, and at least by the end of February 2020 (see the original reports released [?], [?], and [?] for more details).

Before arriving at our final remarks, we want to consider the following regarding the current global state of the COVID-19 epidemic: (1) The virus can be spread by infected and asymptomatic individuals; and (2) Currently, there is no fully effective medicine or treatment. With these conditions, it is important to implement the so-called "dynamic zero-COVID-19 policy" on an ongoing basis in practice. This means that ideally it is best to eliminate all infectious diseases and their epidemics and virus spreading (e.g., for COVID-19 epidemic), but in reality, it is hard to eliminate or keep away from infectious diseases. Thus, designing and establishing reasonable criteria as bottom lines for controlling infectious disease spread is a critical job! The prediction framework and method developed in this paper show that they are able to provide reliable peak periods by using the new concept "Turning Term (Phase) Structure" for infectious disease spreading in a timely and accurate manner, which would also provide adequate time for governments, hospitals, essential industry sectors, and services to meet peak demands and prepare aftermath planning. The associated quantitative criteria can be used to monitor daily changes on an ongoing basis. Therefore, the prediction framework of the "Turning Term Structure" established in this paper for dealing with emergency plans for occurrences such as the COVID-19 epidemic or any other kinds of unexpected natural disasters is expected to be a useful and powerful tool for implementing the so-called "dynamic zero-COVID-19 policy" or emergency plans quickly in practice.

Acknowledgements

All authors express their special thanks to the editors in the office of JSSI for their professional support and comprehensive work, plus thanks go to four anonymous referees for carefully reading, insightful comments, and suggestions which led to significant improvement of our paper' s present version. Our thanks also go to Chengxing Yan for his support regarding this paper' s writing style.

References

[1] Yuan G X, Di L, Gu Y D, et al. The iSEIR model: A dynamic epidemic model for rumor spread in multiplex network with numerical analysis. Working Paper (Internal Report), Soochow University (Suzhou, China), 2020. http://arxiv.org/abs/2003.00144.
[2] Begley S. Once widely criticized, the Wuhan quarantine bought the world time to prepare for COVID-19. Reporting from the frontiers of health and medicine, STATS, 2020. https://www.statnews.com/2020/02/21/coronavirus-wuhan-quarantine-bought-world-time-to-prepare/.
[3] Liu X, Hewings G, Wang S Y, et al. Modeling the situation of COVID-19 and effects of different containment strategies in China with dynamic differential equations and parameters estimation. medRxiv preprint, 2020.

https://doi.org/10.1101/2020.03.09.20033498.
[4] Murray J L. Forecasting COVID-19 impact on hospital bed-days, ICU-days, ventilator days and deaths by US state in the next 4 months. MedRxiv, 2020. doi: 10.1101/2020.03.27.20043752.
[5] Wu J T, Leung K, Bushman M, et al. Estimating clinical severity of COVID-19 from the transmission dynamics in Wuhan, China. Nature Medicine, 2020. https://doi.org/10.1038/s41591-020-0822-7.
[6] Wu J T, Leung K, Leung G M. Nowcasting and forecasting the potential domestic and international spread of the 2019-nCoV: A modelling study. Lancet, 2020, 395: 689–697. https://doi.org/10.1016/S0140-6736(20)30260-9.
[7] Prem K, Liu Y, Russell T W, et al. The effect of control strategies to reduce social mixing on outcomes of the COVID-19 epidemic in Wuhan, China: A modelling study. Lancet Public Health, 2020. https://www.thelancet.com/journals/lanpub/article/PIIS2468-2667(20)30072-4/fulltext.
[8] Li C L, Chen L J, Chen X Y, et al. Retrospective analysis of the possibility of predicting the COVID-19 outbreak from Internet searches and social media data, China, 2020. Euro Surveill, 2020, 25(10): pii=2000199. https://doi.org/10.2807/1560-7917.ES.2020.25.10.2000199.
[9] Lin Q Y, Zhao S, Gao D Z, et al. A conceptual model for the coronavirus disease 2019 (COVID-19) outbreak with individual reaction and governmental action. International Journal of Infectious Diseases, 2020, 93: 211–216.
[10] Kuniya T. Prediction of the epidemic peak of coronavirus disease in Japan. Journal of Clinical Medicine, 2020, 9: 789. doi: 10.3390/jcm9030789.
[11] Roosa K, Lee Y, Luo R, et al. Real-time forecasts of the COVID-19 epidemic in China from February 5th to February 24th, 2020. Infectious Disease Modelling, 2020, 5: 256–263.
[12] Cao Z, Zhang Q, Lu X, et al. Estimating the effective reproduction number of the 2019-nCoV in China. medRxiv, 2020. https://doi.org/10.1101/2020.01.27.20018952.
[13] Cao Z, Zhang Q, Lu X, and et al. Incorporating human movement data to improve epidemiological estimates for 2019-nCoV. MedRxiv, 2020. https://doi.org/10.1101/2020.02.07.20021071.
[14] Cowling B J, Leung G M. Epidemiological research priorities for public health control of the ongoing global novel coronavirus (2019-nCoV) outbreak. Eurosurveillance, 2020. https://doi.org/10.2807/1560-7917.ES.2020.25.6.2000110.
[15] Hermanowicz S W. Forecasting the 2019-nCoV epidemics using a simple (simplistic) model. medRxiv, 2020. https://doi.org/10.1101/2020.02.04.20020461.
[16] Li Q, Guan X, Wu P, et al. Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia. New England Journal of Medicine, 2020. https://doi.org/10.1056/NEJMoa2001316.
[17] Guan W J, Ni Z Y, Hu Y, et al. Clinical characteristics of 2019 novel coronavirus infection in China. New England Journal of Medicine, 2020. https://doi.org/10.1056/NEJMoa2002032.
[18] Gu C L, Zhu J, Zhou K, et al. The infection point about COVID-19 may have passed. Science Bulletin, 2020, 65(11): 865–867.

