Advancing Economic Forecasting and Risk Analysis Models to Meet the Speed, Risk and Sustainability Demands of the 4IR

Managing dynamic complexity will pave the way for a more prosperous and efficient economy that operates with less risk and better predictability

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Introduction

Economic systems that operate through a constantly expanding number of dynamic interactions have become too complex to fully represent using popular econometrics and economic modeling methods. When multiple functions of economy are connected to each other explicitly or through complex topology, the mathematics of these methods grows too complex to deliver reliable predictions. History has shown that an economic crisis, mathematically identified as a singularity[1], may occur even when classic estimations fail to expose a risk. Today's economists borrow their risk modeling methods from the core tenants of physical science with a heavy reliance on the concept of entropy to deal with the volatility of financial systems. While these methods did make it easier to represent the approximate behavior of financial systems once upon a time, they have become meaningless in today's complex environment.

The current lack of predictability and hyper-risk within financial systems is a direct result of dynamic complexity. Dynamic complexity should be considered the enemy of the digital age because its presence erodes stability, hides risk and creates waste within any system that is influenced by the external environment in which it operates. Like an undiagnosed cancer, dynamic complexity consumes valuable resources as it grows without providing any useful return. Traditional forecasting methods are unable to quantify the impact of dynamic complexity, therefore surprises are inevitable because no one can predict how one small change can produce a ripple effect of unintended consequences.

In and of itself, the expansion of subprime loans in the early-to-mid 2000s was considered a manageable risk by economists, policymakers and financial practitioners who took advantage of the Feds interest rate reduction monetary policy to promote new financial instruments, e.g. subprime loans and trading of mortgage-backed securities (MBS). Even as the collapse of the US economy was already happening, the Feds main economic model saw a less-than-5-percent chance that the unemployment rate would rise above 6 percent in two years. The rate actually hit 10 percent, an event that the model said was close to impossible, therefore it was not considered as a plausible risk by policymakers.

As the pace of innovation accelerates in the Fourth Industrial Revolution (4IR), the cause and effect of economic crisis will become nearly instantaneous. Governments and businesses can no longer afford to wait for the warning signs of an economic turmoil, before taking action. To regenerate prosperity for the betterment of humanity, economists, policymakers and financial practitioners must employ new problem-solving approaches. Eliminating the waste and managing the risk caused dynamic complexity will deliver new opportunities for growth and sustainability. But first, economic stakeholders must tame dynamic complexity and simplify decision cycles.

This paper proposes a new approach to economic forecasting and predictive analysis that allows users to uncover a wide scope of unknown risks. Armed with this knowledge, economic stakeholders will be able to quickly take action with confidence in the outcomes—before imbalances proliferate through

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[1] a point at which a given mathematical object is not defined or not well-behaved, for example infinite or not differentiable

financial markets and interdependent subsystems. The suggested use of tensors[2] provides the right formulation to overcome the abused application of entropy and scalar quantities[3] within economics, which neglect the direction of market changes. The utilization of aggregated vectors allows users to more accurately reproduce the magnitude and direction of market behaviors, which in turn allows economists, policymakers and practitioners to predict a wider range of risks and vet which corrective actions will yield the best results.

The Time to Act is Now

Our world is becoming exponentially more complex every day. New financial instruments, technological advancements, regulations, evolving cyber threats, politics, wars, changing consumer preferences and a seemingly endless number of events all drive market fluctuations that may be the trigger of the next financial disaster. But these risks cannot be captured by current forecasting models, because historical data will not expose the probability of something that has never happened before. Further, neither experience nor statistical approaches can reliably predict the propagation of risk in a system as complex and far reaching as economy.

Today's financial systems are supported billions upon billions of complex dynamic interactions that make them vulnerable to failure. One small change (for example, a rise in sub-prime mortgage defaults) can produce a ripple effect of unintended consequences—a.k.a. a global financial crisis. This was not the anomaly of history that policymakers would like citizens to believe.

Today a market collapse can be triggered by a growing number of events that are considered improbable but not impossible—such as stock market panic-selling, bond-market bubble collapse or a sudden increase in credit card defaults. Unless changes are made, these types of economic shocks will increase in frequency and severity at scales that pose serious threats to society. And yet, policymakers are still looking in the rearview mirror. Using outdated financial dynamics models that are reliant on past data and the concept of entropy to explain the disorder of financial markets. Once the full effects of a crisis unfold, they simply claim it was not possible to identify and preemptively respond to unknown risks. But in truth, government regulators and policymakers can do better.

In 2011, former Secretary of the Treasury, Henry Paulson wrote, "In retrospect, the crisis that struck in August 2007 had been building for years. Structural differences in economies of the world that led to what analysts call 'imbalances' that created massive and destabilizing cross-border capital flows. In short we were living beyond our means—on borrowed money and borrowed time."

The use of entropy-based, scalar quantity solutions hid the *"imbalances"* and catastrophic outcomes. The risk would have been evident if policymakers were using a tensor-based solution for risk analysis

[2] An algebraic object analogous to but more general than a vector, represented by an array of components that are functions of the coordinates of a space.
[3] A scalar quantity or scalar is a physical quantity that only has a magnitude—e.g. interest rate of 4%—but does not represent the direction of change.

and prediction. This method shows great promise for its ability to reveal the circumstances that may cause market imbalances and support the level of realism needed to take the right actions at the right time to continuously ensure the most optimal outcome.

The Problem with Thermoeconomics

The laws of thermodynamics have become a reference and inspiration to people charged with determining the risk associated with financial markets and economic systems. The actual laws of thermoeconomics—in particular those dealing with the evaluation of risk—are a transposition of the laws of thermodynamics. These laws have been accepted for many years by financial risk analysts and industry proponents as the right foundation for financial engineering. However, it must be questioned whether the laws of thermodynamics are sufficient to deal with modern financial systems that are becoming increasingly complex and dynamically changing due to both internal and external influences.

The Laws of Thermodynamics

The laws of thermodynamics define fundamental physical quantities (temperature, energy, and entropy) that characterize thermodynamic systems. A thermodynamic system is a precisely specified macroscopic region of the universe, defined by boundaries or walls of particular natures, together with the physical surroundings of that region, which determine processes that are allowed to affect the interior of the region as shown in Figure 1.

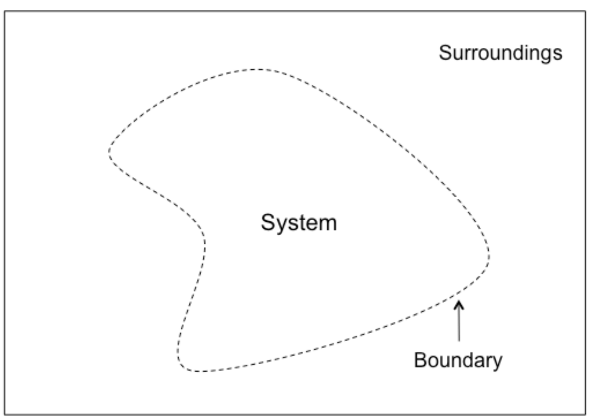

Figure 1. A system can be defined by its boundary and surroundings

There are 4 laws to thermodynamics, which are considered to be some of the most important laws in physics.

- **Zeroth law of thermodynamics:** If two thermodynamic systems are each in thermal equilibrium with a third, then they are in thermal equilibrium with each other.
- **First law of thermodynamics:** Energy can neither be created nor destroyed. It can only change forms. In any process, the total energy of the universe remains the same. For a thermodynamic cycle the net heat supplied to the system equals the net work done by the system.

- **Second law of thermodynamics:** The entropy of an isolated system not in equilibrium will tend to increase over time, approaching a maximum value at equilibrium.
- **Third law of thermodynamics:** As temperature approaches absolute zero, the entropy of a system approaches a constant minimum.

Entropy is a very important concept in the realm of thermodynamics. It's the core idea behind the second and third laws and its presence in our physical world is pervasive. Essentially entropy is a measure of disorder or randomness in a closed, but changing system in which energy can only be transferred in one direction from an ordered state to a disordered state. Higher entropy leads to higher disorder and lowers the availability of the system's energy to do useful work. The classical thermodynamics description assumes a state of equilibrium, although more recent attempts have been made to develop useful definitions of entropy in nonequilibrium economic systems to explain why systems tend towards disorder.

The Transformation from Thermodynamics to Financial Dynamics

At a high level, the laws of thermodynamics and the laws of thermoeconomics equate as follows:

Thermodynamics		Thermoeconomics
Energy	→	Value
Temperature	→	Risk
Entropy	→	Volatility

The concept of entropy is useful to financial risk analysis because it can be extended to represent market volatility or the disorder produced through detailed complexity (inflation in the number of components, connections and interfaces) or produced by dynamic complexity (increase in interdependencies, feedback, enforcement mechanisms, etc.).

But it is questionable whether the laws of thermodynamics are completely transferable to financial dynamics. The laws of thermodynamics involve natural physical properties like energy and temperature. These are bedrock in our physical world, where the behavior of objects is highly predictable through the laws of thermodynamics and other physical laws. And while their behaviors are complex, their complexity is understood—meaning that any influences that cause the system to deviate from its original state or path have been scientifically explained.

