Covid-19: Worldwide Viral Infection Model

Universal Dynamic Engine (UDE) method of mathematical modeling to predict singularities and manage patient low to high risk and critical treatment load

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Introduction

The Covid-19 outbreak has become an unprecedented global public health challenge. The outbreak was first noticed in the city of Wuhan, China. Wuhan is the capital of the Hubei Province and has about 11 million inhabitants. On December 29, 2019, Chinese authorities identified a cluster of similar cases of pneumonia in the city. These cases were soon determined to be caused by a novel coronavirus that was later called *severe acute respiratory syndrome coronavirus 2*, shortened to SARS-CoV-2.[1] The disease is called *coronavirus disease*, shortened to Covid-19.

The first cases of Covid-19 outside of China were identified on January 13 in Thailand and on January 16 in Japan. On January 23, the city of Wuhan and other cities in the region were placed on lockdown by the Chinese Government. Since then Covid-19 has spread and cases have been reported in all world regions. In an ongoing outbreak the final outcomes—death or recovery—for all cases is not yet known.

When news broke of an obscure respiratory disease emerging from the Wuhan market in early January, few imagined that in just over 2 months the world would be facing the worst pandemic since Spanish flu in 1918. With more than 12M people taking commercial flights every day, Covid-19 has spread around our hyper-mobile world with an unprecedented combination of speed and virulence.[2] Further, without widespread testing for Covid-19, it is difficult to know how the pandemic is spreading and how to appropriately respond to it. While it is certain that the total number of Covid-19 cases is higher than the number of known confirmed cases, the total number of Covid-19 cases is not known.[3]

As the Coronavirus spreads, many are predicting that the demand for beds, ventilators and other treatment resources in hospital will far exceed capacity for Covid-19 patients in the near future.[4] [5] [6] Still, public policy and health community responses to Covid-19 are complex decisions that require a delicate balance between protecting health, the economy, and people's well-being and emotional health. In times of crisis, reliance on theoretical models present challenges for decision makers, because they don't always replicate real life well—especially when the virus that causes the pandemic is novel.

This discussion paper is part of URM Forum's ongoing effort to help government, healthcare and business leaders build the universal dynamics engine (UDE) capabilities necessary to accurately represent all system dynamics in all cases. UDE provides a rigorous process that computes the top-down communicating graphs to deal with the direct and indirect, convergent or degenerative solutions necessary to accurately model the complex, adaptive dynamics of non-linear, open systems.

The aim of the presented CV-19 model is to show healthcare system participants how they might use it to gain a more complete view of reality as needed to make decisions with more confidence in the outcomes. UDE has been successfully applied for a wide range of healthcare, economic and business uses as the preferred way to predictively characterize dynamic systems under specific conditions; identify singularities and metrics, which define the characteristics of the system under different scenarios of increasing volume and structural changes; and validate the applicability of any proposed corrective solutions.

Timeline and Clinical Characteristics of the Coronavirus

Origin: Wuhan, China December 2019

Early December 2019, first pneumonia cases of unknown origin were identified in Wuhan—capital city of Hubei province[7] (see Figure 1). The pathogen was identified as novel enveloped RNA beta coronavirus—named severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), which has a phylogenetic similarity to SARS-CoV. Patients with infection have been documented in both hospitals and family settings.[8]

The first cases of Covid-19 outside of China were identified on January 13, 2020 in Thailand and on January 16 in Japan. On January 23, the city of Wuhan and other cities in the region were placed on lockdown by the Chinese Government. On January 30, World Health Organization (WHO) declared coronavirus disease 2019 (Covid-19) a public health emergency of international concern.[9]

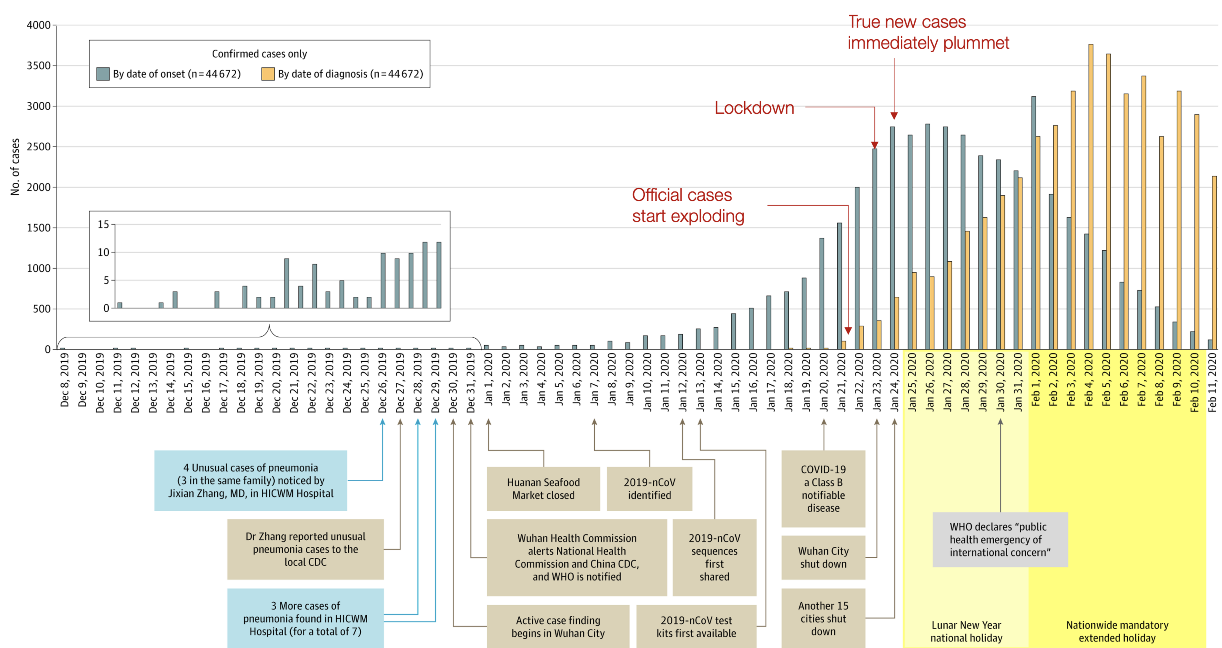

Figure 1. Timeline Covid-19 Events in Hubei[10]

Since then, many countries have experienced exponential growth in the number of documented Covid-19 cases (see Figure 2). As of March 30, 2020, WHO reported a total of 693,224 laboratory-confirmed cases documented globally impacting 202 countries, areas or territories with cases and a total of 33,106 deaths.[11]

The time from symptom onset to death ranges from 2 to 8 weeks for Covid-19.[12] This means that some people who are currently infected with Covid-19 will die at a later date, which is important to keep in mind when comparing the current number of deaths with the current number of cases.

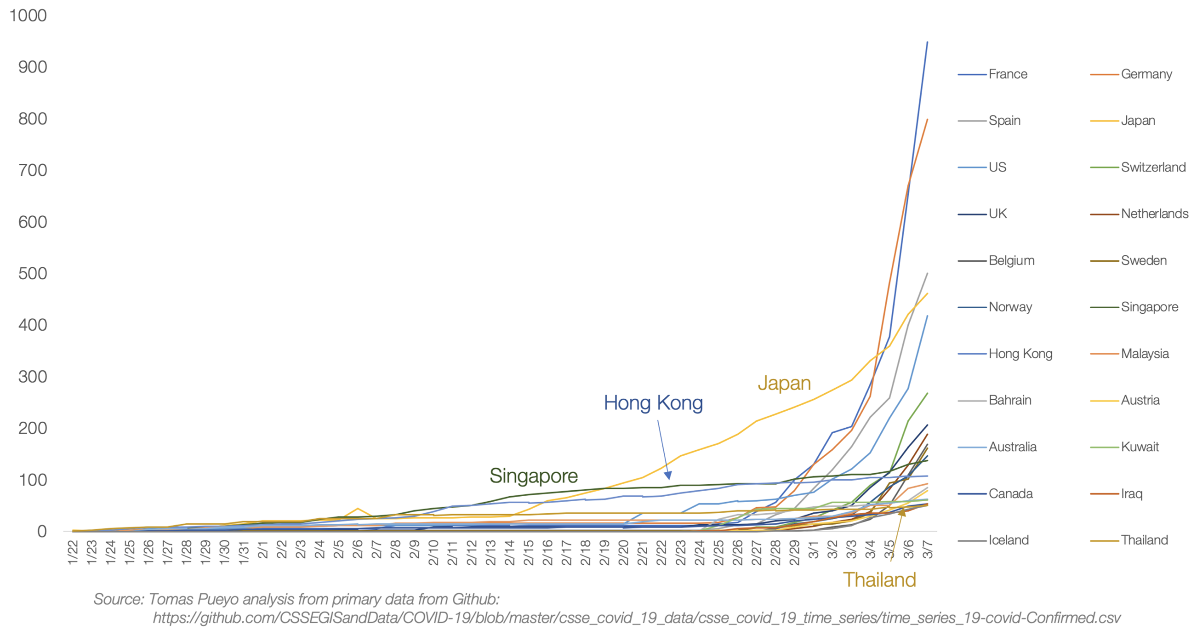

Figure 2. Time series of Covid-19 cases by country Jan 22 – Mar 7, 2020[10]

Studies show the severity of some cases of Covid-19 mimic that of SARS- CoV.[8] Given the rapid spread of Covid-19, the authors of this study postulate that an updated analysis of cases throughout mainland China would help identify the clinical characteristics and severity of symptoms that define the disease.

Transmission tree reconstruction has been used to specify the contribution of individual cases and locations to overall transmission of Covid-19.[13] In building the analysis, the focus was on determining 'who infected whom' during the outbreak. The goal being to yield new insight into the transmission dynamics of the infectious disease, to subsequently inform infection control policies and hospital preparedness.

Observed Development of Covid-19 Propagation

A lack of publicly available contact tracing data on cases of novel coronavirus makes it difficult for the global public health community to determine the true pandemic risk of this novel virus.[14] Many countries are under testing citizens due to Covid-19 test kit shortages and challenges administering the test[15] (See Figures 3, 4 and 5). Therefore, there isn't adequate testing data to predict the total number of infected people worldwide.

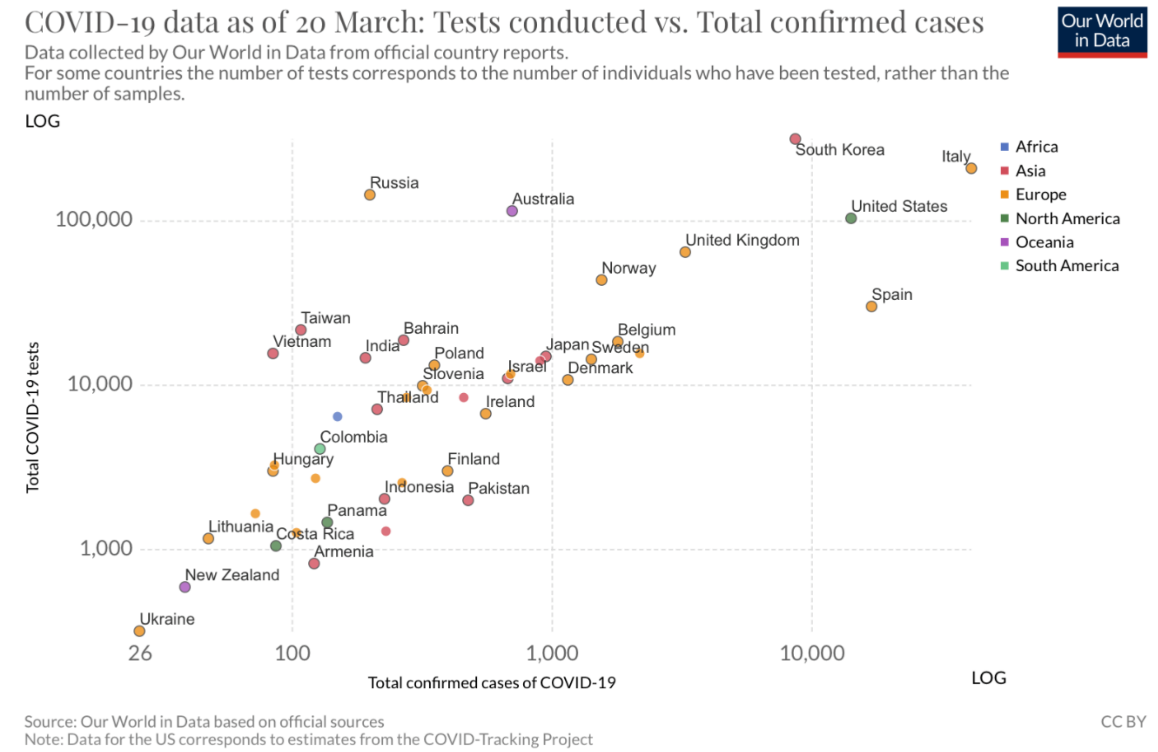

Figure 3. Tests conducted vs. total number of confirmed cases[16]