[19] Hu Z X, Ge Q Y, Li S D, et al. Artificial intelligence forecasting of COVID-19 in China. Arxiv.org, 2020. https://arxiv.org/ftp/arxiv/papers/2002/2002.07112.pdf.
[20] Zhao J D, Jia J G, Qian Y, et al. Modeling the COVID-19 outbreak and government control measures based on epidemic dynamics (in Chinese). Report, 2020.
[21] Yan Y, Chen Y, Liu K J, et al. Modeling and prediction for the trend of outbreak of NCP based on a time-delay dynamic system (in Chinese). Scientia Sinica Mathematica, 2020, 50(3): 385–392. https://doi.org/10.1360/SSM-2020-0026.
[22] Wang X, Tang S Y, Chen Y, et al. When will be the resumption of work in Wuhan and its surrounding areas during COVID-19 epidemic? A data-driven network modeling analysis (in Chinese). Scientia Sinica Mathematica, 2020, 50(7): 969–978. https://doi.org/10.1360/SSM-2020-0037.
[23] Tang S Y, Tang B, Bragazzi N L, et al. Analysis of COVID-19 epidemic traced data and stochastic discrete transmission dynamic model (in Chinese). Scientia Sinica Mathematica, 2020, 50(8): 1071–1086. https://doi.org/10.1360/SSM-2020-0053.
[24] Huang S Z, Peng Z H, Jin Z. Studies of the strategies for controlling the COVID-19 epidemic in China: Estimation of control efficacy and suggestions for policy makers (in Chinese). Scientia Sinica Mathematica, 2020, 50(6): 885–898. https://doi.org/10.1360/SSM-2020-0043.
[25] Cui H J, Hu T. Nonlinear regression in COVID-19 forecasting (in Chinese). Scientia Sinica Mathematica, 2021, 51(8): 1267–1278. https://doi.org/10.1360/SSM-2020-0055.
[26] Huang N E, Qiao F. A data driven time-dependent transmission rate for tracking an epidemic: A case study of 2019-nCoV. Science Bulletin, 2020, 65: 425–427.
[27] Ross R. 1902 Nobel Laureate in Medicine, 1902. http://www.nobelprizes.com/nobel/medicine/1902a.html.
[28] Jia J S, Lu X, Yuan Y, et al. Population flow drives spatio-temporal distribution of COVID-19 in China. Nature, 2020, 582: 389–394.
[29] Yuan G X, Di L, Yang Z, et al. The prediction for COVID-19 by using the concept of term structure for the turning period. Procedia Computer Science, 2021, 187: 284–293.
[30] Kermack W O, McKendrick A G. A contribution to the mathematical theory of epidemics. Proceedings of the Royal Society A Mathematical Physical and Engineering Sciences, 1927, 115(772): 700–721. https://doi.org/10.1098/rspa.1927.0118.
[31] Bailey N T J. The mathematical theory of epidemics. Hafner Publishing Co., New York, 1957, viii: 194.
[32] Yuan G X. A brief explanation for the concept called "Turning Period" for COVID-19 in China. Working Paper, 2020.
[33] Yuan G X. Novel coronavirus infection (NCP/COVID-19) epidemic analysis report (February 11th). Report by Wind Financial Terminal, 2020.
[34] China Xinhua News Agency. China has changed course of COVID-19 outbreak through pragmatic approach: WHO expert said. 2020. http://english.cctv.com/2020/02/26/ARTIGoEEqepxqrFvX8Qvcycn200226.shtml.

[35] National Health Commission of PRC. China-WHO Joint report on COVID-19-February 16-24. 2020. http://www.nhc.gov.cn/jkj/s3578/202002/87fd92510d094e4b9bad597608f5cc2c.shtm
[36] Tan S. Feature: The Modern-Day Nostradamus: George Yuan. Asian Pacific Biotech News, 2020, 24(3): 32-37. https://www.asiabiotech.com/24/2403/24030032x.html.
[37] Hull J. Options futures and other derivatives. 10th ed. Pearson Education Inc, 2018.
[38] Yuan G X. The fight against the new coronavirus entered the second half. 2020. https://mp.weixin.qq.com/s/azAkcR7nzST-dppDHFUZ0g.
[39] Van den Driessche P, Watmough J. Reproduction numbers and subthreshold endemic equilibria for compartmental models of disease transmission. Mathematical Biosciences, 2002, 180(1-2): 29-48.
[40] Zhao L, Wang J, Chen Y, et al. SIHR rumor spreading model in social networks. Physica A, 2012, 391: 2444-2453.
[41] Systems Engineering Society of China. The analysis of the COVID-19 epidemic situation by SESC Financial Systems Engineering Technical Committee. 2020. http://www.sesc.org.cn/htm/article/article1199.htm.

Note: Figure translations are in progress. See original paper for figures.