Financial systems are not wholly natural physical properties. They are human-made creations that combine some physical entities and some non-physical entities, including human emotions. Financial systems normally behave according to patterns and trends, but sometimes exhibit behaviors that are new and unexpected because they are not wholly physical. These systems are relatively novel in regard to their existence and our understandings of their behavior. Often the complexity of financial markets and the structure of constantly changing financial systems are not well understood. Therefore, there are many unexplained influences that can cause the system to deviate from its projected state or path.

Further, traditional economic models are incomplete models of reality because economic systems are not inclined to maintain a state of equilibrium for more than a very short period time (similar to meteorological or most nuclear or gravitational systems).

Challenges in using thermodynamics as the basis of financial risk modeling:

- Complex human-made systems are not inclined to maintain a long-term state of equilibrium, which means the predictability of the system will be limited to a very short period of time when the initial conditions vary in small amplitudes and frequencies
- Complexities can only be dealt with once recognized, because models cannot reliably predict the structural evolution and systemic behavior of multiple-level interactions
- Only closed systems that reach equilibrium are captured in the model—external influences are largely ignored or treated through the use of probability-based corrections that ignore outlier scenarios (which are almost always the root trigger of economic turmoil)

It is difficult to determine small resonances[4] when using statistical mechanics to deal with randomness, therefore economic forecasting based on thermoeconomics do not typically provide the long-term representation necessary to guide the best decisions at the speed necessary to achieve the most optimal outcome. Without a universal mathematical formulation that can be applied to accurately represent all system dynamics in all cases, economists and financial risk analysts must rely on a number of domain specific, probability-based solutions that provide competing views of reality and only cover known system states. This creates risk, inefficiencies and waste that make it difficult for systems to fulfill the goals for which they were created.

One of the most important concepts in systems theory is the notion of interdependence between systems (or subsystems). Systems rarely exist in isolation. For example, the mortgage industry may impact and be directly impacted by monetary policy, real estate, economic growth and employment rates or indirectly impacted by less obvious factors, like political turmoil. It is important to understand these interdependences or else changes made to one system may affect another in unwanted ways, as was the case in the 2007-2008 economic crisis.

Our proposed universal dynamics engine (UDE) shows great promise in providing the universal mathematical solution needed to accurately represent complex dynamics across any financial ecosystem. This will help economists, governmental leaders, policymakers, and practitioners regain a holistic view of interdependencies across all financial instruments and understand structural influences as necessary to judiciously maintain balance between competing priorities, like economic growth and social responsibility. Further, the combination of UDE with artificial intelligence (AI) and machine learning provides the capabilities leaders need to automate decision cycles in accordance with the speed, risk and efficiency requirements of the 4IR.

[4] The tendency of a system to vibrate with increasing amplitudes at some frequencies of excitation

Understanding the Influence of Dynamic Complexity

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. 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. Generally, the effects of dynamic complexity build over time due to frequent system changes and the accrual of systemic debt.

The effects of dynamic complexity are often hidden and dormant within a system. In this case, its influences on system efficiency may be trivial and go unnoticed up to a certain point in time and load level. As the demands on the system increase, the detrimental impacts of dynamic complexity increase. In certain cases, the magnitude of dynamic complexity can grow quickly. Then, the effects of dynamic complexity will damage the performance, efficiency and cost factors of the system. If the effects of dynamic complexity become predominant, a singularity—or a breaking point—will occur, which means the system will no longer deliver according to its set objectives.

To achieve better predictability, economists and practitioners must be able to expose new, dangerous patterns of behavior in time to take corrective actions and know which actions will yield the desired results—as it may relate to any number of factors including sustainable employment, stable price, and moderate interest rates. However, dynamic complexity is not measurable in absolute metrics like mass is in grams. Instead, it is measurable on a relative scale that identifies whether the effect of dynamic complexity in a system is increasing and at what rate.

Experience-based and statistical methods of prediction and risk management are inadequate when dealing with problems caused by dynamic complexity because its contribution remains hidden until it's too late to avoid unwanted outcomes. To measure the effects of dynamic complexity and reliably predict its nonobvious consequences, UDE relies on the NARS model.[5] 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 economy and all financial 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.[6]

In the early stages, dynamic complexity is like a hidden cancer. Finding a single cancer cell in the human body is like looking for a specific grain of sand in a sandbox. And like cancer, often the disease will only be discovered once unexplained symptoms appear. To proactively treat dynamic complexity before it

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[5] Abu el Ata, Nabil and Rudolf Schmandt. *Predictive Risk Assessment in Risk Modeling.* Patent Application 20150339263. Filed: May 21, 2015.

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

negatively impacts financial systems, diagnostics are needed to reliably reveal its future impact. System modeling and mathematical emulation can be used to provoke the existence of dynamic complexity through two hidden exerted system properties: (1) the degree of interdependencies among system components, and (2) the multiple perturbations exerted by internal and external influences on both components and the edges connecting them directly or indirectly.

Successful risk determination and mitigation is dependent on how well the system is understood. Further, the evolution of dynamic complexity and the amount of time before the system will hit the singularity (singularities) through the intensification of stress on the dependencies and intertwined structures forming the system must be correctly identified. Knowing what conditions will cause singularities allows policymakers to understand how a financial system can be stressed to the point at which it will no longer meet its objectives, and proactively put the risk management practices into place to avoid these unwanted situations. The proposed UDE approach privileges the use of a patented, scientific notion of dynamic complexity that encapsulates the dynamic behavior of multiple interdependent functions, and how the specific mechanics of each component contributes to the overall dynamic signature of the system.

Dynamic Complexity is the Indicative Universal Tensor Metric (Vector Space)

Any system, whether it be economic, business, bio-spherical, financial or medical, will over time and space create dynamic complexity. Every economic crisis from the Great Depression to the Great Recession and those yet to be named, spins out of control due to system stakeholders' inability to identify, deal with, control and predict dynamic complexity. But the problem of dynamic complexity is not exclusive to financial markets. It can also be blamed for other high-profile failures of information technology, like the 2020 Iowa caucus reporting debacle, security breaches and pandemics. The challenge of using linear-based models to inform decisions related to open systems will always be exposed when dynamic complexity is present.

Dynamic complexity is a loss, formed overtime and produced through the gradual increase of interdependencies among system constituents. Such interdependencies not only involve adjacent constituents in a graph, but all other influences formed by non-adjacent components and at any level carrying multiple order indirect perturbations. Which means, the behavior of any human-made system will be difficult to predict or manage when the influence of dynamic complexity is not taken into account or well understood.

Almost every human-made system is dependent on some form of information technology today. Our research shows that dynamic complexity commonly accounts for 20 to 60 percent of a technology-dependent system's overall resource consumption. This dramatically reduces, by at least the same proportions, the volume and service quality the system is able to produce. In current modeling methods, the service base line is updated to reflect this reality without considering the root cause of this phenomena. More adventurous decision makers may consider the symptoms of dynamic complexity, including any domino effect or pressure in spacetime, without qualifying what force is driving the systemic change. In either case, the risks caused by dynamic complexity cannot be adequately managed until after the symptoms appear. At this point, unwanted outcomes become unavoidable and the available corrective actions may be limited.

Dynamic Complexity: Key Questions and Answers

- *Why is dynamic complexity always discovered too late?* Copernicus rightly said, "To know that we know what we know, and to know that we do not know what we do not know, that is true knowledge." Dynamic complexity is a mechanical process of a system that can only be defined at a topological level, while accounting for the interdependencies at multiple levels.
- *Why must dynamic complexity be systematically determined?* To control its evolution in a way that allows for the timely implementation of the best curative actions.

From our experience, it is clear that new tools and methodologies are needed to augment traditional risk analysis practices in order to take back control of financial systems. The intended goal is to guide rather than react to market fluctuations in ways that yield the desired outcomes, including the ability to execute a complete system disruption, when and if the dynamics of financial markets no longer meet the goals of society.

After decades of hyper-transformation, during which rapidly evolving digital technologies, globalization, and massive investment flows have stressed and reshaped every aspect of society, a tipping point has been reached. Socio-economic dynamics have left many people and communities economically disadvantaged and politically polarized. Combined with increasing anxiety that the earth's climate is changing faster than the planet can withstand, a heightened sense of risk and insecurity has emerged globally.

The time has come to welcome the Fourth Industrial Revolution and transform economic paradigms as quickly as possible to:

- Fight the waste created by the wild application of capitalism over the past century to ensure sustainable financial models.
- Solve the inequitable distribution of wealth to support the continuation of capitalism, which depends upon the prosperity of large consumer populations.
- Tame the dynamic complexity that makes it difficult to anticipate and preemptively stop a crisis before it negatively impacts the efficiency and cost management objectives of financial systems.
- Leverage machine learning and artificial intelligence to accelerate and improve decision making processes with accurate mathematical models that make it possible to build and adapt sprawling dynamic financial ecosystems without creating unintended outcomes.

A Scientific Approach to Forecasting and Risk Analysis

Every human-made system is built using a set of detailed methods, procedures and routines created to carry out a specific activity, perform a duty, or solve a problem. In the context of the economy, systems should be organized and purposeful structures that consist of interrelated and interdependent elements including components, entities, factors, members, and parts. 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.

All systems have (a) inputs, outputs and feedback mechanisms, (b) display properties that are different than the whole but are not possessed by any of the individual elements, and (c) have boundaries that can be defined by a system observer. As such, the scope of the system can be delineated by its boundary, which makes it possible to describe which elements are inside and outside the system.