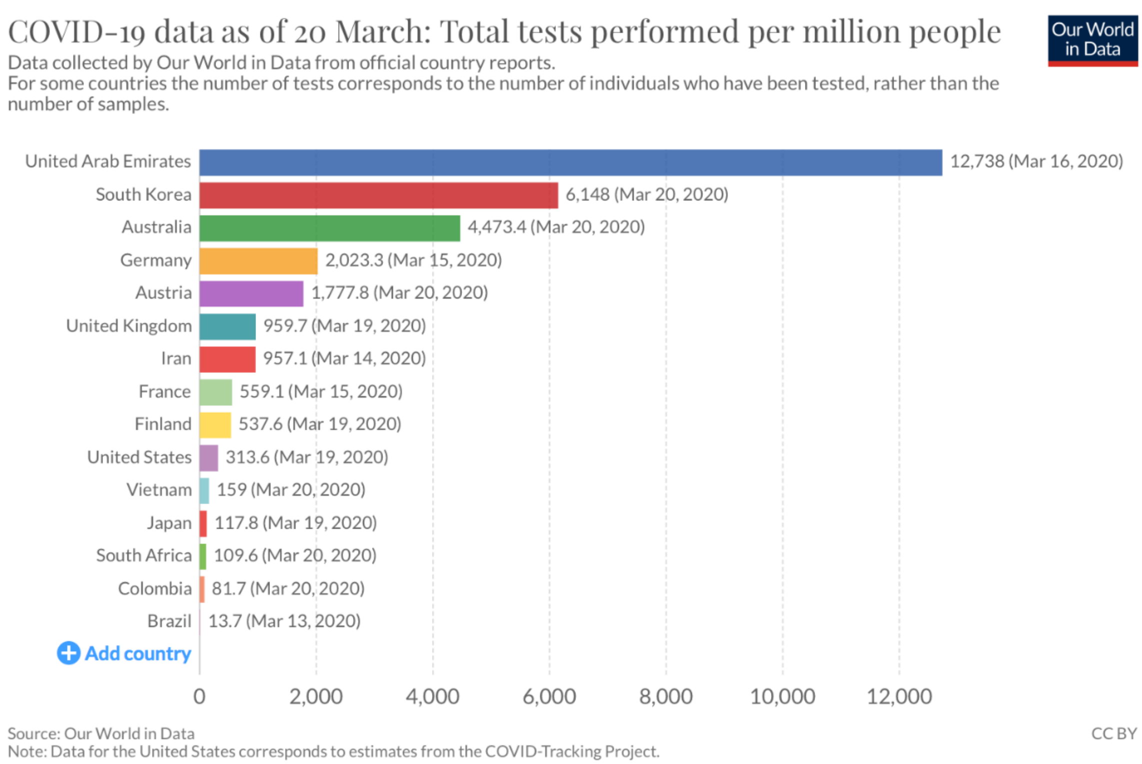

Figure 4. Total test performed per million of people[17]

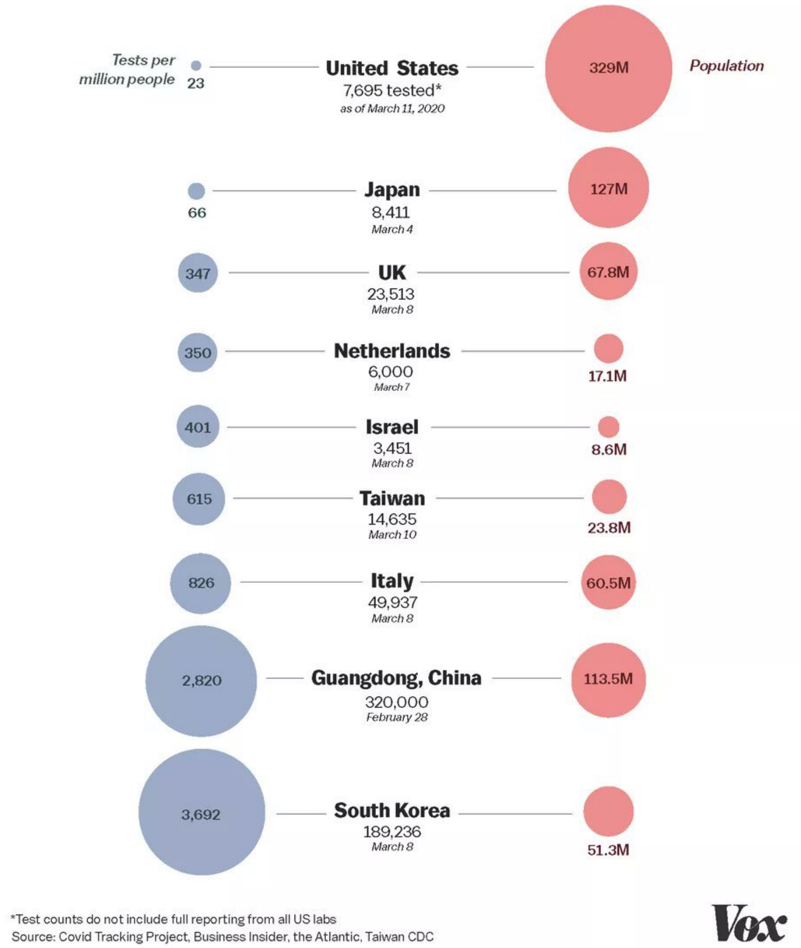

Figure 5. A snapshot of early Covid-19 testing per capita[18]

An absence of a cure threatens world populations and imposes social distancing as the interim solution.[19] [20] Estimates, using a summation formula, show the following projections for the number of new infections over a 30 day period, across three scenarios as shown in Table 1.[21]

Table 1. Projected number of new Covid-19 infections over a 30 day period, across three scenarios

Scenario	5 Day Period	30 Day Period
No social distancing practiced	1 person infects 2.5* others	**406** people infected as a result
50% reduction in social exposure	1 person infects 1.25* others	**15** people infected as a result
75% reduction in social exposure	1 person infects 0.625* others	**2.5** people infected as a result

**For estimations only. It is not possible to infect only a fraction of another person.*

In parallel to social distancing measures, the research community is deconstructing the characteristics of the virus to create a cure and vaccine.[22] [23] The biomedical sector is making valiant effort to keep pace with the spread of coronavirus.[2] Researchers have gathered information about Covid-19 far more quickly than for any previous emerging disease—making full use of advancing technology, particularly in genetics and data analysis. Scientists already know the virus's full genome, the sequence of around 30,000 biochemical "letters" in its genetic code. Labs around the world are using this to diagnose Covid-19—or its absence—through what is known as PCR (polymerase chain reaction) testing, which amplifies and identifies any genetic material from the virus in patient samples.

Both public and private sectors are working urgently to improve speed and accuracy of PCR kits and scale up production. Research-funding agencies must provide adequate support for two different types of testing: (1) Using gene sequencing equipment to track viral mutations, genetic letter by letter, as Covid-19 infection moves within countries and around the world. The work is already underway and completely open—with genomes posted on the internet when they are completed; and , (2) Genomic monitoring, has shown no significant changes that would affect the virulence or transmissibility of Covid-19, though there are preliminary signs that the virus might have two distinct strains.

Timeline Comparison SARS vs. Covid-19

As seen in Figure 6, the timeline of events for the SARS outbreak (left) from the first case to final worldwide containment. The timeline of events for the Covid-19 outbreak (right) from the onset of symptoms for the first case on December 8, 2019 to status on February 20, 2020. Over the course of the first 2 months, more than 70,000 cases have been confirmed and many more are suspected.

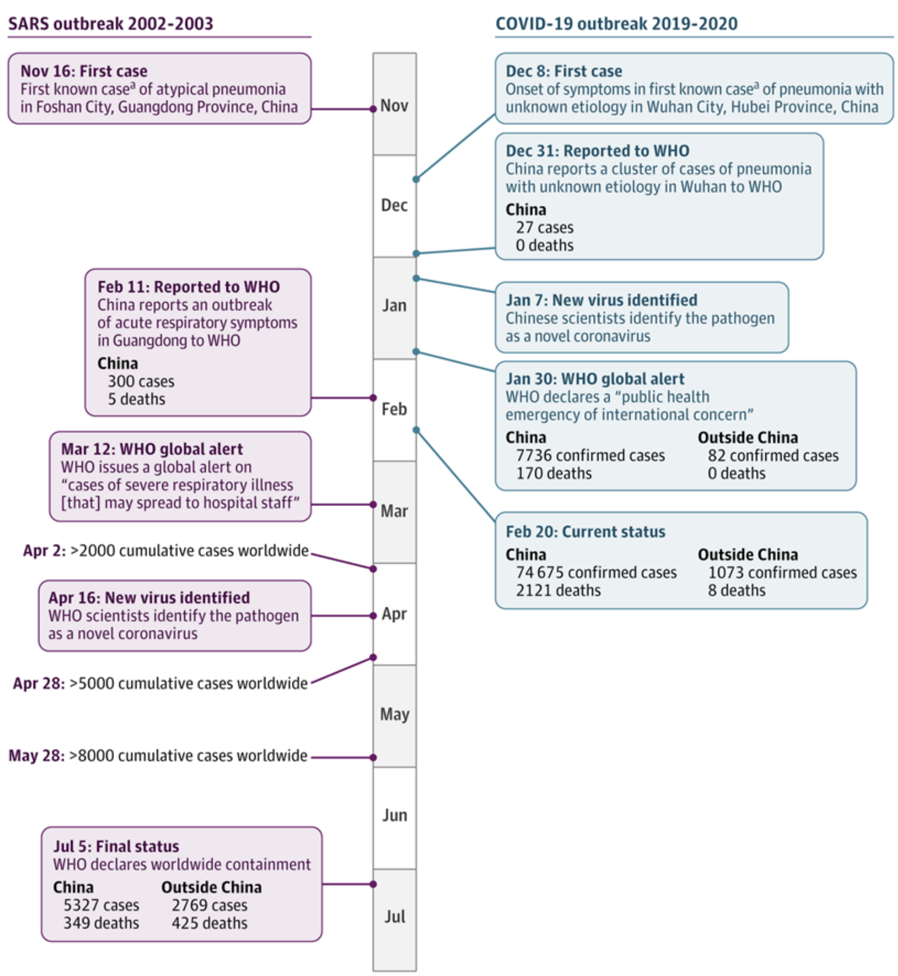

Figure 6. Timeline comparing the Severe Acute Respiratory Syndrome (SARS) and Coronavirus Disease 2019 (COVID-19) outbreaks[24] [a] Identified retrospectively. WHO announced Covid-19 to become a Pandemic on 11 March 2020

China Observes Decline of Virus Transmissibility Following Rigorous Confinement Policy

Case definition: Chinese Center for Disease Control and Prevention[25]

A suspected or probable case meets: (1) three clinical criteria, or (2) two clinical criteria and one epidemiological criterion

- **Clinical criteria:** fever; radiographic evidence of pneumonia or acute respiratory distress syndrome; and low or normal white blood cell count or low lymphocyte count.
- **Epidemiological criteria:** living in Wuhan or travel history to Wuhan within 14 days before symptom onset; contact with patients with fever and symptoms of respiratory infection within 14 days before symptom onset; and a link to any confirmed cases or clusters of suspected cases.

Figure 7 shows the epidemic curves for Wuhan, Chongqing, Beijing, Shanghai, Guangzhou, and Shenzhen with a R_0 of 2·68, assuming 0%, 25%, or 50% decrease in transmissibility across all cities, together with 0% or 50% reduction in inter-city mobility after Wuhan was quarantined on 23 January 2020.

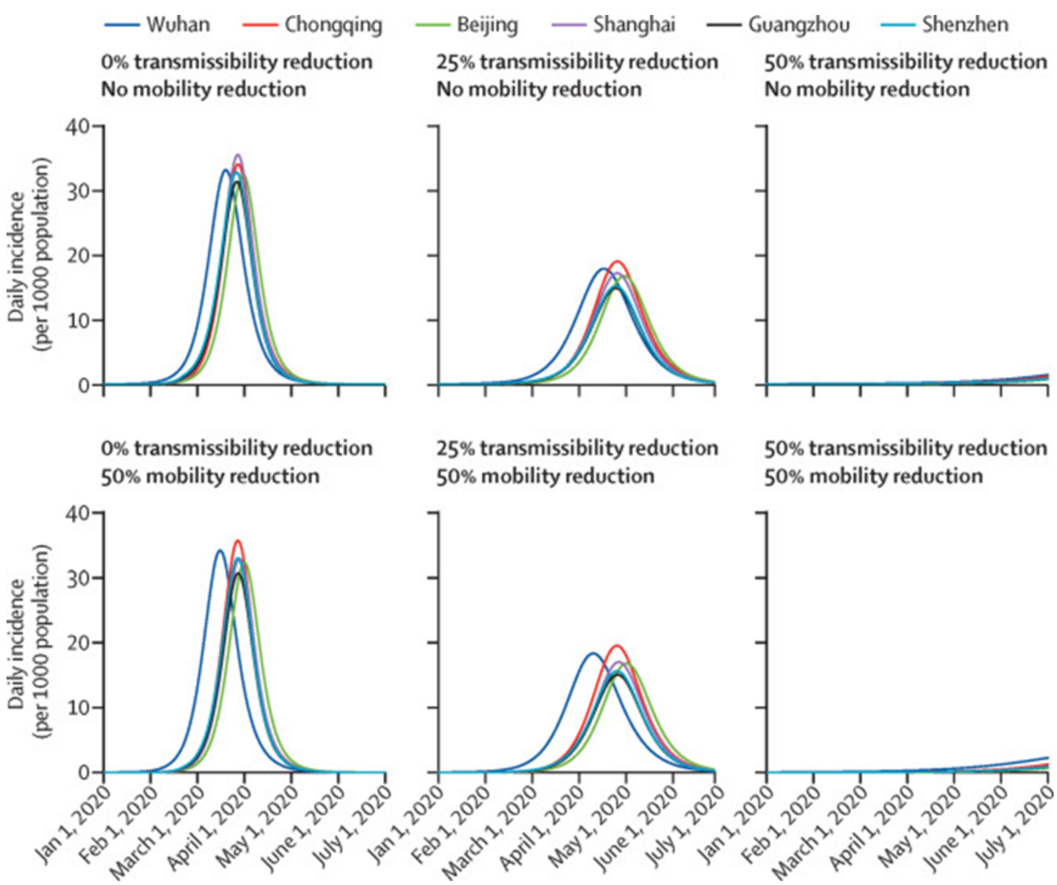

Figure 7. Epidemic curves for Wuhan, Chongqing, Beijing, Shanghai, Guangzhou, and Shenzhen[25]

Researchers of the study suggest that if transmissibility was reduced by 25% in all cities domestically, then both the growth rate and magnitude of local epidemics would be substantially reduced; the epidemic peak would be delayed by about 1 month and its magnitude reduced by about 50%. A 50% reduction in transmissibility would push the viral reproductive number to about 1·3, in which case the epidemic would grow slowly without peaking during the first half of 2020.