In theory, a system should be able to maintain an internal steady-state, known as homeostasis, despite a changing external environment. From an economic perspective, homeostasis refers to a financial system's ability to maintain its state of equilibrium by counteracting internal and external turbulences through contextual variety absorption. Homeostasis employs feedback mechanisms to maintain the dynamic equilibrium of a self-regulating system, similar to the way a tight-rope walker maintains balance on the rope.

A financial market is an ecosystem that is comprised of multiple subsystems—including stock markets, bond markets, commodities market, derivatives, etc.—where traders buy and sell assets. At any point, an external factor, such as a collapse of the housing market, panic selling, political unrest or natural disaster, may disrupt the steady-state of the financial market, but the system should have mechanisms in place to return the system to an optimal state. Currently, the enforcement of laws and regulations combined with the use of pre-determined models provide the mechanisms designed to return markets to a perceived state of equilibrium.

However, financial systems do not necessarily return to an original state of equilibrium after a crisis or introduction of new innovations, like algorithmic trading, nor are they inherently stable as many economic theories claim. Theories, like noise trader theory, account for bubbles and fluctuations in markets, but they tend to treat these as small ripples on an otherwise calm ocean. Treating economic crises as anomalies is convenient, but ignores the reality that financial markets are inherently crisis prone because the effects of a change are not proportional to cause. This causes economists to underestimate the risk of new scenarios, which are most often the cause of major market disturbances. For instance, a slight increase in the mortgage default rate represented as a Markovian process and using probability distributions would not expose the risk of a global financial crisis.

Perturbation Theory

The presence of deterministic chaos within financial markets—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. 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 the US economy, as presented in Figure 2. Additionally, perturbation theory allows for predictions that correspond to variations in initial conditions and influences of intensity patterns, which is often the case in economic systems.

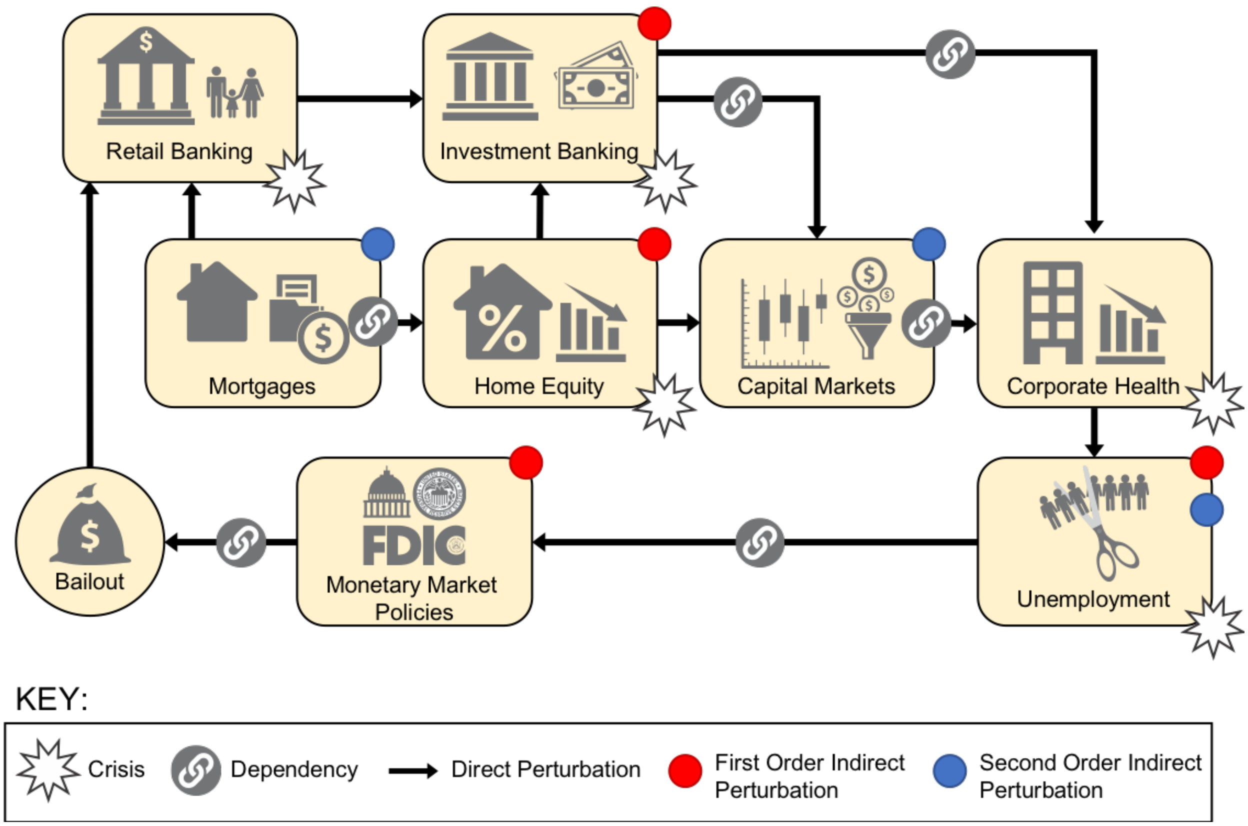

Figure 2. Use of perturbation theory to accurately capture cause and effect relationships within US economy

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. 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 3).

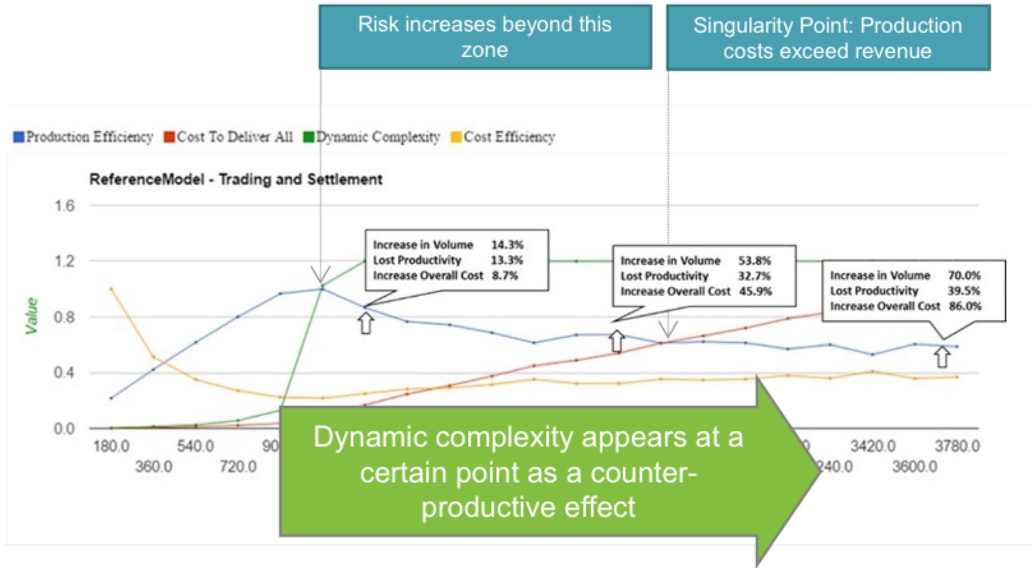

Figure 3. Perturbation theory based graph predictively reveals the effects of dynamic complexity and point of singularity

A key advantage of the method is that prior knowledge of what may cause an eventual crisis 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.

Disruptive Cycles

In 1953, Russian economist Nikolái Kondrátieff proposed that global development happens in 40-60 year *long-term cycles*. These cycles are characterized by periods of economic growth followed by periods of depression, which can be represented as a sinusoidal curve, now called *Kondratieff waves* or *K-waves* as illustrated in Figure 4.[7] Technology and the transfer of capital are considered major contributing factors in K-cycles. The introduction of innovative technologies spurs business growth through transformation programs and risk taking. This in turn encourages new investment and lending. Due to the multiplier effect, economies rapidly expand as a result.[8] This creates cycles of expansion and contraction, which each drive increasingly bigger economic booms and busts. In our modern times, these fluctuations are further exacerbated by global funding mechanisms that expand local problems to a worldwide stage, making the negative impacts of each cycle more political than economic.

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[7] Mager, N.H. (1987). *The Kondratiev Waves*. New York: Greenwood Press. ISBN-13: 9780275921491.

[8] Quigley, Christopher. *Kondratieff Waves and the Greater Depression of 2013 – 2020.* Financial Sense. Web. FEB 24, 2012. Accessed 16 January 2020.

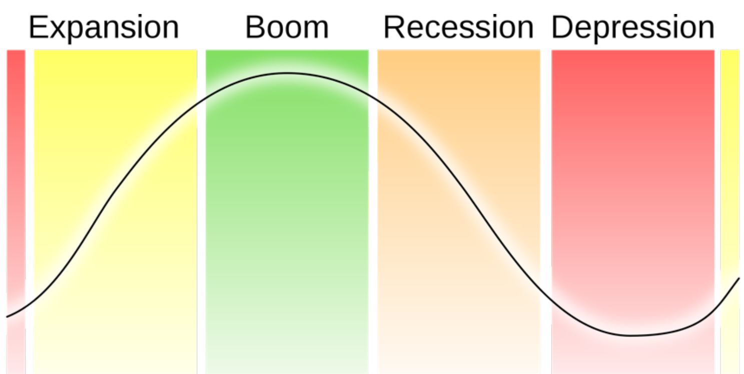

Figure 4. Kondratieff waves or K-waves

Economist, Joseph Schumpeter modified the original concept of Kondrátieff by linking the cycles to innovations. Their accumulation leads to technological revolutions, which transform societies and launch Kondratieff waves (see Figure 5). Each long wave brings new ways of doing things more efficiently, increasing economic productivity and boosting the pace of growth. Periods of business transformation during which new technologies are adopted fuel this growth. For example, as the internet grew in popularity in the 1990s, businesses began to take advantage of the web as a better, faster and cheaper way to support their goals and objectives. Schumpeter claims that each wave of innovation does not last equally, and that their length is shortened due to the rapid development of new technologies.[9]

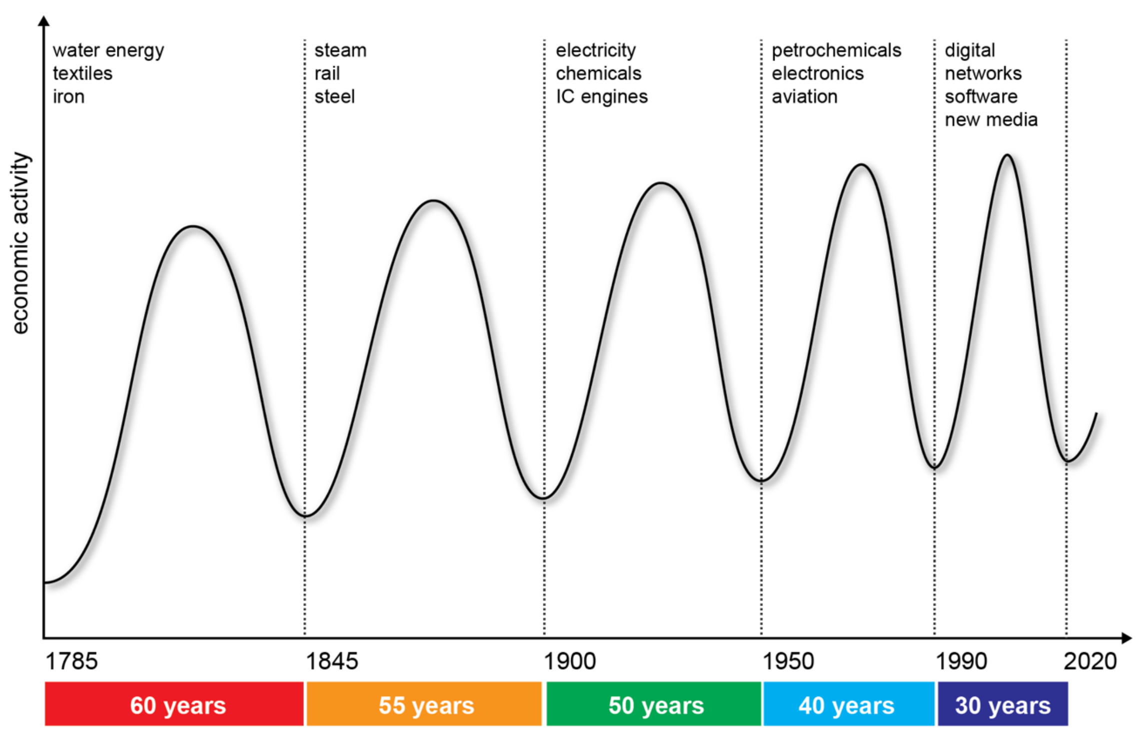

Figure 5. Schumpeter's long waves of innovation

[9] Schumpeter, J.A. *The Theory of Economic Development.* Routledge; New edition (January 2, 1981). ISBN-10: 0878556982. ISBN-13: 978-0878556984.

The process of economic growth form long waves of relatively productive years that are interrupted somewhat irregularly by troughs of relatively bad years of economic growth. Throughout history, one economy generally takes the lead in economic growth by assuming the primary responsibility for generating the innovations that fuel the surges of pervasive technological change. Some parts of the world economy are able to imitate, absorb and even improve on the innovations. To the extent that they can, these economies can close the technological gap between the sophistication of their own economic activities and that of the system's lead economy.

Revolutionary waves typically last until the gains of a disruptive paradigm fall close to the pre-transformation level. Once a new technology, which originally increased productivity due to the utilization of new resources, reaches its limits, it is not possible to overcome this limit without using another new technology. The seeds of the next revolution begin to form as economic productivity declines.

Technological revolutions help businesses operate more efficiently, which increases economic productivity, boosts economic growth and creates wealth. There is no doubt that the introduction of digital networks, software and new media innovations over the last few decades has fueled a period of economic expansion, but today many organizations are experiencing considerable loss in productivity and quality of service paired with cost inflation due to the growing effects of dynamic complexity. As more energy is absorbed in nonproductive activities, a period of economic contraction is entered that cannot be resolved without disruption (see Figure 6).

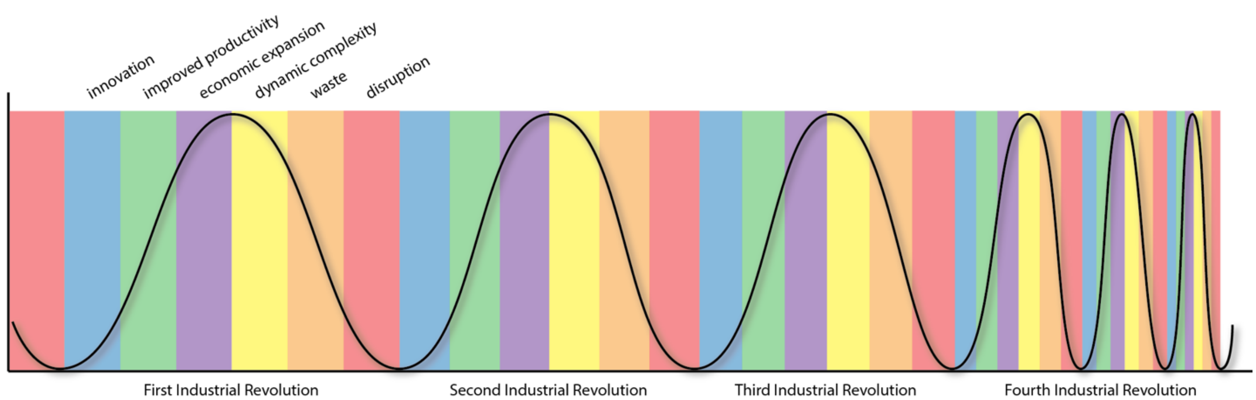

Figure 6. Dynamic complexity builds during long wave cycles

There are good reasons to think that the 4IR might be different than its predecessors. In fact, we may be embarking on an age of multiple, overlapping technological revolutions, which might be best understood as the era of hyper-automation. The progress of our generation will be promoted by a complex web of new technologies. Unlike previous revolutions that had a focused set of innovations that proliferated to other countries and industries from a single point of origin, today's innovations are highly complex and simultaneous spreading across diverse fields, rapidly inflicting repercussions worldwide.

The goals of the 4IR and the continuation of capitalism depend on recognizing the importance of multiple stakeholders and the need to promote social, environmental and financial value. Better distribution of wealth and more efficient usage of resources cannot be achieved when dynamic complexity is absorbing energy for nonproductive uses. Identifying and removing dynamic complexity will improve the predictability of financial markets, increase policymakers' control over crises and reduce systemic waste. This provides the strong foundation necessary to create a new order of capitalism that judiciously fuels growth, sustained shareholder returns and societal well-being. As such, managing dynamic complexity will be essential to remove economic roadblocks that could prevent growth, prosperity and sustainability in the 4IR.

UDE 3-Phase Methodology

UDE uses a 3-phase methodology to construct the emulator, validate the accuracy, diagnose risk and identify the appropriate prescriptive actions (see Figure 7).