The outbreak curve in China started to flatten in late February (see Figure 8). These improvements were obtained through rigorous confinement policy applied on regions and cities for multiple weeks. On March 31, 2020, Ma Xiaowei, director of the National Health Commission, said that the country had contained the virus, with Wuhan reaching a milestone of 63,000 Covid-19 patients discharged.[26]

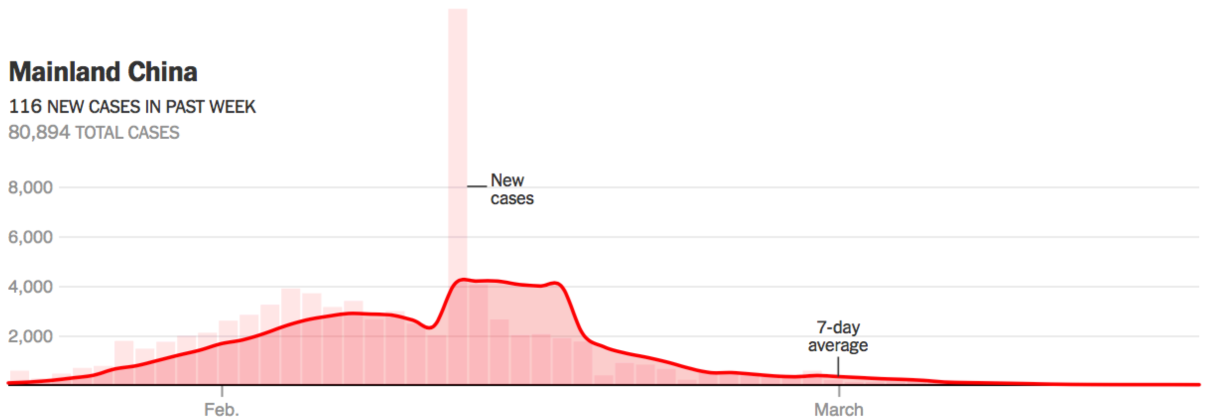

Figure 8. Number of new confirmed cases each day in Mainland China[27]

Covid-19 Decision Criticality

Public health organizations and epidemiologists are recommending substantial and even draconian measures that limit population mobility be seriously and immediately considered in affected areas to drastically reduce within-population contact rates of Covid-19 through cancellation of mass gatherings, school closures, and instituting work-from-home arrangements, etc.[25] Social distancing is seen as the only viable option to control spread—making treatment more manageable and providing more time for development of cure and vaccination.

Covid-19 is an exponential threat, which means there is urgency in taking decisions on how to slow the spread of the disease because every day counts. Delaying the social distancing decision by 1 day can result in 100s - 1,000s of cases per community (see Figure 9). Under exponential growth, 500 deaths grow to more than 1 million deaths after 11 doubling times, therefore exponential growth leads to very large numbers very quickly, even when starting from a low base. Reducing the peak of the outbreak will allow the healthcare system to provide care for more people.

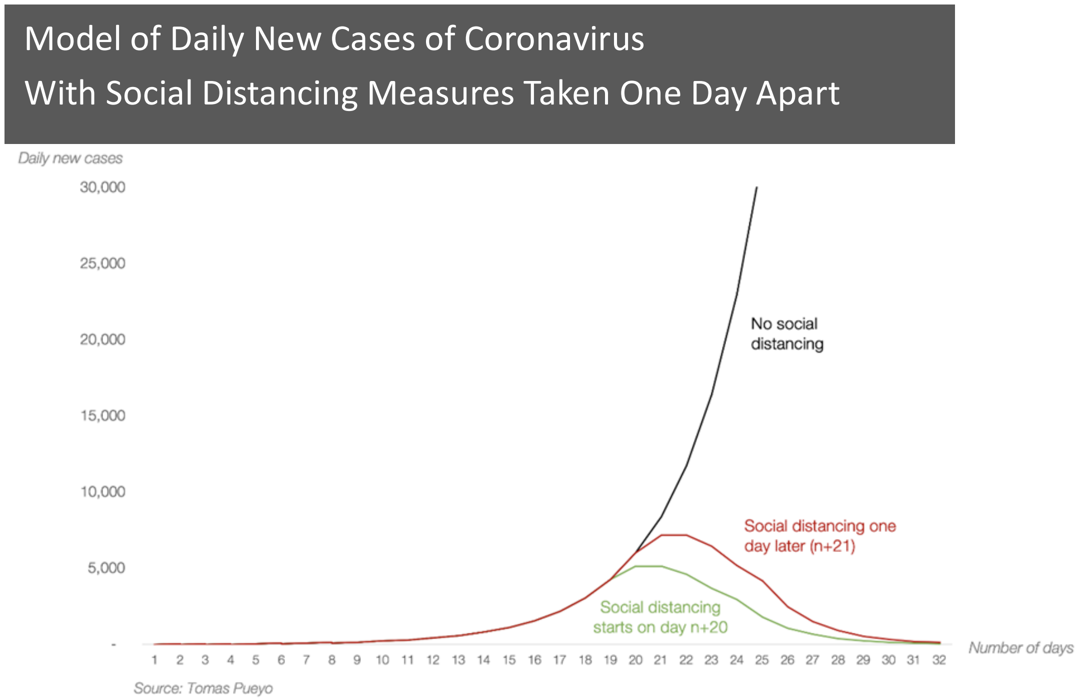

Figure 9. Model of daily new cases of coronavirus with social distancing measures take 1 day apart[10]

Covid-19 can be mild in the majority of cases, but for a portion of the population —especially among the elderly or those with pre-existing conditions—it can be very severe. Many of these patients will require treatment in intensive care units (ICUs). The WHO reports that "about a quarter of severe and critical cases require mechanical ventilation."[28]

In turn governments and other bodies must respond quickly to lower the rate of infection, so that the epidemic is spread out over time and the peak demand on the healthcare system is lower. Containment measures are intended to avoid an outbreak trajectory in which a large number of people get sick at the same time as visualized in Figure 10.

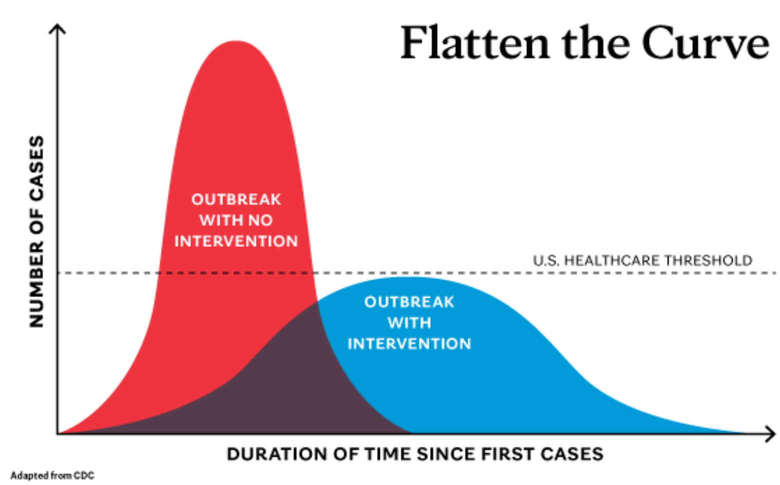

Figure 10. Goal of Covid-19 mitigation measures is to slow virus transmissibility[29]

By flattening the curve, the healthcare system is able to treat more people—even if the same number of people get sick—because they're not all happening simultaneously. Otherwise, the number needing treatment at the same time can get so large that health systems are overwhelmed, and become unable to provide adequate care for some patients.[30]

What and how much should be done is highly contextually specific and there is no one-size-fits-all set of prescriptive interventions that would be appropriate across all settings. Should containment fail and local transmission is established, mitigation measures according to plans that were executed during previous major outbreaks, such as those of SARS, MERS, or pandemic influenza, could serve as useful reference templates.[25]

Universal Dynamics Engine (UDE) Key Concepts

To measure the effects of dynamic complexity and reliably predict its nonobvious consequences, UDE relies on the NARS model.[31] This provides a rigorous process that computes the top-down communicating graphs to deal with the direct and indirect, convergent or degenerative solutions necessary to accurately model the complex, adaptive dynamics of a non-linear open system, like the global healthcare and all subsystems which contribute to its overall performance. UDE deals with not only interdependencies involving adjacent constituents in a graph, but all other influences formed by non-adjacent components and at any level carrying multiple order indirect perturbations.[*]

Dynamic Complexity

An important concept in systems theory is the notion of interdependence between systems (or subsystems). Healthcare is comprised of multiple self-contained but interrelated subsystems that deliver healthcare services to meet the health needs of target populations. These elements continually influence one another (directly or indirectly) to maintain their activity and the existence of the system, as needed to achieve the goal of the system.

Understanding the interdependence between organization of people, institutions, and resources is vital to building and managing a complete healthcare system. If these relationships are not well understood changes made to one part of the chain may affect another in unwanted ways.

Dynamic complexity is a detrimental property of any open, complex system (or environment) that reflects the behavioral influences caused by interactions between components as the workload increases over time.[32] If a system operates with a high level of dynamic complexity it means a lot of energy is wasted on duplicative or non-productive activities.

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[*] a deviation of a system, moving object, or process from its regular or normal state of path, caused by an outside influence

It is difficult to determine small resonances† when using statistical mechanics to deal with randomness. Therefore, long-term representation becomes a challenge. Without a universal mathematical formulation that can be applied to accurately represent all system dynamics in all cases, healthcare system participants must rely on a number of domain specific, probability-based solutions that incomplete views of reality or a wide range of possible outcomes.

Errors in any estimates of factors that shape the course of an outbreak[33]—including how many people are susceptible, how many are infectious, and how many are recovered (or dead) and presumably immune—can send a model wildly off course. In the autumn of 2014, modelers at CDC projected that the Ebola outbreak in West Africa could reach 550,000 to 1.4 million cases in Liberia and Sierra Leone by late January if nothing changed.[34] As it happened, heroic efforts to isolate patients, trace contacts, and stop unsafe burial practices kept the number of cases to 28,600 (and 11,325 deaths).[35] This variability points to the need for a more reliable method of modeling and predictive analysis for the purpose of strategic planning and response to potential epidemics.

Perturbation Theory

The presence of deterministic chaos within healthcare systems—meaning that the apparently-random states of disorder and irregularities are governed by deterministic laws that are highly sensitive to initial conditions—demands non-linear treatment. Perturbation theory provides the mathematical basis necessary to predict how a tiny change in one of the variables, might result in a totally different outcome than expected.[36] This is useful to predict the behavior of any system in which the effects are extremely sensitive to changes in the conditions that cause them.

Perturbation theory uses mathematical methods to find an approximate (quasi-exact) solution to a problem, by starting from the exact solution of a related, simpler problem and continuously add more inequalities until the mathematical representation fits the real one. A critical feature of the technique is a middle step that breaks the problem into solvable and perturbation parts.

Perturbation theory is used to reveal the significant interdependencies in systems that produce dynamic complexity. Perturbation theory provides the foundational solution of dynamic complexity in systems that produces a large spectrum of dynamics and have an exact solution if and only if all or most individual and significant inequalities are explicitly represented in the solution.

Using this method, an accurate formulation of dynamic complexity can be provided that is representative of the web of dependencies and inequalities even in systems as complex and expansive as a global healthcare system, as presented in Figure 11. Additionally, perturbation theory allows for predictions that correspond to variations in initial conditions and influences of intensity patterns, which is often the case in a pandemic.

† The tendency of a system to vibrate with increasing amplitudes at some frequencies of excitation

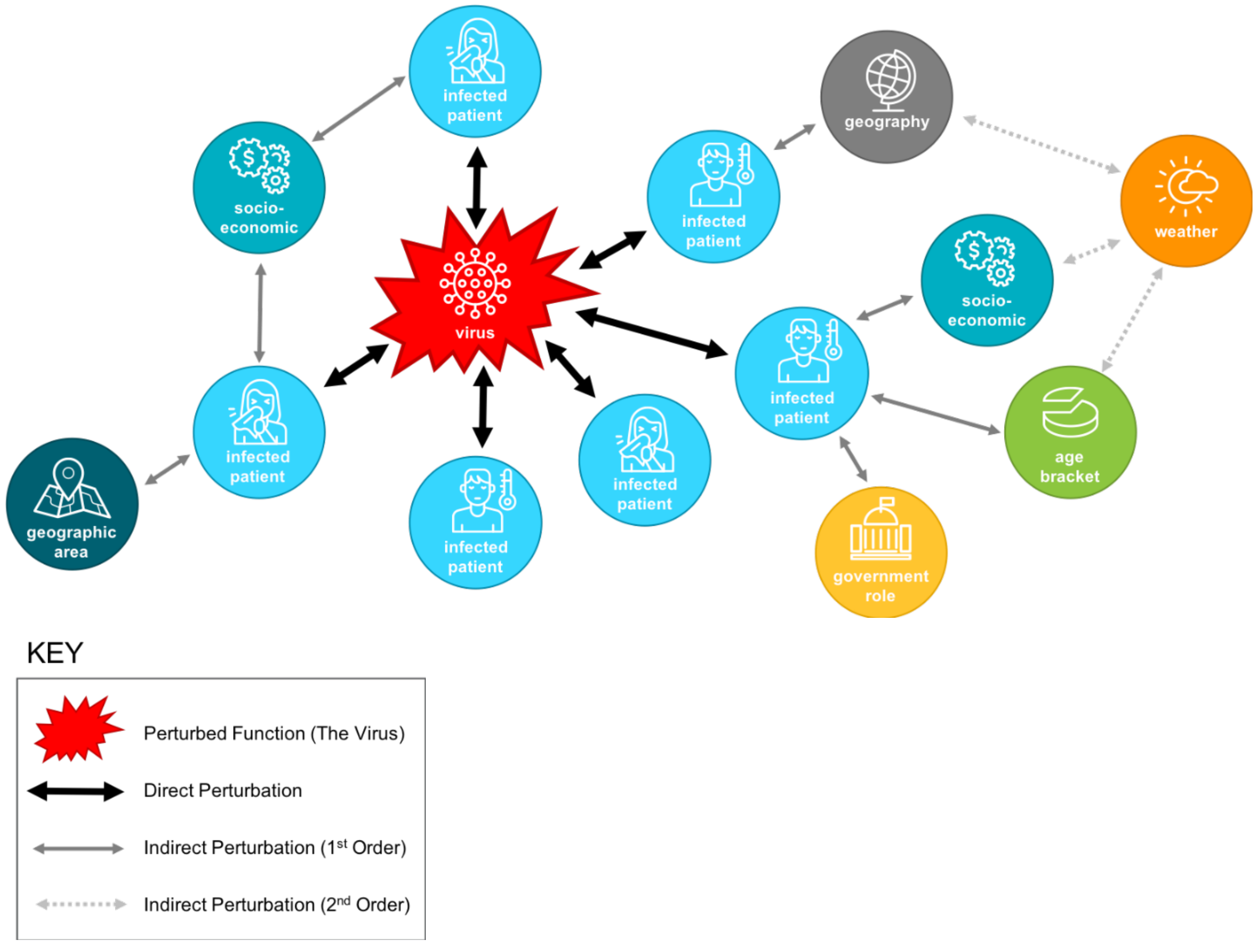

Figure 11. Use of perturbation theory accurately captures cause and effect relationship of virus propagation

Perturbation theory has successfully been applied in many case studies ranging from economic, healthcare and corporate management modeling to industry transformation and information technology optimization.[36] In each case, the singularity point has been determined with sufficient accuracy. This allows system stakeholders to know the conditions under which dynamic complexity would become predominant and the predictability of the system chaotic (see Figure 12).