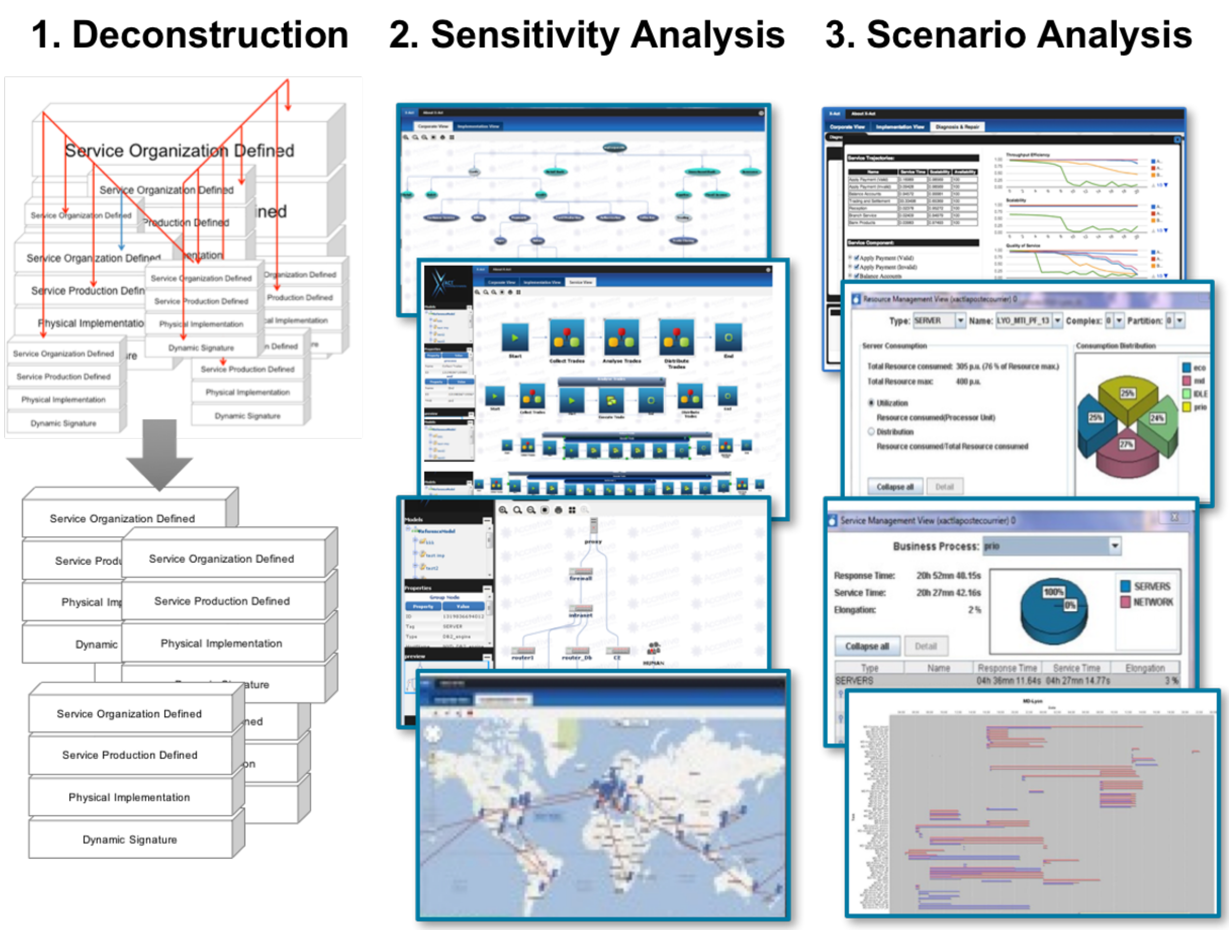

Figure 7. 3 Phase Methodology

Phase 1: Deconstruction

To begin the dynamic complexity discovery process, the system is first deconstructed using *emulative deconstruction theory*[10] to understand its constituent components and dependencies among them (see Figure 8). 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.

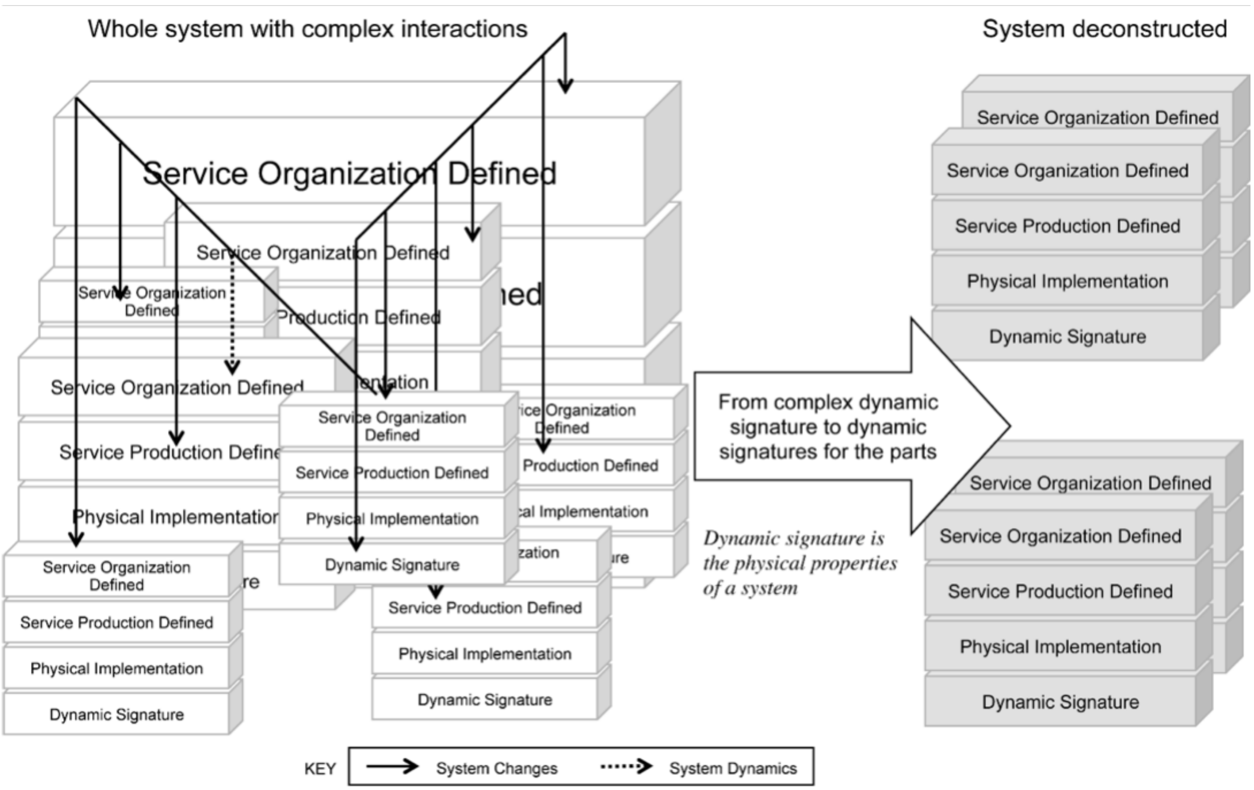

Figure 8. System deconstruction

The seven-stage methodology 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. 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.

[10] Abu el Ata, Nabil and Annie Drucbert. *Leading from Under the Sword of Damocles.* Springer. 1st ed. 2017 edition Print. 20 March 2018. ISBN-10: 3662562995 ISBN-13: 978-3662562994.

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.

Phase 2: Sensitivity Analysis

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. Sensitivity analysis is 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. This helps to identify which actions are needed to decrease risk and explore viable and proactive remedial options that secure an acceptable risk mitigation strategy.

The goal of Phase 2 is to 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 (see Figure 9).

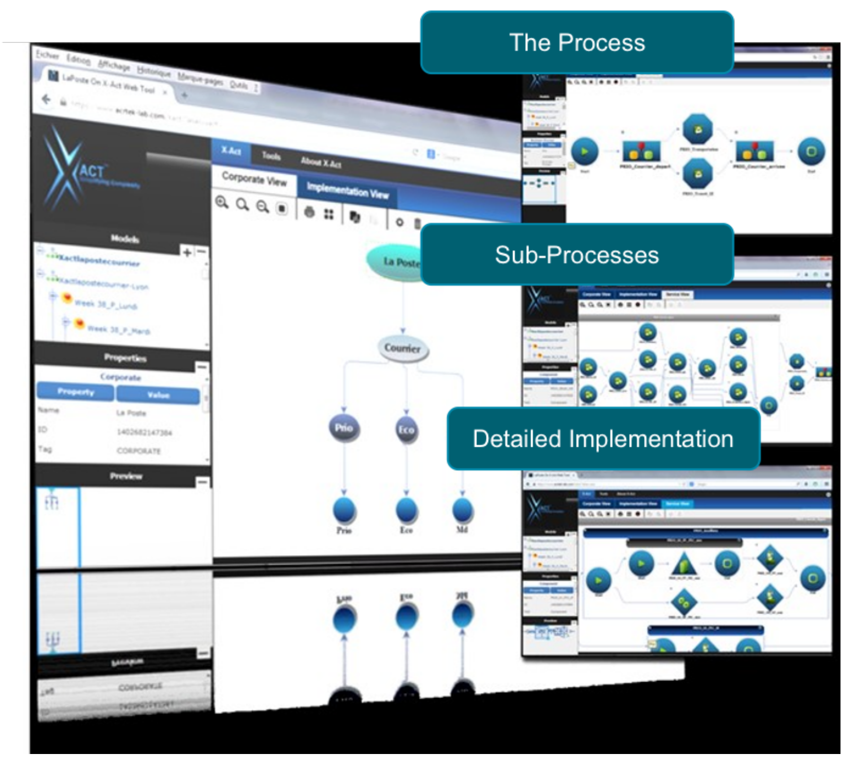

Figure 9. Sensitivity analysis

Phase 3: Scenario Analysis

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.

The goal of phase 3 is to 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.

Using the emulator built in phase 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. 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 10).