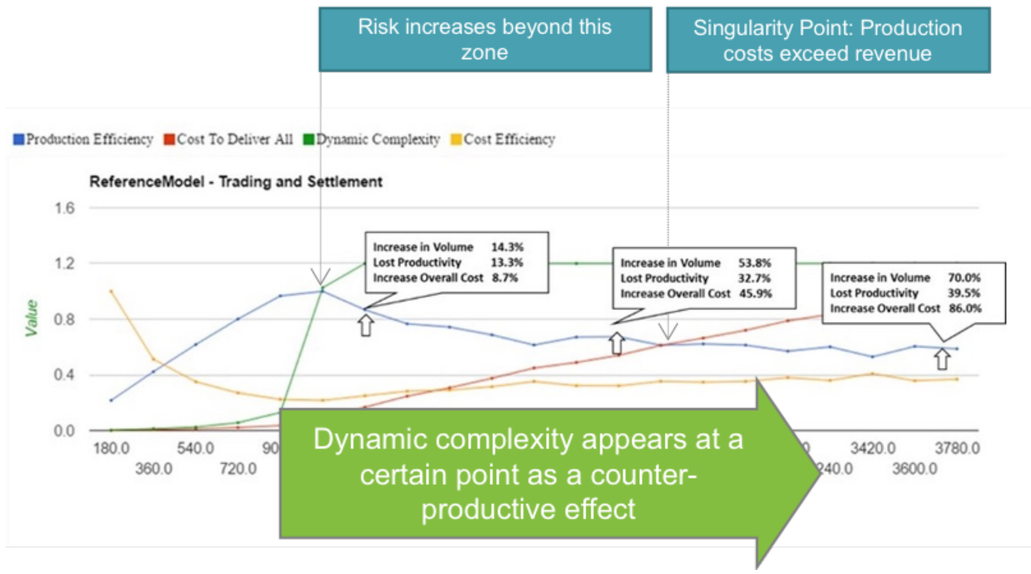

Figure 12. Perturbation theory based graph predictively reveals effects of dynamic complexity and singularity

A key advantage of the method is that prior knowledge of what may cause an eventual singularity is not needed. Only the variables and present conditions of the system need to be known in order to test how any future changes may impact the system's behavior. In essence, the goal is to identify chaotic processes because they basically work as amplifiers by turning small causes into large effects. Once the causes are known, any system changes which may indicate a risk is building can be closely monitored. As risks increase, system owners can proactively take actions to avoid an unwanted outcome.

UDE Methodology Outcome

As shown in figure 13, the outcome of the UDE methodology is a visualization of data as a curve, which allows modelers to find singularities and explore corrective solutions.

- Each point on curve predictively characterizes the system under specific conditions;
- Visualization helps identify singularities and metrics, which define the characteristics of the system at a specific point in time;
- Scenario analysis can then be used to identify the best corrective solutions.

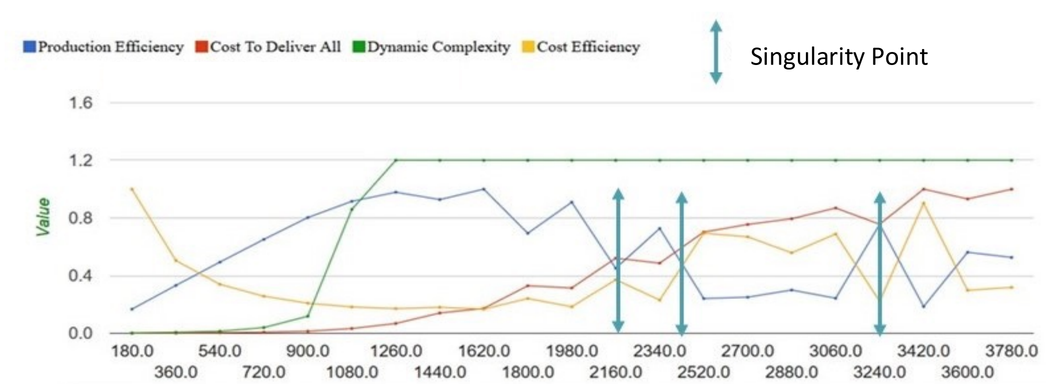

Figure 13. UDE methodology visualizes data as curve to find singularities and explore corrective solutions

Key Characteristics of UDE Method

The goal of UDE method is to build a replication of a complex problem that allows representation of a system through a hierarchy of graphs and the interconnections that produce the analytics of the observed dynamics.

- The method does not use data correlation analysis or probabilities.
- Instead, the use of tensor-based solutions replicates all dynamics that produce an outcome.
- This allows the identification of outcomes with no historical precedent, which may be treated as an outlier event or ignored in statistical methods.
- Key differentiators of UDE method:
    - Mathematical-based analytics;
    - Replication of real world into system of equations to accurately create digital twin;
    - Supports testing a host of scenarios with the aim to discover which scenarios will produce a singularity.

UDE treats each system function separately and concurrently builds the interdependencies through a complex graph that depicts perturbations exerted on each function by fluctuations at each function due to all others (see Figure 14).

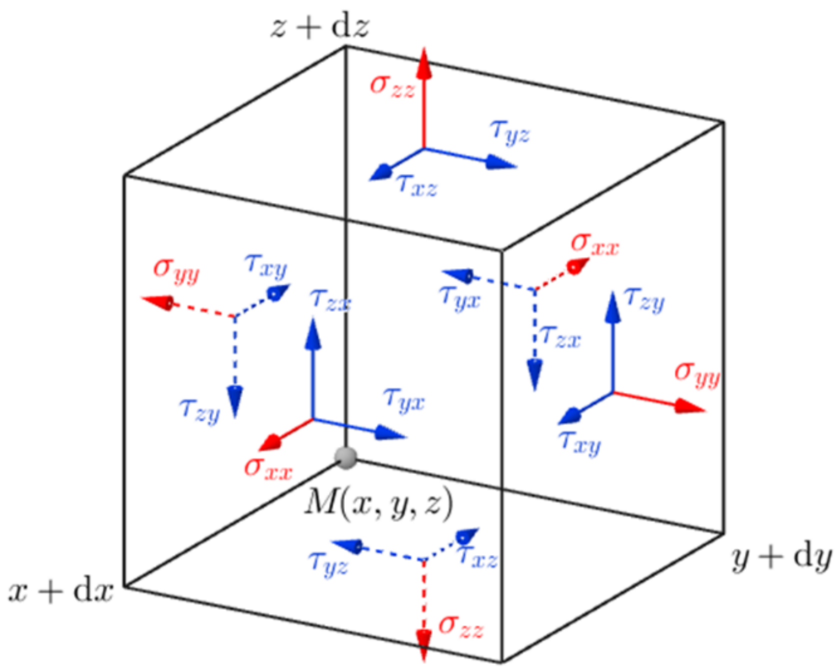

Figure 14. Tensor-based solution used for UDE

Why Use a Graph-based Solution to Simulate Complex Dynamics?

Use of perturbation theory allows users to simulate components interdependencies at a graph structure plane (leaf) that pushes down the inheritance that occur to lower level interdependencies leaf's (see Figure 15). The lowest plane involves the physical implementation platform that is shared by all upper graph's leaf's and therefore translates interdependencies into time-space perturbations that impact and may produce risk on three dimensions: productivity, service quality and cost.

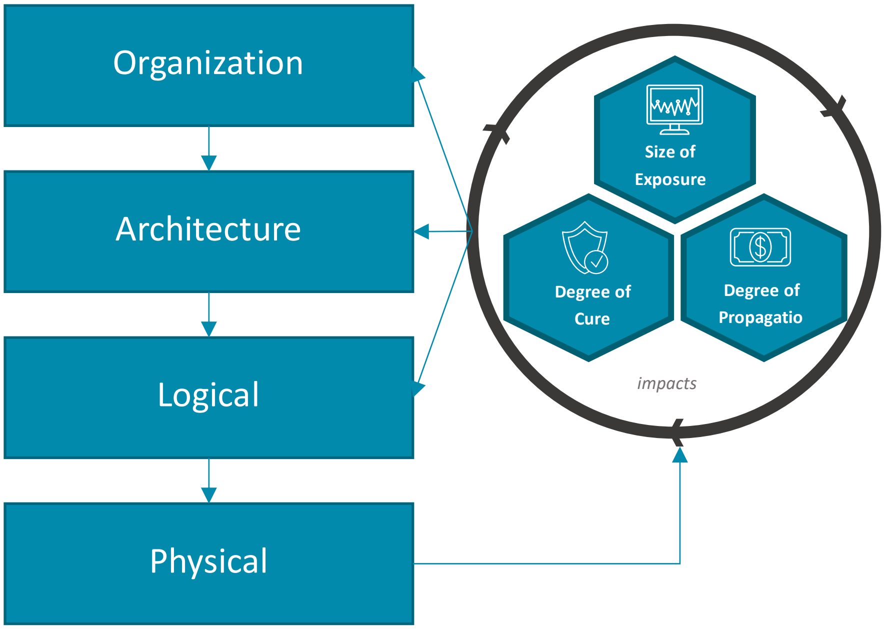

Figure 15. Use of perturbation theory allows users to simulate components interdependencies at a graph structure plane (leaf) that pushes down the inheritance that occur to lower level interdependencies leaf's

Once the computation is performed using perturbation algorithms and solvers, the results will be analyzed and propagated back to all graph's leaf's and components at the upper layers. Such propagation is crucial to translate the relation of "cause-to-effect" originated at any level as a result of computation.

The Mathematical Treatise

NARS is a patent-pending process that uses an advanced perturbation theory based algorithm, which includes a powerful solver and cognitive remediation rules.[31] NARS model expresses and solves Euler-Lagrange PDE's through a graph representation that depicts all possible interdependencies at a graph leaf level as well as interdependencies that happen at lower level leaves that form the full system—in this case, "a healthcare system."

Some vertex and edges are influencing and influenced, but not necessarily adjacent or even near to a target constituent, therefore the full structure needs to be computed as all constituents are influencing all and each other. This point is crucial because the connections between components are active and carry one or more types of the following functions:

- *Connector communicator:* For example, delay of medical intervention (e.g. testing hierarchy) ;
- *Connector contaminator:* That carry a change impacting the followers (e.g. triage of cases); and/or
- *Connector communicator contaminator:* Action that may produce a domino effect (e.g. incomplete account for pre-existing conditions).

NARS dynamic complexity representation discovers both the risk at each function/vertex/station, but also through the perturbed graph with the three connectors outlined above. The model is therefore able to play all possible scenarios of stress analysis to determine limits and thresholds.

NARS model relies on the use of the degenerative perturbation theory. This allows the modeler to obtain a highly accurate solution of the global representation and shows the in/out influence of each constituent at a computation point with all initial conditions and direct and indirect perturbations involved from the outset.

Mathematical Emulation Using Graph Theory

Graph theory provides us with a mathematical non-linear data structure capable of representing various kinds of physical structure—consisting of a group of vertices (or nodes) and set of edges that connect the two vertices.

Properties of a graph:

- A vertex in a graph can be connected to any number of other vertices using edges;
- An edge can be bidirected or directed;
- An edge can be weighted.

Graph theory encapsulates all characteristics, dynamic behaviors and dependencies among system components to reproduce the exact behavior and adhere to all the rules of the system being emulated so that predictive analysis can be performed.

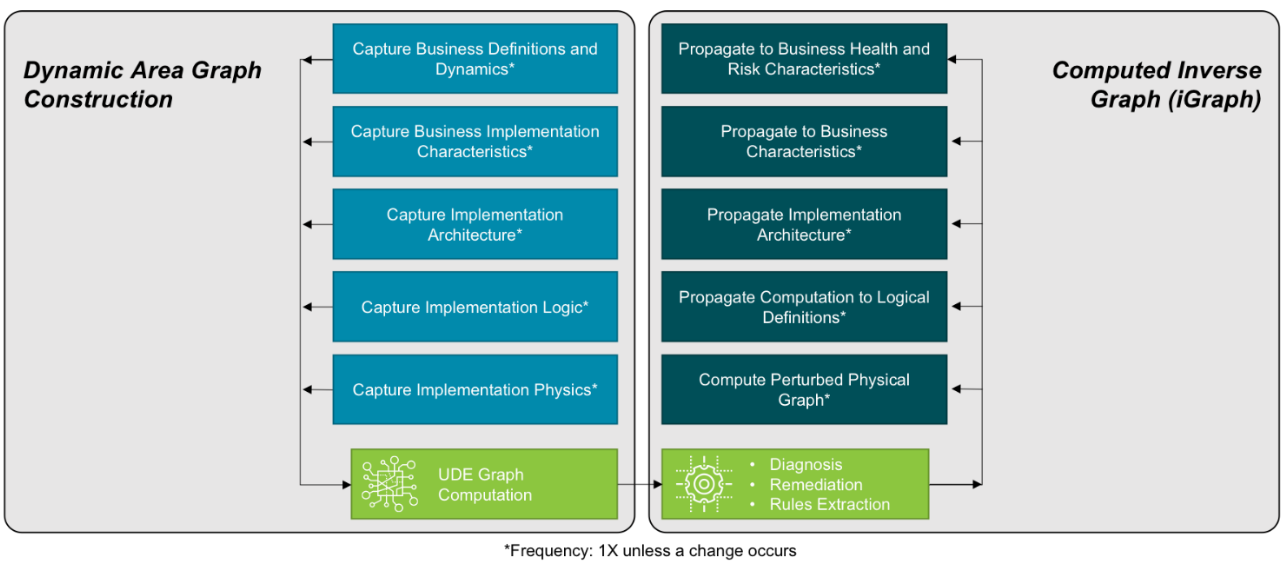

Figure 16. Circular discovery of dynamic complexity

The Circular Discovery of Dynamic Complexity

The process shown in Figure 16 depicts the foundational approach to dynamic complexity determination, which starts with a baseline dynamic complexity graph, identifies the possible and potential origin of a forming crisis through scenarios that cover changes at any level and determine the thresholds of those discovered origins.