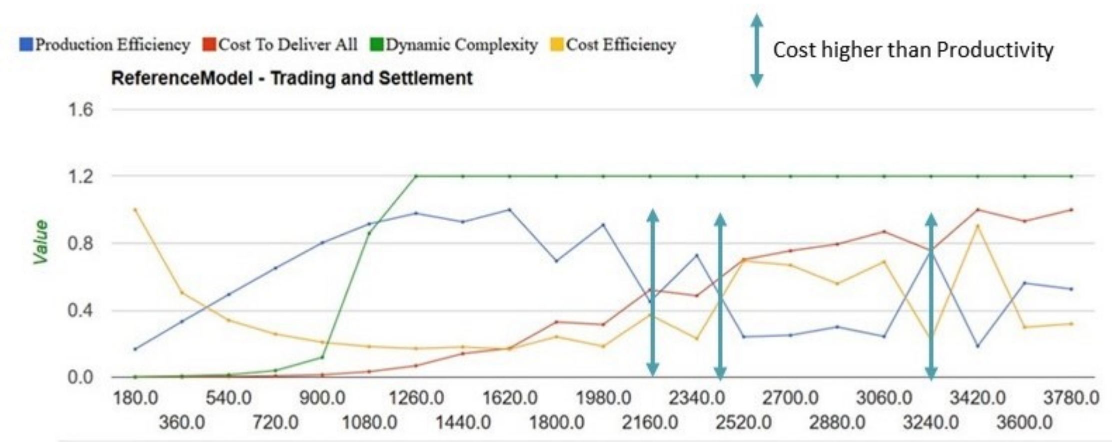

Figure 10. Stress testing results

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.[11] 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 for example of "a market definition." Some vertex and edges are influencing and influenced, but not necessarily adjacent or even near to a target constituent, therefore:

- The system cannot be considered a closed loop, so entropy determination has short sustainability

[11] Abu el Ata, Nabil and Rudolf Schmandt. *Predictive Risk Assessment in Risk Modeling.* Patent Application 20150339263. Filed: May 21, 2015.

- 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:* examples include parameters like default payment for mortgage, delay to deliver within a supply chain or corporate announcement
    - *Connector contaminator:* generally, through a transformation process these parameters create a wider and deeper result, e.g. the uncontrolled use of CDO's, CLO's, impact of pandemic on multiple activities or the use of deposits on speculative activities
    - *Connector communicator contaminator:* shortage in action can produce domino effects that once observed generally lead to multiple concurrent areas of crisis that prevent any staged treatment. For example, the ability to get a mortgage with "neither income or assets" or the proliferation of credit card debt encouraged by issuers who hope they can control the risk through escalation of interest rates.

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. For example to obtain a mortgage in France, the applicant's liabilities—including rents, mortgages and other regular expenses—must be no more than 30% of his/her net household income to qualify for the loan. In other countries, consumer credit, level of savings, content of portfolios and credit risk are usually determined at functional level with little to no consolidation. Mathematically, this situation may at a certain point in time and under certain characterizations lead to an unexpected economic crisis.

NARS model relies on the use of the degenerative perturbation theory. This allows us 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.

Through graph theory, we 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 (see Figure 11).

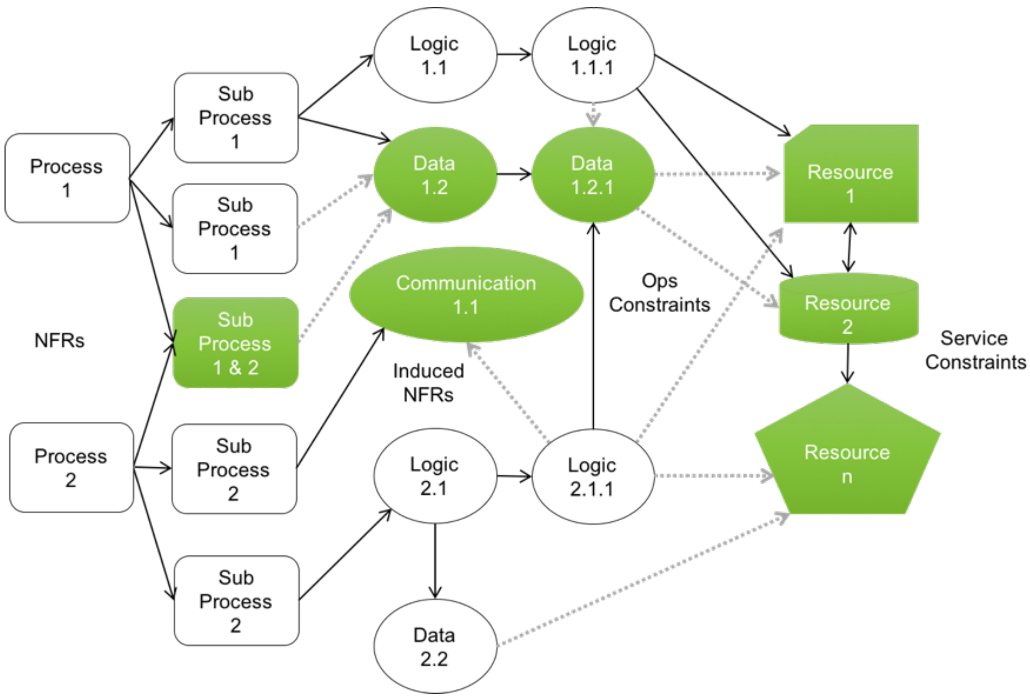

Figure 11. Use of graph theory encapsulates all characteristics, dynamic behaviors and dependencies among system components

The Circular Discovery of Dynamic Complexity

The process shown in Figure 12 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.

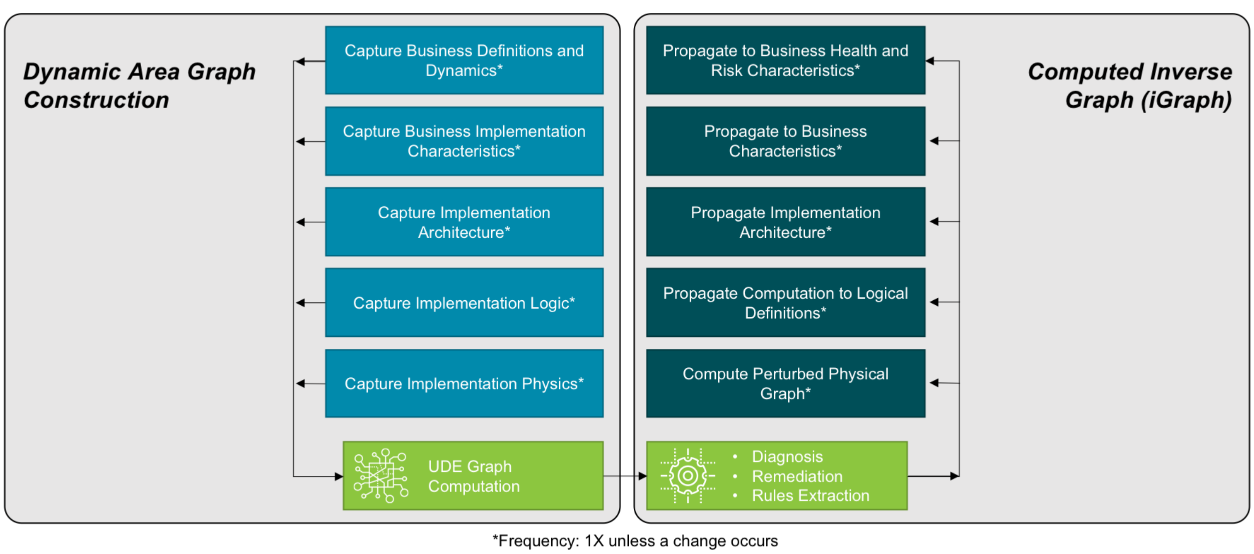

Figure 12. Circular discovery of dynamic complexity

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:

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

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

$\boldsymbol{\sigma}^{(i)}$ 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:

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

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

Further assume that:

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

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

and the first order indirect perturbation is:

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

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,

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

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

Therefore:

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

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

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

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

The matrix is determined by:

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

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:

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

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

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

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

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

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

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

NARS Modeling of US Economy

To demonstrate the practicality of using the UDE method for risk determination in economic forecasting and analysis, this section presents how the modeling of US economic interdependencies can be improved using NARS. The presented US economy model covers 2003—2018 and clearly identifies that the 2007-2008 economic melting was triggered by the housing bust that created the consequential effect on all US economy functions.

Comparison of NARS vs. Basic Structure of the Federal Reserve Bank US Economic Model

The FRB/US model looks at each market function separately from others and builds the dependencies through a simple point-to-point connectors graph. The base functions of the graph are:[12]

- **Households.** There are liquidity-constrained and unconstrained households. Liquidity-constrained households spend all their income each quarter. In contrast, other households consume and invest based on their assessment of their lifetime resources. This assessment contains different aggregate average propensities to spend out of different types of income, reflecting variations in the distribution of different types of income across age groups. In addition, future labor and transfer income is discounted at a rate substantially higher than the discount rate on future income from non-human wealth, reflecting uninsurable individual income risk. Unconstrained households face adjustment costs that cause them to adjust their spending gradually in response to changes in expected income and property wealth. As in the national income and product accounts, total spending by households consists of consumption of nondurable goods and non-housing services, purchases of durable consumer goods, and consumption of housing services. Movements in these three components of total spending are modeled separately. Labor supply is assumed to be independent of wealth both in the long-run and at higher frequencies. Movements in labor force participation are driven by social norms in the long run, represented by a stochastic trend, and by the availability of jobs in the short run.
- **Firms***.* Forward-looking firms solve optimization problems to determine their hiring and investment. Firms' fixed investment is disaggregated into spending on durable equipment, intellectual property, and nonresidential structures, and is modeled in line with standard neoclassical investment theory. In particular, the desired level of investment is a function of the user cost of capital, the expected level and growth rate of output, and depreciation, with movements of actual spending toward this desired level slowed by adjustment costs. Business fixed investment is also affected by current business output directly, which could capture either the effects of sales on liquidity-constrained firms' ability to invest, or sentiment effects. Businesses also aim to keep aggregate hours in line with the expected aggregate level of production and real compensation per hour (adjusted for trend labor productivity), but costly adjustment of both their workforces and the workweek may cause them to temporarily deviate from the desired longer-run level of hours in response to shocks.
- **Domestic financial sector and monetary policy***.* A variety of interest rates, including yields on Treasury securities at several maturities, BBB corporate bond yields, auto loan rates, and conventional 30-year residential mortgage rates, are determined as the expected average value of the federal funds rate over the appropriate holding period plus endogenous term/risk premiums. Equity prices equal the present discounted value of corporate earnings, where the discount rate equals the expected real yield on 30-year Treasury bonds plus an endogenous equity premium. Monetary policy is modeled as a simple rule for the federal funds rate subject to the zero-lower bound on nominal interest rates; the parameters of the policy rule used in simulations can be modified as desired. In addition, the model allows for the imposition of the policy thresholds that were part of FOMC statements from December 2012 to January 2014 for the rates of unemployment and projected inflation that would need to be crossed before the funds rate would be allowed to rise from its effective lower bound.