Mathematical Perturbation Treatment of Risk

The application of perturbation theory on objects covers physical characteristics, speed and accelerations (Abu el Ata, Chapront, Delaunay and Poincare). The dependencies among different objects are represented in the theory as inequalities. The inequality represents an instance of interaction, which may be a direct impact (two nodes in a graph linked through an edge) or through more complex topology.

The NARS model uses Lagrange PDE and Abu el Ata solutions. Lagrange PDE represents the dynamics and the Abu el Ata proposed solution obtains the convergence. Hamilton defined a function that is used to describe a dynamic system (such as the motion of a particle) in terms of components of momentum and coordinates of space and time and that is equal to the total energy of the system when time is not explicitly part of the function.

Such processes produce conditions for which the perturbed solution comes closer to the real problem, such as including the gravitational effect of a third body. The *conditions* are a formula (or several) that represent reality in the form of correction(s). The slight changes that result from accommodating the perturbation, which themselves may have been simplified yet again, are used as corrections to the approximate solution. Sometimes, even only one cycle of corrections provides an excellent approximate answer to what the real solution should be.

In some systems these corrections correspond to a deviation from the ideal world and in such cases the calibration process provides an interesting indication as to what actions should be employed to evolve the system to more closely match an ideal world (IT systems, medical diagnosis and economic outlook).

A cycle of correction may be insufficient to come close to a stable solution. A partially corrected solution can be re-used as the new starting point for yet another cycle of perturbations involving direct and indirect corrections. The power of a solution method is one that will stop the solution after a reasonable number of cycles without sacrificing the accuracy and robustness of the outcome.

Our foundational work considers any dynamic system as open, continuous and deterministic in nature and its state at any point of time is expressed through a disturbed function. The function is defined and computed at any point in time at the bottom of a graph then propagates to the higher layers of the graph hierarchy. We call this last process the inverse graph (iGraph).

Mathematical Treatment of Topological Constraint on the Perturbed Graph Control -1

The perturbation theory approach involves a dynamic system of Lagrange-like partial differential equations that represent the dynamic behavior of a cost function and a solution that will capture both direct and indirect perturbations around a base of the un-perturbed solution.

Conceptually, the solution can be expressed with perturbation theory such that any metric X can be expressed in the form:

$$X = X_0 + \sum_M X_M^{(d)} + \sum_N X_N^{(i)}$$

General equation that involves a cause at any order perturbation

Where:

X_0 is the initial value of a metric (e.g., function or characteristic);

$X_M^{(d)}$ is the calculated direct impact due to M causes; the direct impact translates the impact of adjacent node in the graph to a specific node through an edge; and,

$X_N^{(i)}$ is the calculated indirect impact due to N causes (un-adjacent nodes) exerted on the perturbed function. Such effect could happen as a first order perturbation and may also happen as second, third, etc. order perturbations.

The significance has a considerable importance as an unapparent statistically uncorrelated effect can have an important effect on the basic function. In simpler terms, a statistically unlikely risk can appear and even translates sometimes into singularity due to multiple orders of interactions.

Mathematical Treatment of Topological Constraint on the Perturbed Graph Control -2

In more detail, consider the following vector:$\sigma = \sigma(k)$, where k=1, 2 . . . k and where σ is a function of time and represents the metrics that describe corporate, financial, business, and technology engineering characteristics and behavior.

Further consider that:

$\sigma^{(c)}$ represents the unperturbed value of a metric, or its minimum admitted value for simplicity;

$\sigma^{(d)}$ represents a measure of a perturbed metric due to the direct impact applied on the perturbing function X^d; and

$\sigma^{(i)}$ represents the indirect perturbation due to the perturbed effect of metrics against each other or the perturbing function $X^{(i)}$ due to an external impact.

In general, the system of equations that represent the variations can have the form:

$$\frac{d\boldsymbol{\sigma}}{d\boldsymbol{t}} = \boldsymbol{X}^{(c)}\left(\boldsymbol{\sigma}^{(c)}\right) + \boldsymbol{X}^{(d)}\left(\boldsymbol{\sigma}^{(d)}\right) + (\boldsymbol{X}^{\boldsymbol{i}}\ (\boldsymbol{\sigma}^{(i)})$$

where $X^{(c)}$ represents a basic function.

Further assume that:

σ' and **σ''** are vectors representing σ through different coordinates, and that **$\sigma^{(0)}$, $\sigma'^{(0)}$**, and **$\sigma''^{(0)}$** represent the unperturbed values of a metric. Then, the first order direct perturbation is:

$$\frac{d\sigma}{dt} = \sum_{k=1}^{K}\left(\frac{dX^{(c)}}{d\sigma_k}\left(\sigma_k^{(c)}, \sigma'^{(0)}_k\right)\sigma_k^{(d)} + \frac{dX^{(d)}}{d\sigma_k}\left(\sigma_k^{(c)}, \sigma'^{(0)}_k, \sigma''^{(0)}_k\right)\right) \qquad \textbf{(1)}$$

and the first order indirect perturbation is:

$$\frac{d\sigma}{dt} = \sum_{k=1}^{K} \frac{dX}{d\sigma_k} (\sigma_k^{(c)}, {\sigma'}_k^{(0)}) \sigma_k^{(1)} + \sum_{k=1}^{K} \frac{dX^{(c)}}{d{\sigma'}_k^{(0)}} {\sigma'}_k^{(i)} \quad \textbf{(2)}$$

Mathematical Treatment of Topological Constraint on the Perturbed Graph Control -3

This separation seems artificial from a theoretical point of view, but it is natural from a practical point of view, as the origin of perturbation on $X^{(d)}$ and $\sigma^{(i)}$ are different. Next,

$$\sigma'^{(1)} = \sum_{k=1}^{K} \sum_{n=1}^{m} C_{k,n}^{(i)} \, e^{-\sum(n_n^* \chi_n)}$$

$C_{k,n}^{(i)}$ a matrix of numerical vectors, n_1*, n_2*, . . . n_m* are normalization constants and $\chi_1,\ \chi_2,\ \ldots.,\ \chi_m$ are the perturbing variables (function in time).

Therefore:

$$\frac{dX^{(c)}}{d\sigma_k},\ X^{(d)}\ and\ \sum_k \frac{dX^{(c)}}{d{\sigma'}_k^{(0)}} {\sigma'}_k^{(i)}$$

are known functions in time and can solve the two system equations (1) and (2) in the form:

$$\frac{d\sigma}{dt} = U(t)\sigma + v(t) \quad \textbf{(3)}$$

where U (t) is a square matrix (K x K) and *v* (t) is a known vectoral function.

The matrix is determined by:

$$\frac{dY}{dt} = U(t)Y \quad \textbf{(4)}$$

Mathematical Treatment of Topological Constraint on the Perturbed Graph Control -4

with $Y(t_o) = I$ **(5)**

where *I* is a unit matrix and therefore equation (3) becomes:

$$\sigma = Y(t)\sigma(t_0) + \int_{t_0}^{t} Y(t)Y^1(\tau)v(\tau)d\tau$$

and with $X^{(c)} = (X_K^{(c)})$ U specified in the form

$$v(t) = ((\frac{dK_K^{(c)}}{d\sigma_K}))$$

The formula $\frac{d\sigma}{dt} = U(t)\sigma$ forms the system of equations equivalent to the un-perturbed expression:

$$\frac{d\sigma^{(c)}}{dt} = X^{(c)}\ (\sigma_K^{(c)})$$

where the solution Y in equation (4) is known if the partial derivatives of the unperturbed problem is computed with respect to the K integration constants such as by determining

$((\frac{d\sigma_K^{(c)}}{dC_i}))$ with the condition of equation (5).

Universal Dynamics Engine 3-Step Methodology

Universal Dynamics Engine (UDE) is an advanced mathematical modeling method used to accurately represent a high level of interdependent components organized in hierarchy of graphs that is comprised of the following 3 steps:

- **Step 1: Deconstruction** collect all necessary knowledge and parameters as needed to meet the goals of steps 2-3;
- **Step 2: Sensitivity Analysis** build the model using UDE, which is based on perturbation theory and allows modelers to:
    - Replicate the problem by computing the 'digital twin';
    - Validate the model to ensure metrics match real system characteristics within 2 - 3% of reality;
    - Use model to perform scenario analysis to discover points of risk and which actions may achieve the desired results for the real system;
- **Step 3: Scenario Analysis** Incrementally increase the model submitted load to identify the singularity point (or chaos point). Stress testing the model in this manner allows modelers to discover the conditions under which quality will deteriorate, the system will hit a capacity limit and/or the cost to deliver begins to inflate.

Step 1: Deconstruction

Goal: Deconstruct structures into components, building blocks, interdependencies, interactions and other dynamics to understand, predict, reconstruct, and operate improved, transformed or innovated structures.

To begin the dynamic complexity discovery process, the system is first deconstructed using *emulative deconstruction theory*[37] to understand its constituent components and dependencies among them (see Figure 17). Deconstruction is analogous to how a doctor, meteorologist, biologist, or engineer will diagnose an eventual problem.

This step does not alter the system characteristics or behavior in any way other than is necessary to understand the interdependencies and dynamic properties that can impact each link and node. To successfully achieve this goal, it is important to map the interdependencies, topology of structures, justification of choices, operational constraints, modes of operations, and data available to discover the hidden structures that were formed over time.

Reason for Deconstruction

The right level of understanding is required in order to build a serious and robust relational model that relates the cause to effect for any business, human activity or natural phenomena. Generally, if modeling is performed before a phenomena appears or during the preparation phase of a business or human activity, we must rely on accumulated knowledge, which will sharpen our understanding over time.

If risk mitigation or problem resolution is required during the middle of a process (like the global outbreak of Covid-19), knowledge must be identified or sometimes built through collective experience, extracted measurements, process documentations and past observations. When creating a digital twin (*mathematical* *replication of real process dynamics)* through modeling and analysis, we rarely can obtain a full understanding of the process being analyzed from the onset. This systematically leads to a deficiency in the model's ability to accurately represent reality. Therefore, we need reliable methods to create the missing data in order to deliver the required content into a modeling specification.

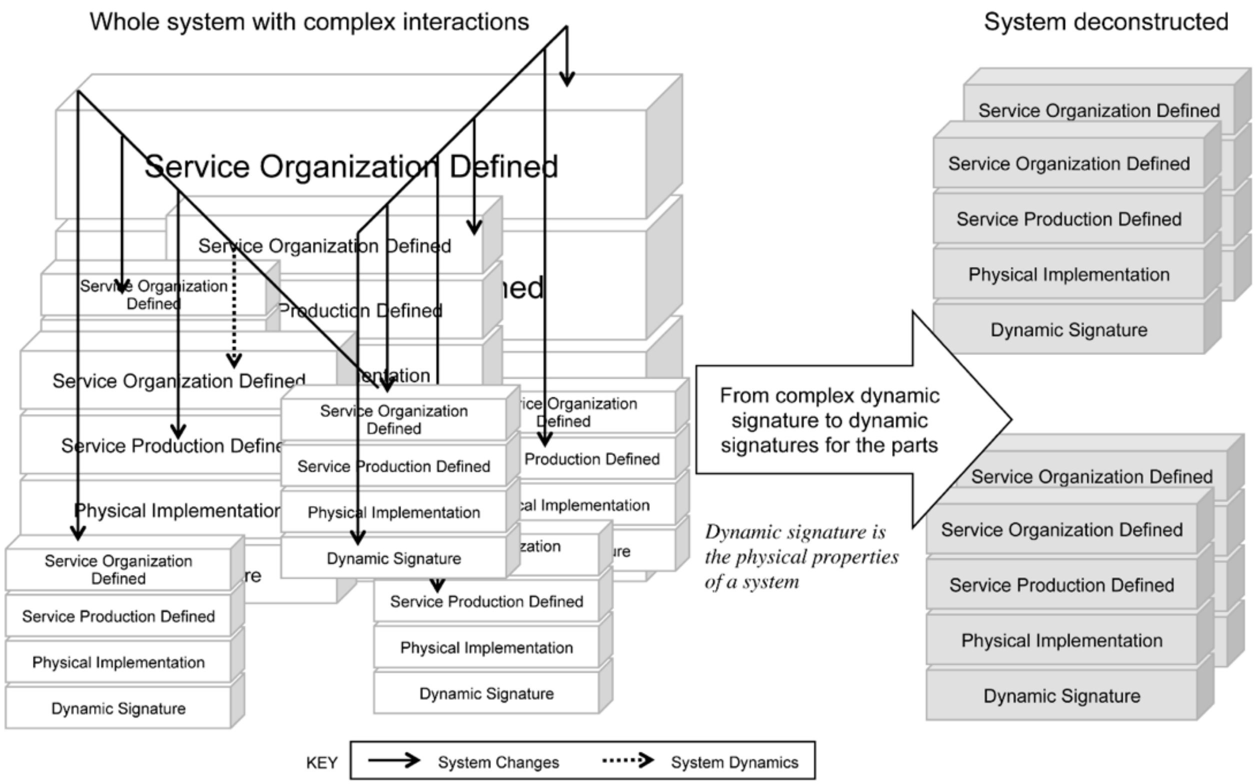

Figure 17. Deconstruction of whole system into dynamic signatures for the parts

In order to bridge this knowledge gap between a process and its representative digital twin, we promote the use of deconstruction to collect the foundational and dynamic characteristics of the process by building a hierarchy of graphs—each representing a layer definition as well as its connections mechanisms to lower level graphs. Today, most viral outbreaks, economic threats, consequential business dynamics or ecological crisis require a deconstruction process to understand the constituents of their structures in order to identify the determinant parameters that govern their observed characteristics. Dynamics deconstruction is crucial to understand what causes will yield which effects under different scenarios and conditions.

Deconstruction Process

The deconstruction process allows the right discovery of the hierarchical graphs to adequately represent and model risk management for organizations. In all fields of life, deconstruction is the privileged way to build the digital twin of system dynamics in order to obtain the right diagnosis, identify the real cause of misfunctioning systems and support the move from diagnosis to action to cure, optimize or disrupt.

In order to achieve this goal, system analysis should rely on the proposed deconstruction method to capture the right data, knowledge and expertise to build a hierarchy of interconnected graphs that show both the topologies and dynamic interactions. Mathematical modeling will rely on such graphs to perform sensitivity analysis in Step 2 and discover limits and singularity points under different scenarios that involve an evolution of initial conditions in Step 3.