[12] Brayton, Flint et al. The FRB/US Model: A Tool for Macroeconomic Policy Analysis. Federal Reserve. April 2014. Web. Accessed 13 February 2020.

- **Supply-side**. The key production sector in FRB/US is the nonfarm business sector plus imported energy. The production function in this sector is Cobb-Douglas with potential output depending on the sustainable full-employment level of labor input, actual capital services, trend energy services, and the trend component of multi-factor productivity. Because there is no wealth effect on long-run labor supply in FRB/US, the sustainable level of aggregate hours depends on the overall population and the trend components of the participation rate and the workweek, where the latter two factors follow stochastic trends.
- **Price and wage setting**. The key inflation measures modeled in FRB/US are for core PCE prices and ECI hourly compensation, following the New Keynesian Phillips curve specification in the presence of nonzero trend inflation developed in Cogley and Sbordone (2008). In addition to slack and expectations of future inflation, other important determinants of total consumer price inflation include movements in the relative prices of food, energy, and non-energy imports.
- **Other**. The government sector includes disaggregated components of spending and a wide range of tax rates and credits at both the federal and the state and local levels. Simulations can be run under fiscal rules that adjust the trend component of average personal income tax rates to stabilize the ratio of either the budget surplus or debt to GDP. The foreign sector affects domestic real activity through equations for imports and exports of goods and services that depend on real activity in the rest of the world and the terms of trade. The trade-weighted dollar exchange rate is modeled assuming uncovered interest parity, which links the expected real return on safe long-run assets abroad to those in the U.S., plus a country-risk premium that depends on the level of U.S. net foreign indebtedness. Foreign short-term and long-term nominal interest rates are modeled jointly with foreign inflation and foreign real activity in reduced form.

What Differentiates the NARS Model from the FRB/US Model?

The NARS model looks at each market function separately from others and concurrently builds the interdependencies through a complex graph that depicts the perturbations exerted on each function by the fluctuations at each function due to all others. Such perturbations are a function of spacetime and generally represented through a **tensor** that represents the variants and covariances in the same time. With simplification (first order perturbation in 3-axis x, y, z), the tensor is illustrated in Figure 13.

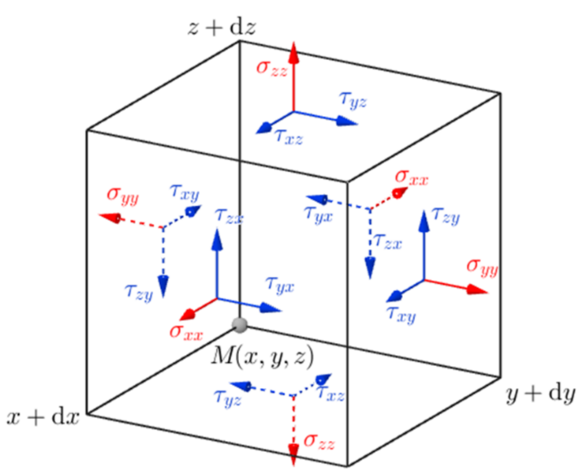

Figure 13. NARS model represents perturbations through a tensor

NARS allows multiple order perturbations to be represented to cover the direct effect, as shown ($\sigma_{i,j}$ and $\tau_{i,j}$), as well as all possible indirect multiple order effects. The results of deconstruction and sensitivity analysis are shown in Figures 14-16.

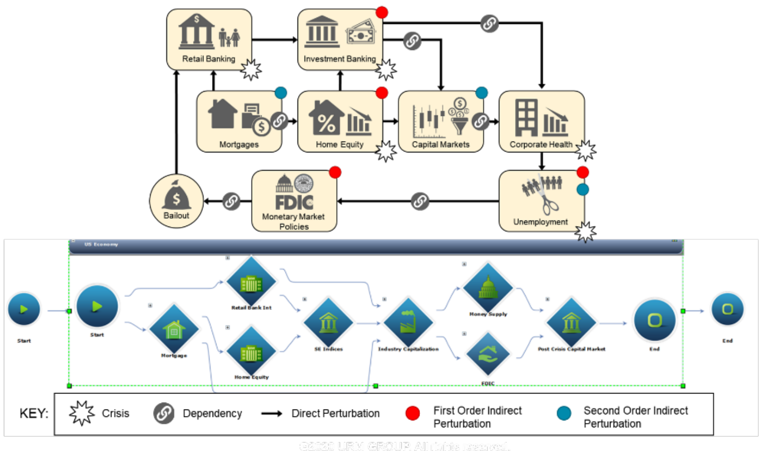

Figure 14. NARS global economic modeling and distributed graph computation

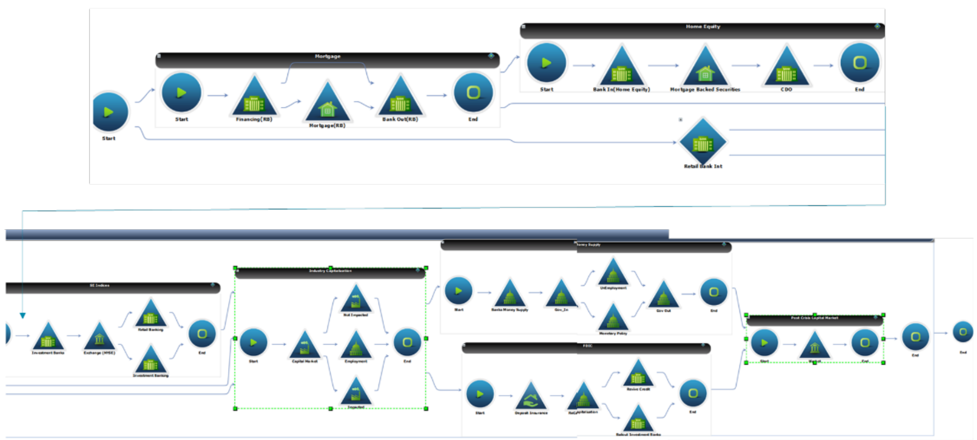

Figure 15. Detailed structure of US economy and active communications

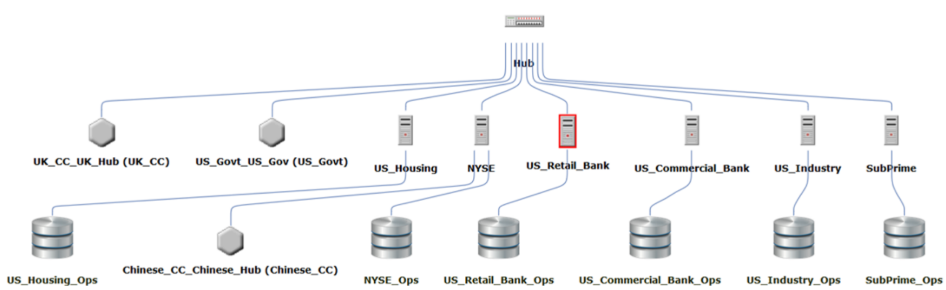

Figure 16. Physical and network mapping of logical demand graph

The ability to cover direct and indirect effects is key to this simple 2007-2008 economic modeling case, which shows the effect was produced at the housing function, proliferated to employment and monetary policy levels, and the capital market in between.

Table 1 shows the scope and interdependencies covered in the presented US economy case.

Economy Role	Direct Impact	1st order Indirect	2nd Order Indirect
US Gov	Capital Market	Monetary Policy	Deposit Insurance
US Gov	Employment	Corporate finances	Growth
US Housing	Regular	Guarantees	Interest Rates
US Housing	Mortgage Backed Securities	Dry-up Policy	Lenders reorg
NYSE	Exchange	Stress Test	Fed/Recapitalization
NYSE	Market Projections	Recapitalization	Banking Bailout
US Retail Bank	Financing	Growth	Rescue / Monetary Policy
US Retail Bank	Bank Out	Revive Credit	Treat Toxic Assets
US Commercial Bank	Bank In (Home Equity)	Investment Banks	Bailout Investment Banks
US Commercial Bank	CDO	Deposit/Investment	Reorg _ Regulation
US Industry	Finances	Corporate strategy	Tariffs
US Industry	Capital Market	Investment	Employment
Multi-year mortgage	Mortgage/Lenders	Interest rate/Risk	Regulation
Subprime Grouping	Lenders/Commercial	CDO	Bond/OTC

Table 1. NARS US economy model scope and interdependency strategy scenarios

NARS Modeling Results

The US economy 2003—2018 model indicates that negative economic effects were possible through multiple structures (e.g. credit card debt and enforcement of commercial tariffs) as a direct effect of dynamic complexity. In agreement with the actual market conditions of the time, the NARS model of the 2007-2008 US economy replicated the shortage of liquidity within 3% (Figure 17).