Causal Deconstruction Method

Our causal deconstruction method is a seven-stage scientific methodology (see figure 18) that is used to understand the constituent components of a system and any dependencies by establishing the base dynamics, deconstructing complexity, constructing an emulator, predicting singularities, comparing to the actual system, defining improvements and monitoring the execution.[36]

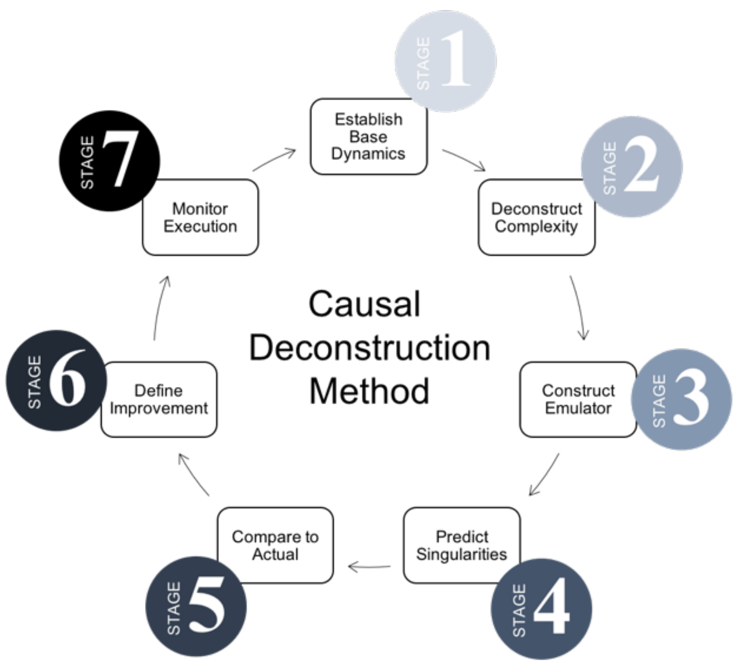

Figure 18. Causal deconstruction method

Causal deconstruction uncovers results that often defy the common wisdom that stops at the wrong level of analysis and usually produces a host of misleading conclusions. This method promotes the right approach of analysis and mathematics capable of solving the problem within an environment where dynamic complexity has become the major risk.

Through the use of deconstruction theory, it becomes clear that the overall performance of a system (defined in terms of quantity, quality and cost) does not always represent the expected output of the system given the accumulated characteristics of the constituent components, generally due to a loss in energy. Like the binding of energy at the atomic level, the release of energy within human-made systems may represents a predetermined, but unknown risk. The risk forms because the transfer of energy tends to—sometimes dramatically—reduce the quantity the system is able to produce, negatively affects the system's service quality and inflates the cost to deliver the desired outcomes.

Using the NARS model, we can provide accurate formulation that is representative of the web of dependencies and inequalities. This allows for predictions that correspond to variations in initial conditions and influences of intensity patterns. Data capture for digital twin modeling represents three views: corporate view, service view, and implementation view as outlined in figure 19 and table 2.

Data Capture for Digital Twin Modeling

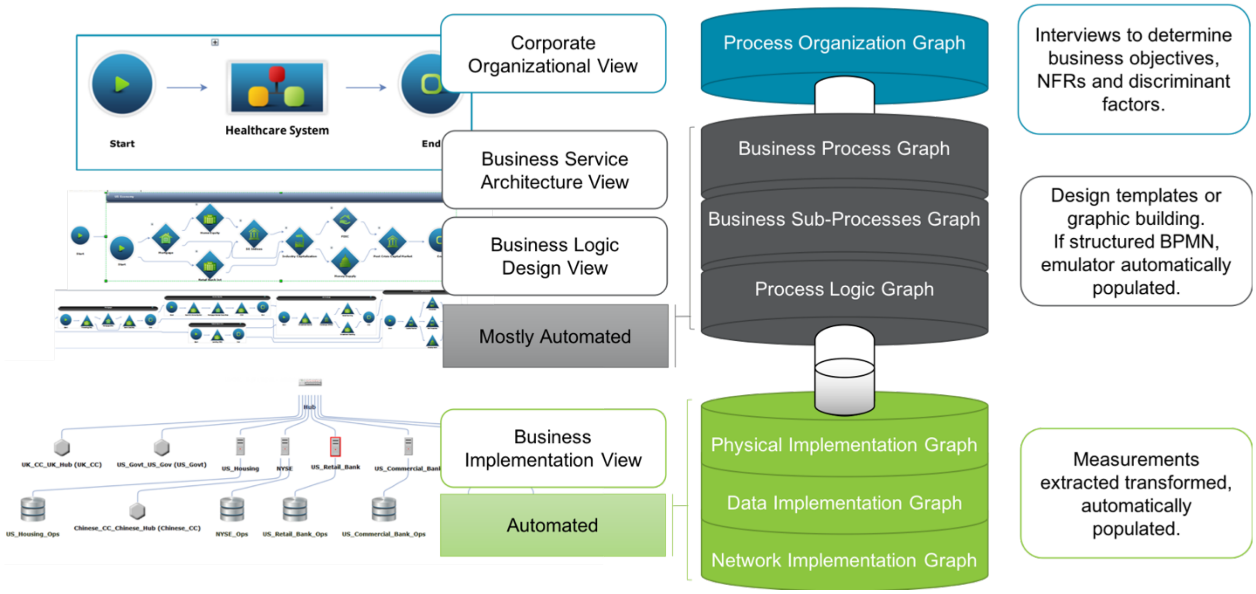

Figure 19. Data capture for digital twin modeling

Table 2. Information Collection Represents Three Views

Corporate View	Shows the top-down organization of the business, i.e. division/sector/activity—whether it be insurance, retail banking, credit card, etc.—to business service trajectory, which could be anything including settlement , trading, payment, car production, different mail processing, car/plan maintenance, etc.
Service View	Shows the service trajectory (mail service, settlement, etc.) and the hierarchy of service: • Business processes (input, posting, cycling, etc.) • Business components (customer processing, payment processing, etc.) • Up to the lowest logical level (balance accounts, update information, etc.) and the logical server (human, truck, mainframe, database messaging, etc.)
Implementation View	composed of two levels: • Local level: Transforms the logical server into one or many physical servers (each with its own processing mode, physics, space and energy characteristics) • Global view: Shows geographic location of components spread over a larger structure (e.g. Google maps)

Application for Covid-19

To determine singularity point and find which solutions will effectively limit virus propagation it is necessary to solve a 3-body problem that takes into account the size of exposure, degree of propagation and degree of cure as shown in Figure 20. The NARS model allows multiple order perturbations to cover the direct effect, as well as all possible indirect multiple order effects.

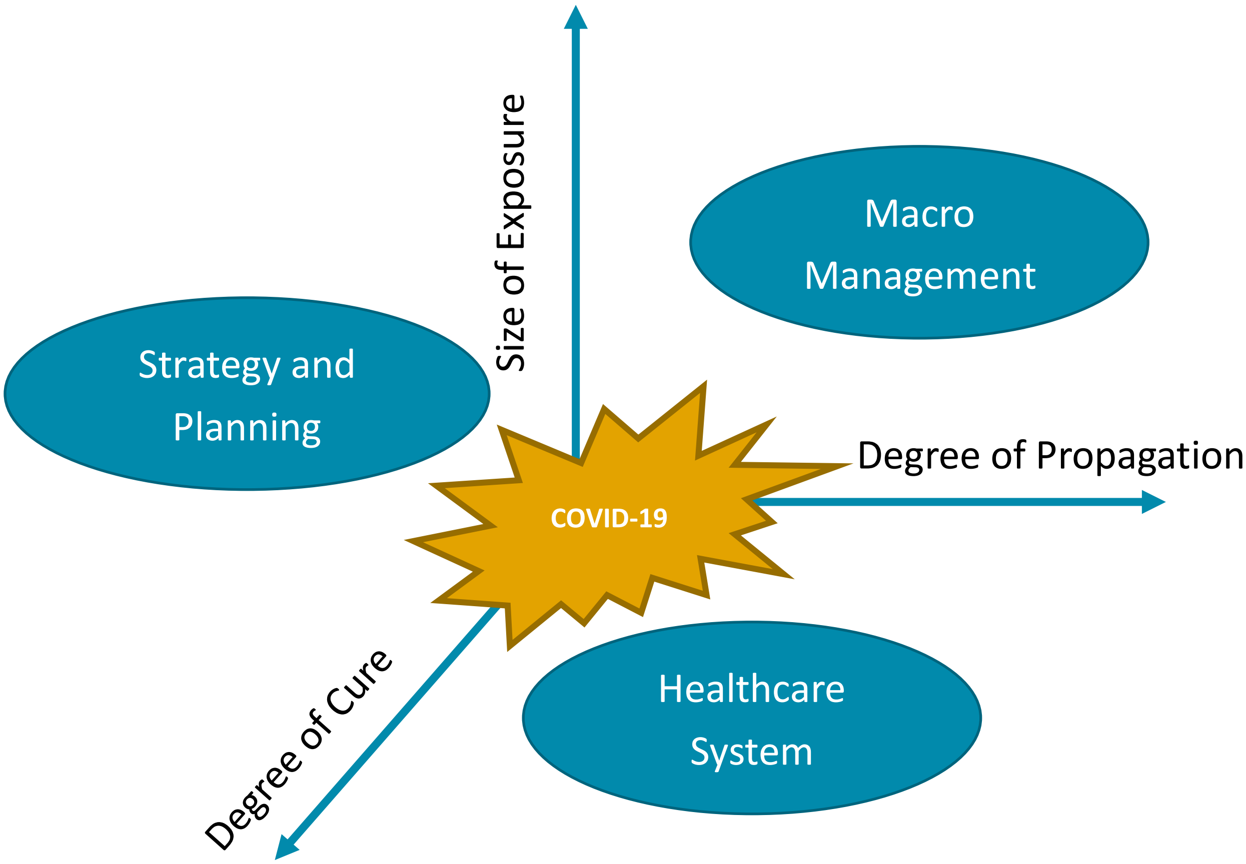

Figure 20. Illustration of Covid-19 influences on the healthcare system, strategy and planning and marco management of the pandemic

Step 2: Sensitivity Analysis

Goal: Identify the determinant variables within all possible variables and organize them into direct (between adjacent vertex) or indirect (of many orders on non-adjacent vertices) impacts. Then, build the perturbed representation that delivers the solution.

Sensitivity analysis is used to determine how different values of an independent variable impact a particular dependent variable under a given set of assumptions. Sensitivity analysis is performed component by component rather globally in order to calibrate the emulator and ensure it accurately represents the digital twin of the system being modeled (see figure 21).

Figure 21. Perturbed digital twin representation of the solution

Dynamic complexity is caused by interdependencies and contentions that increase as load increases—causing loss in productivity and inflation in costs. Sensitivity analysis is the method used to uncover these cause and effects. Analogous to the detailed, function-oriented tests a medical doctor may request to determine overall health of an organ, such as glucose or cardio tests, sensitivity analysis helps to identify which actions are needed to decrease risk and explore viable and proactive remedial options that secure an acceptable risk mitigation strategy in Step 3.

Step 3: Scenario Analysis

Goal: Construct the remedy and mitigation actions, certify the solution pertinence and discover additional variables and interrelationships that can be dependably used to predict the occurrence of previously known as well unknown risk behaviors.

To identify the risks or singularities that may be caused by dynamic complexity, it is important to test a system beyond normal operational capacity to find the breaking points and observe the results when various conditions change. Using the emulator built in step 2, the next step is to deploy the scenarios under different patterns of initial conditions and dynamic constraints to identify the conditions under which risk will increase and use the corresponding information to diagnose the case (see figure 22).

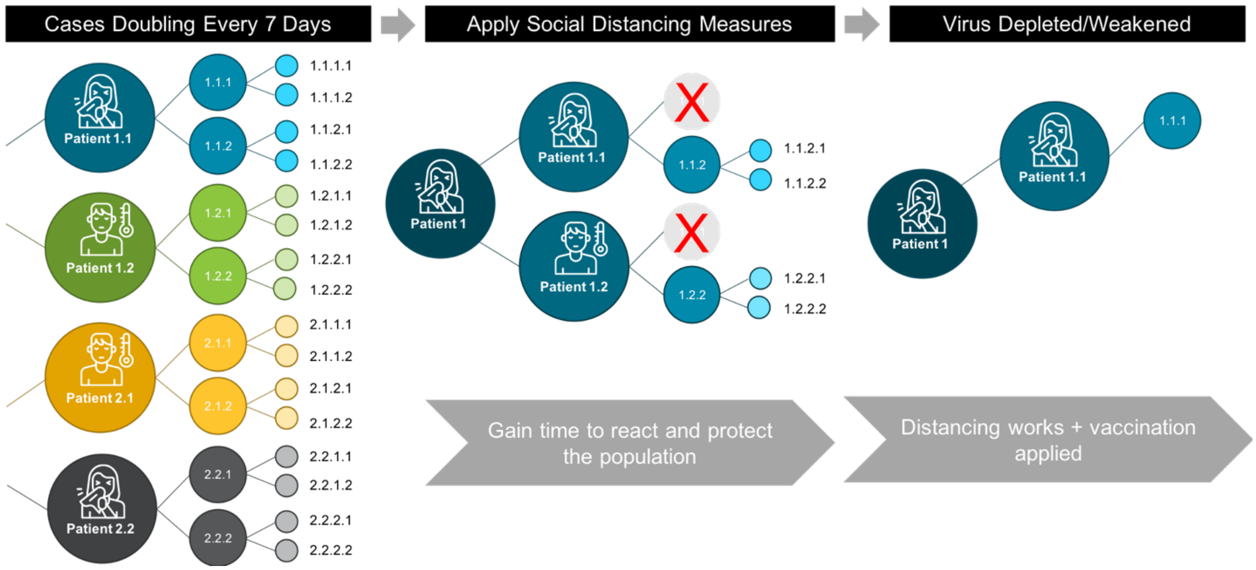

Figure 22. Scenario, staged treatment for Covid-19 outbreak

By modifying the parameters of each scenario within the emulator, one by one, by group, or by domain, to represent possible changes, it is possible to extrapolate each time the point at which the system will hit a singularity (see figure 23).

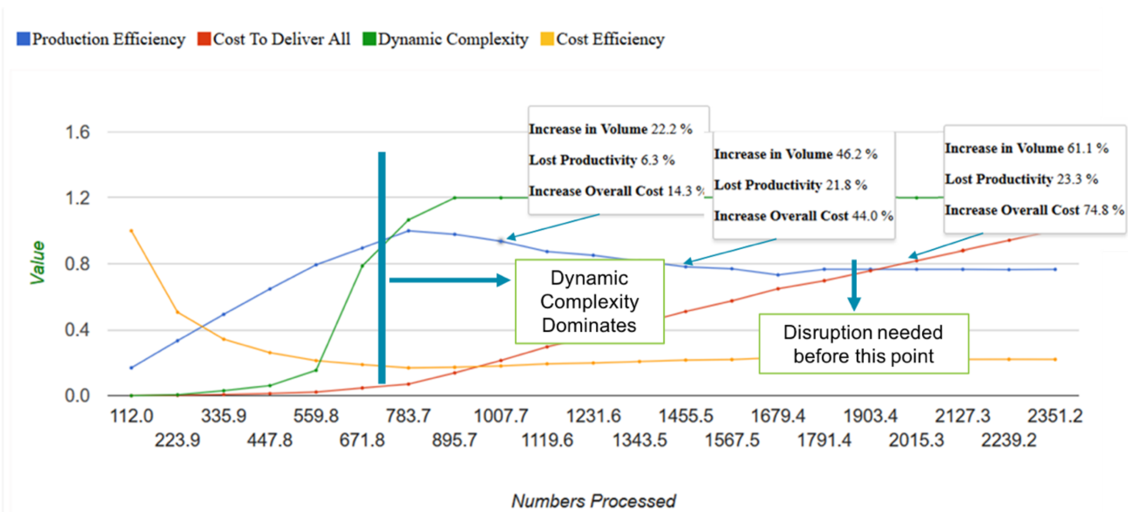

Figure 23. Computation of data as curve identifies risks and exploration of remedial options

CV-19 Model Example: Covid-19 Crisis Management in Germany

The following section provides an example of the applicability of UDE and the NARS model to provide the mathematical solution necessary to accurately represent complex dynamics in healthcare systems. The goal being to help governmental leaders, policymakers and medical providers gain a holistic view of interdependencies across complex healthcare ecosystems and understand influences as necessary to judiciously maintain balance between competing priorities, like economy, physical health and mental health.

In the absence of historical Covid-19 propagation and risk profile data, analogies were used to quickly build the CV-19 Model for major healthcare sites in Germany with continuous updates based on daily developments. Possible change scenarios were applied on the mathematical model to avoid statistical manipulation that may result in the wrong representation.

Deconstruction: CV-19 Model Construction

In building the mathematical model following the UDE deconstruction method (see figure 23) for Covid-19 patient treatment in Berlin, Frankfort and München, the following key considerations were taken into account:

- Covid-19 is a devastating virus with questionable trace and origin (so far);
- The virus puts the entire world at risk and may lead to cataclysm if not stopped;
- Reducing propagation has two advantages: (1) slow down the infesting process, and (2) gain time to find a solution: (a) vaccination to protect citizens not yet affected, and (b) cure to treat infected patients;
- Both vaccine and cure solutions require advanced research, cooperation and crucial financial support;
- Out of the crisis, the world will become a different place.

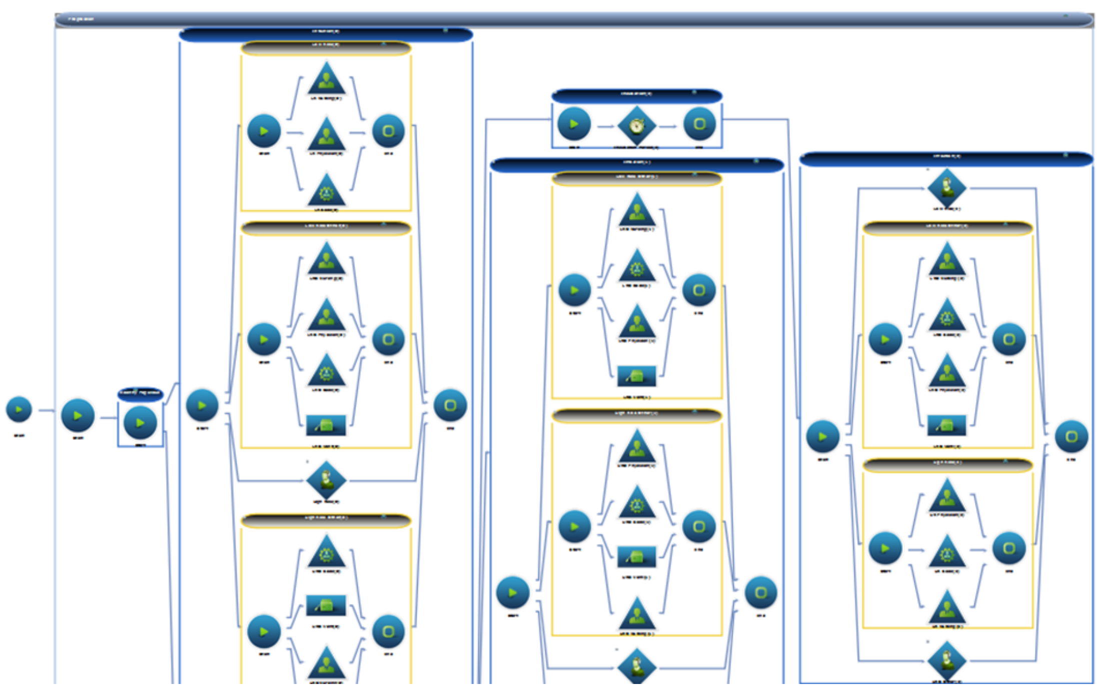

Figure 23. CV-19 model for Covid-19 patient treatment in Berlin, Frankfort and München

Sensitivity Analysis: CV-19 Modeling Foundation

For the propagation and treatment of Covid-19 patients in Germany metropolitan areas of Berlin, Frankfurt and München, we divided patients (table 3) into five classes, which varied in contamination severity and size. Furhter, multiple change parameter scenarios were considered as outlined below for the construction of the digital twin (see figure 24).

Table 3. Patient Classes

Class of Patient	Risk Category	Assumption Hospital*	Need for Ventilator*
LR	Low Risk	2	0
LROBED	Low risk with potential risk	4	2
HRBED	High risk	7	0
HROBED	High risk with potential criticality	14	5

*Number of days

Patient distribution across healthcare sites in Germany:

- Berlin 45%
- Frankfurt 35%
- München 20%

Possible change parameter scenarios:

- Volume of infected population
- Percentage of each patient risk category
- Length of treatment for each patient risk category
- Total capacity of beds
- Total capacity of critical beds
- Rate of recovery
- Geographic zone
- Gender
- Age
- Data capture and representativeness

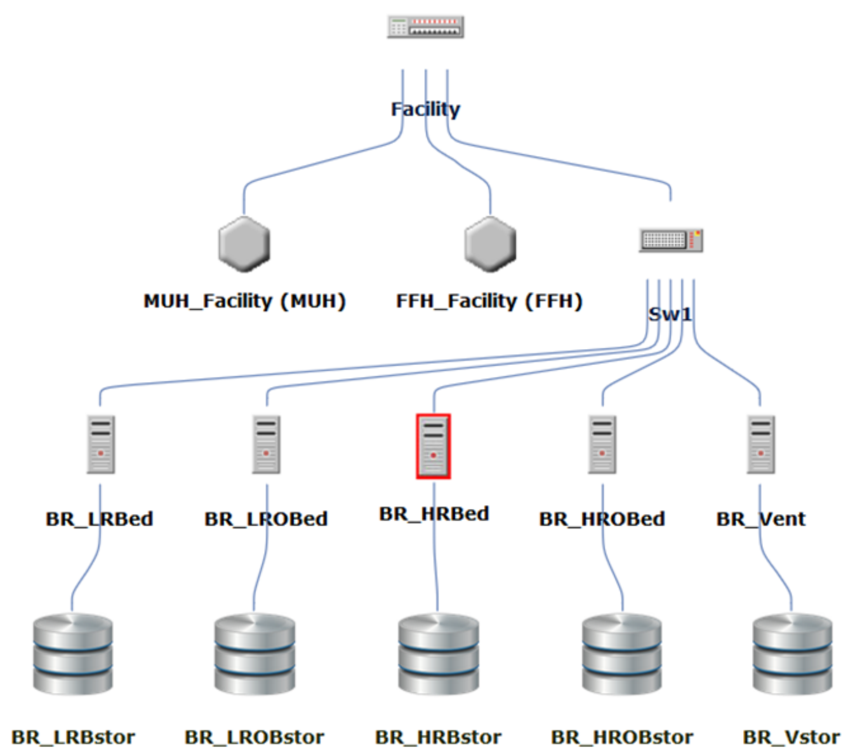

Figure 24. Digital twin of healthcare site in Germany

Scenario Analysis: UDE Prediction of Covid-19 Propagation

The case presented in figure 25 covers the treatment of 5 patient classes in Berlin, Frankfort & München with a baseline start date of March 15, 2020. As the number of patients increases, a shortage of patient treatment infrastructure occurs at clusters greater than 250 beds.

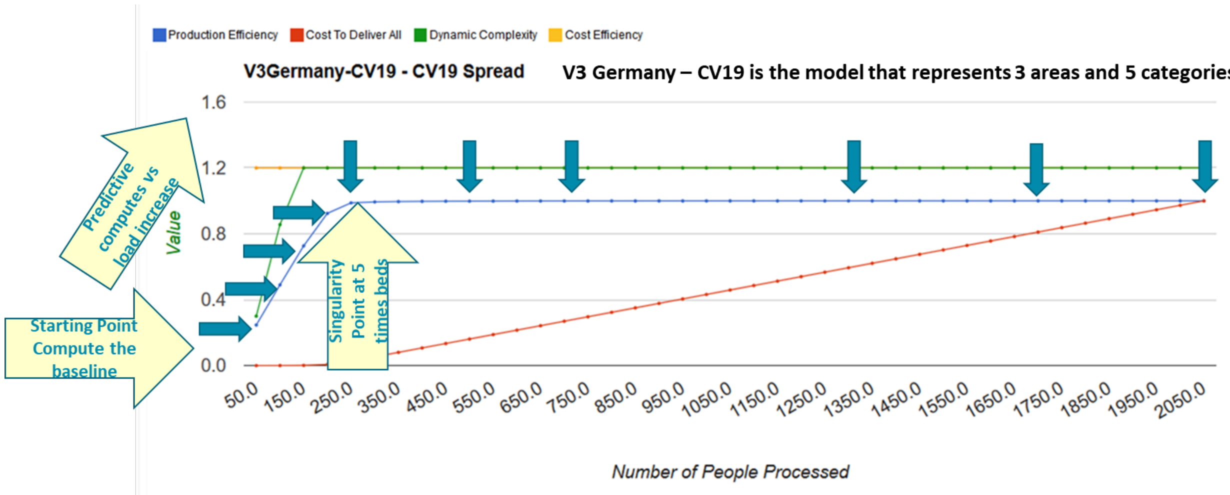

Figure 25. Scenario analysis for gradual load increase (demand for hospital beds) in Covid-19 propagation

We also applied scenarios to represent countries, cities and can address geographic areas. Within 4 weeks the speed of propagation in all scenarios is faster than the rate of extension and exceeds the timely availability of patient treatment infrastructure based on the proposed distribution of infected population between the five patient classes outlined in table 3.

Figure 26 indicates that with any baseline number of beds, the acceleration of virus contamination will present a real resource rarefication threat at 5 times the available beds on March 23, 2020—leading to a critical decision point to either dramatically increase in the number of beds/resources available to treat patients and/or shorten the duration of treatment.

Applying gradual load increase on CV-19 model shows shortage in hospital beds at clusters greater than 250 beds

Process Time (days)	Confinement Cycle time (days)	Testing Time (days)	Patients Department Baseline	Patients x 5	Bed Shortage	Action Required (baseline is 10 days per bed)
514.00	14	4	50	250	264.00	10.28
830.21	14	4	100	500	330.21	8.30
1030.17	14	4	150	750	280.17	6.87
1130.83	14	4	200	1000	130.83	5.65
1191.38	14	4	250	1250	-58.63	4.77
1323.79	14	4	500	2500	-1176.21	2.65
1358.00	14	4	750	3750	-2392.00	1.81
1376.42	14	4	1000	5000	-3623.58	1.38
1396.67	14	4	1500	7500	-6103.33	0.93
1404.67	14	4	2000	10000	-8595.33	0.70

Assumption: Beds are initially clustered in sets of 50 beds. A big or small hospital will contain several clusters

Possible Scenarios Parameters:

- Number of available beds
- Percentage of patient category
- Geography
- Initial conditions
- Healthcare maturity
- Decision hierarchy

Critical Decision Point:

- Shorten duration of treatment to serve more patients
- Discover efficient cure to compress bed usage to serve more patients
- Reduce the patient flow through vaccination

Figure 26. Predictive search for the singularity point

Update of CV-19 Model with New Data

In the following case, we updated the initial conditions of the CV-19 model scenarios in order to continuously size the capacity of the medical platform to absorb the dramatic increase of patients based on case data from a retrospective, multi-center cohort study, published on March 9, 2020.[38]

The study included all adult inpatients (≥18 years old) with laboratory-confirmed COVID-19 from Jinyintan Hospital and Wuhan Pulmonary Hospital (Wuhan, China) who had been discharged or had died by Jan 31, 2020. Table 4 summarizes the demographics and clinical characteristics of the 191 patients included in the study.

Table 4. Demographic and clinical characteristics

	Total (n=191)	**Non-Survivor** (n=54)	**Survivor** (n=137)
Age, years	56.0 (46.0-67.0)	69.0 (63.0-76.0)	52.0 (45.0-58.0)
Gender	--	--	--
Female	72 (38%)	16 (30%)	56 (41%)
Male	119 (62%)	38 (70%)	81 (59%)
Current smoker	11 (6%)	5 (9%)	6 (4%)
Preexisting conditions	91 (48%)	36 (67%)	55 (40%)
Hypertension	58 (30%)	26 (48%)	32 (23%)
Diabetes	36 (19%)	17 (31%)	19 (14%)
Coronary heart disease	15 (8%)	13 (24%)	2 (1%)
Chronic obstructive lung disease	6 (3%)	4 (7%)	2 (1%)
Carcinoma	2 (1%)	0	2 (1%)
Chronic kidney disease	2 (1%)	2 (4%)	0
Other	22 (12%)	11 (20%)	11 (8%)
Respiratory rate >24 breath per min	56 (29%)	34 (63%)	22 (16%)
Pulse ≥125 beats per min	2 (1%)	2 (4%)	0
Disease severity status	--	--	--
General	72 (38%)	0	72 (53%)
Severe	66 (35%)	12 (22%)	54 (39%)
Critical	53 (28%)	42 (78%)	11 (8%)

The UDE modeling methods allows us to measure the impacts of patients with 1 pre-existing condition, 2 pre-existing conditions and more, to determine the influence on the availability of resources to treat the incoming patients. The model projection is increased from the base point by gradual increasing the number of patients/required beds.

Table 5 shows the scenario analysis results as the system is stressed with more patients with various pre-existing conditions. The green shading highlights the impact of patients with pre-existing conditions.

Table 5. Scenario analysis detailed results by patient class – Mathematical Prediction

Comorbidity Risk	Survivor/non Survivor	Arrival Rate 0	Arrival Rate 1	Arrival Rate 2	Arrival Rate 3	Arrival Rate 4	Arrival Rate 5	Arrival Rate 10	Arrival Rate 15	Arrival Rate 20
Exp_Hist	Survivor_Exp_Hist	59.1	88.7	118.3	147.8	177.4	207.0	354.8	502.6	650.5
BioMale	Non-Survivor_Male	37.4	56.2	74.9	93.6	112.3	131.0	224.6	318.2	411.8
BioFemale	Non-Survivor_Female	16.0	24.1	32.1	40.1	48.1	56.2	96.3	136.4	176.5
Hypertention	Non-Survivor_Hypertention	35.8	53.7	71.7	89.6	107.5	125.4	215.0	304.6	394.1
Diabetes	Non-Survivor_Diabetes	25.7	38.5	51.3	64.2	77.0	89.8	154.0	218.2	282.4
pulse125	Infected_Pulse125	1.9	2.9	3.8	4.8	5.7	6.7	11.5	16.2	21.0
chronicLung	Non-Survivor_Chronic_Lung	12.8	19.3	25.7	32.1	38.5	44.9	77.0	109.1	141.2
coronary_heart	Non-Survivor_Coronary_Heart	16.6	24.9	33.2	41.4	49.7	58.0	99.5	140.9	182.4
coronary_heart	Survivor_Coronary_Heart	1.4	2.1	2.8	3.4	4.1	4.8	8.3	11.7	15.1
snd_msg	Infected_PMP	1.0	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
chronicLung	Survivor_Chronic_Lung	1.4	2.1	2.8	3.4	4.1	4.8	8.3	11.7	15.1
chronicLung	Infected_chronicLung	5.7	8.6	11.5	14.3	17.2	20.1	34.4	48.7	63.0
Diabetes	Survivor_Diabetes	19.3	28.9	38.5	48.1	57.8	67.4	115.5	163.6	211.8
chronicKidney	Infected_chronic_Kidney	1.9	2.9	3.8	4.8	5.7	6.7	11.5	16.2	21.0
coronaryHeart	Infected_Coronary_Heart	15.3	22.9	30.6	38.2	45.8	53.5	91.7	129.9	168.1
chronic_kidney	Survivor_Chronic_Kidney	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
smoker	Infected_smoker	11.5	17.2	22.9	28.7	34.4	40.1	68.8	97.4	126.1
smoker	Survivor_smoker	5.5	8.3	11.0	13.8	16.5	19.3	33.0	46.8	60.5
Hypertention	Survivor_Hypertention	31.6	47.4	63.3	79.1	94.9	110.7	189.8	268.9	347.9
pulse125	Survivor_Pulse125	1.4	2.1	2.8	3.4	4.1	4.8	8.3	11.7	15.1
Exp_Hist	Infected_Exp_Hist	72.6	108.9	145.2	181.5	217.7	254.0	435.5	616.9	798.4
pulse125	Non-Survivor_Pulse125	2.1	3.2	4.3	5.3	6.4	7.5	12.8	18.2	23.5
BioMale	Survivor_Male	81.1	121.7	162.3	202.8	243.4	284.0	486.8	689.7	892.5
snd_msg	Infected_PMC	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
respRate	Infected_respRate	55.4	83.1	110.8	138.5	166.2	193.9	332.3	470.8	609.3
Chronic_Kidney	Non-Survivor_Chronic_Kidney	3.7	5.6	7.5	9.4	11.2	13.1	22.5	31.8	41.2
BioFemale	Infected_Female	72.6	108.9	145.2	181.5	217.7	254.0	435.5	616.9	798.4
Diabetes	Infected_Diabetes	36.3	54.4	72.6	90.7	108.9	127.0	217.7	308.5	399.2
Exp_Hist	Non-Survivor_Exp_Hist	13.9	20.9	27.8	34.8	41.7	48.7	83.4	118.2	153.0
rcv_msg	Infected_PMC	1.0	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
rcv_msg	Infected_PMP	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4
respRate	Survivor_Resp_Rate	22.0	33.0	44.0	55.0	66.0	77.0	132.0	187.0	242.0
smoker	Non-Survivor_smoker	4.8	7.2	9.6	12.0	14.4	16.8	28.9	40.9	52.9
Hypertention	Infected_Hypertention	57.3	86.0	114.6	143.3	171.9	200.6	343.8	487.1	630.3
BioMale	Infected_Male	118.4	177.6	236.8	296.1	355.3	414.5	710.5	1006.6	1302.6
respRate	Non-Survivor_RespRate	33.7	50.5	67.4	84.2	101.1	117.9	202.2	286.4	370.6
BioFemale	Survivor_Female	56.4	84.6	112.8	141.0	169.1	197.3	338.3	479.3	620.2

In this case, the queuing of patients starts to become a critical problem when dynamic complexity exceeds 0.8 as shown in figure 27. The CV-19 model predicted a singularity on February 20 for the cluster of 191 patients, which represents the limit of the medical system at 7 times the capacity of the starting point. At this point, fatalities would start to occur due to a shortage in the hospital's capacity to treat patients.

At about 1100 patients, hospital resources would be highly constrained. At 1432.5 patients, the patient manageability would become a critical problem as patients start to die because the necessary treatment resources are unavailable. The pressure would become a short-term management challenge that would require the prioritization of target treatments.

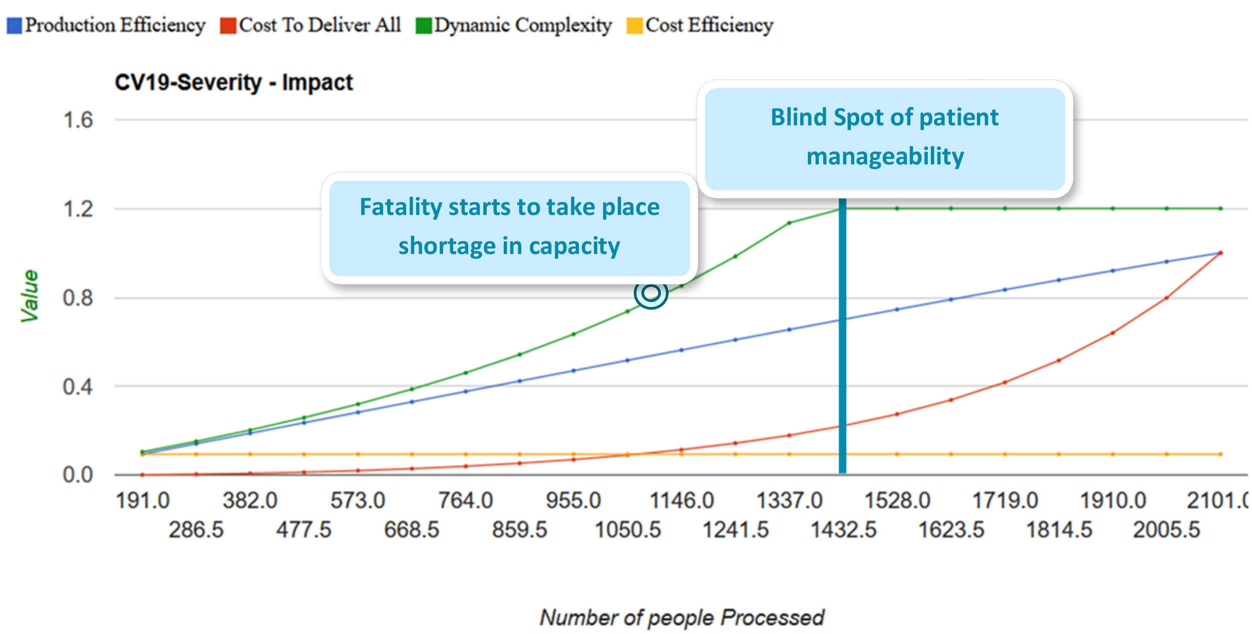

Figure 27. Scenario analysis of Jinyintan Hospital and Wuhan Pulmonary Hospital patient class impact on hospital resources

Discussion: The Critical Interpretation of CV-19 Results

To stop the Covid-19 outbreak, we must overcome 3 major challenges: (1) find a cure, (2) find a vaccine, and (3) manage the propagation. We concentrated on the propagation, since the search for a cure and vaccine are in discovery and early testing processes, and little can be done to further accelerate these tasks. That said, until clinical advances take place, managing the propagation is crucial to human health and safety as well as the dependability of healthcare services.

Our predictive analysis addresses the requirements for clinical infrastructure that is efficient and evolves to face the virus propagation. The CV-19 predictive modeling results provide critical insights to support decision preparedness. In the first CV-19 model, five classes of patients were represented, which varied in contamination severity and size. Our conclusion points to a gradual rarefication of hospital beds and equipment to face the outbreak. In short, the world has not prepared for such a large-scale outbreak.

We believe shortening the treatment duration (from an average of 10 days to one day, for example) is not an option for the time being. Therefore, reducing the flow of affected population represents the only serious decision alternative. Our assumption is that 5 days of treatment is likely to become the average in the future.

At this point, confinement and social distancing are the most urgent actions, which must be strictly applied in order to avoid a dramatic cycle of patient treatment. In parallel, patient management including off-site treatment and testing protocols will be of strategic importance and may provide room to help other geographic regions that are facing resource shortages.

In the second CV-19 model, we found that the coronavirus accelerates the impact of pre-existing conditions and strains hospital resources. The main origin of the limit is derived from the absence of a cure and consequently accelerated use of the medical platform during an Covid-19 outbreak. The pre-existing conditions of Covid-19 patients in the severe and critical categories lead to unexpected issues and extends the duration of treatment. As a patient with pre-existing conditions impose a more complex curative protocol to compensate or normalize his/her history ahead of treating the complications due to the direct impact of the virus. This finding is supported by recently published research, which concluded that myocardial injury has a significant association with a fatal outcome for Covid-19 patients.[39]

More than 50% of the infected population have at least 1.5 pre-existing conditions—some of which are highly risky even without the added strain of the Covid-19 infection. The size of population with undiagnosed or unmanaged pre-existing conditions represents a major challenge to the preparedness of many healthcare systems throughout the world to face the demands for Covid-19 patient care. Obviously, pre-existing condition parameters are partially or fully out of control from the point of the infection discovery. In such cases, we recommend enlarging the testing protocol to include or even establish the status of pre-existing conditions before selecting and applying a coronavirus course of treatment.

Clearly, with the development of a cure and vaccination, the picture can change—hopefully, even significantly, which would provide an opportunity to minimize the global consequences of the current Covid-19 outbreak and its impacts on citizens, economy, cross-border cooperation and healthcare systems. In any case, we are sure the world will become vastly different in the aftermath of this pandemic.

Considering the economic and societal consequences of the current Covid-19 pandemic, future measures to diagnose and treat pre-existing heart, lung, kidney and diabetes diseases may be justifiable to overcome the burden a novel virus outbreak, like Covid-19, places on the healthcare system. In this case, the CV-19 model could be used to further explore the impacts of a decision and validate the benefits of preventative treatment.

Conclusion

Healthcare systems are not closed loop, linear systems. Therefore, they cannot be accurately modeled without accounting for various elements (components) of the system which continually influence one another (directly or indirectly) to maintain the system in line with the goals of the system. In the case of a pandemic, these goals include slowing the spread of the disease and providing the highest quality of care possible for those infected.

If the relationships between various components of a dynamic system are not well understood, changes made to one part of the chain may affect another in unwanted ways. For instance, treating Covid-19 patients without understanding the influence of pre-existing conditions may place more strain on already overwhelmed medical personnel and hospital resources. A universal mathematical formulation is needed to accurately represent all system dynamics in all cases to provide healthcare system participants with a more complete view of reality. This allows stakeholders to make decisions with more confidence in the outcomes than would be possible if using mechanistic models that may provide a wide range of possibilities and miss new risks due to their dependence on historical data.

The universal dynamics engine (UDE) and NARS method of modeling, detailed in this paper, is executed through 3 steps—deconstruction, sensitivity analysis and scenario analysis—in order to accurately represent a high level of interdependent components organized in hierarchy of graphs. Scenario analysis helps modelers construct the remedy and mitigation actions, certify the solution pertinence and discover additional variables and interrelationships that can be dependably used to predict the occurrence of previously known as well as unknown risk behaviors.

Through the use of deconstruction theory, it becomes clear that the overall performance of a system (defined in terms of quantity, quality and cost) does not always represent the expected output of the system given the accumulated characteristics of the constituent components, generally due to a loss in energy. Causal deconstruction allows modelers to uncover results that often defy the common wisdom that stops at the wrong level of analysis and usually produces a host of misleading conclusions.

Using UDE, modelers can promote the right approach of analysis and mathematics capable of solving the problem within an environment where dynamic complexity has become the major risk. The CV-19 model, which was used to create the digital twin of Covid-19 Crisis Management in Germany, can be applied to help provide critical decision insights as needed to guide actions for any country's or geographic region's response to the current pandemic as well as monitor and plan activities in order to avoid a future crisis.

The dynamics of our mobile and hyperconnected world amplify the risks. Through the participation of a larger number of constituents, the CV-19 model can be expanded to identify thresholds and help support preparedness for a wider variety of parameters and situations as they relate to any dynamic system, which is influenced directly and indirectly by any number of internal and external forces—including travel patterns, weather, government response and/or socio-economics.

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