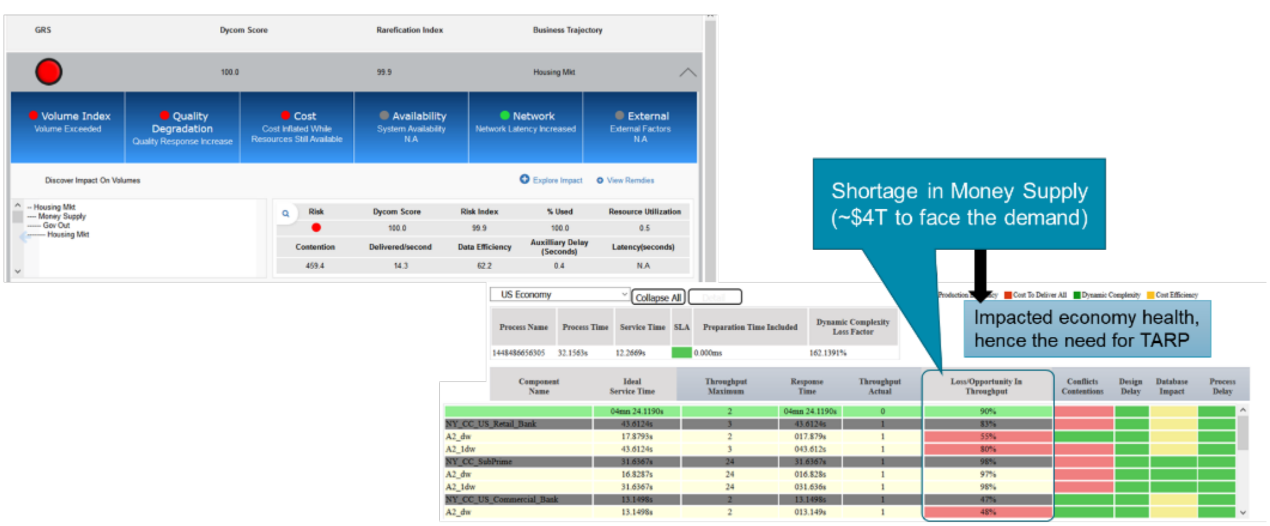

Figure 17. NARS predictive emulation results for 2008 US economy (volume per function)

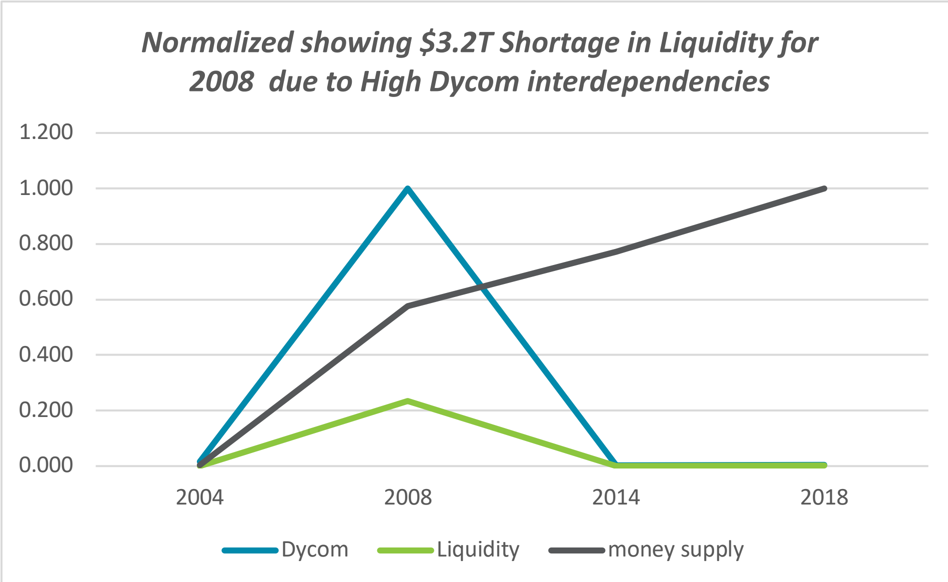

Figure 18. NARS predictive results show shortage in liquidity due to dynamic complexity

The same NARS base model was used to study the subsequent years of US economy to confirm that the emulated effects of market dynamics aligned with those that were directly observed. Figure 18 shows the liquidity due to dynamic complexity in 2008. Gradually, the money supply shortage began to ease from 2010 and turned positive around 2013-2014. At that point, the economy started to regain strength through 2018 with the stock market hitting all-time highs, an unprecedented volume of investments and the best employment rates in decades.

However, the mortgage industry is still grappling with changes, as the total outstanding mortgage debt surpasses $10 trillion. With 63% of US homeowners having a mortgage, individuals owned $25.6 trillion in real estate in the US by 2018. A number which is increasing by 6 million home sales every year. With an average delinquency rate of 2.67%, that rate went to 11.54% in January 2010 and as high as 16.6% for some weeks in 2007-2008.

Obviously, the mortgage industry is a foundational component of the US economy. Still other constituents can also accelerate new domino effects, as discovered through NARS model scenarios. The major economic areas/functions are connected to each other through connectors that can at any moment in time create a crisis contamination effect that may hit any function—directly or indirectly. On the horizon, new risks are forming due to worldwide political instability, tariff wars, regional tensions and the growing debt of many countries. Further, the specter of Coronavirus may become yet another factor of instability.

Table 2 shows the possible scenarios revealed by the NARS model that may cause an economic crisis or precipitate the consequential melting of the economy. Impacting scenarios could also occur at lower levels and at the level of the rules that govern each function. There are many examples of impacting scenarios, but some key examples include the mortgage acceptance requirements, credit rule versus risk of default, government interventions during panic situations and the telescoping between politics and economy.

Economy Function	Year	Intensities	Weight	Dycom	Year	Intensities	Weight	Dycom	% liquidity	Year	Intensities	Weight	DynComp	% liquidity	Year	Intensities	Weight	Dycom	% liquidity
US Gov treasury	2004	52.080	5.071	459.391	2008	62.120	5.088	461.265	0.284	2014	90.606	6.533	619.734	0.284	2018	101.250	8.412	826.381	0.288
US Gov Social	2004	33.600	3.571	351.345	2008	36.603	3.576	351.864	0.001	2014	48.323	4.551	474.930	0.273	2018	65.430	5.556	601.450	0.221
US Housing	2004	1.050	0.808	0.131	2008	1.050	0.808	0.131	0.000	2014	1.050	0.808	0.131	0.000	2018	1.050	0.808	0.131	0.000
US Housing Incentivized	2004	2.800	0.704	1.013	2008	2.500	0.703	0.857	-0.001	2014	3.000	0.704	1.120	0.002	2018	4.499	0.711	1.977	0.010
NYSE Corporate	2004	2.800	0.844	0.837	2008	2.500	0.826	0.722	-0.021	2014	8.224	0.844	3.993	0.022	2018	17.999	1.268	39.990	0.503
NYSE Indexes	2004	16.800	0.959	32.743	2008	12.996	0.794	12.332	-0.173	2014	28.187	2.826	304.001	2.561	2018	29.621	3.122	294.589	0.105
US Retail Bank	2004	16.240	1.101	21.480	2008	10.999	0.897	6.675	-0.185	2014	16.905	1.150	26.930	0.282	2018	21.117	1.732	111.756	0.506
US Retail Bank	2004	22.400	1.947	146.110	2008	15.102	0.873	20.072	-0.552	2014	20.100	1.477	86.714	0.692	2018	20.958	1.560	121.021	0.056
US Commercial Bank	2004	14.000	0.939	12.668	2008	12.144	0.915	8.345	-0.025	2014	12.253	0.938	8.276	0.025	2018	12.523	0.908	9.199	(0.032)
US Commercial Bank	2004	3.360	0.730	1.269	2008	1.800	0.734	0.485	0.005	2014	4.619	0.768	1.891	0.046	2018	2.499	0.726	0.828	(0.055)
US Industry Positioning	2004	15.120	1.047	15.483	2008	12.598	0.983	8.415	-0.061	2014	23.142	2.243	147.556	1.280	2018	26.458	2.834	212.818	0.264
US Industry Fed	2004	16.800	1.021	29.055	2008	13.998	0.898	13.364	-0.121	2014	18.121	1.140	44.123	0.270	2018	20.999	1.659	109.701	0.455
Subprime Grouping	2004	14.000	0.266	1.316	2008	18.198	5.254	409.255	18.758	2014	1.000	0.495	2.183	(0.906)	2018	1.000	0.616	3.776	0.243
Multiyear Mortgage	2004	16.800	0.251	1.812	2008	21.396	6.043	534.861	23.036	2014	7.121	6.924	71.292	0.146	2018	4.937	0.767	57.523	(0.889)

Table 2. Scenarios that may cause an economic crisis

This simple demonstration shows that the dynamic complexity of a system, which may be produced through all possible interdependencies, must be included in the emulation of economy or else it will forcibly lead to a shortage in analysis and ultimately false predictability. The absence of such a robust approach today leads economists to generally consider a crisis as an exception or statistical outlier that is then discovered too late and therefore reduces the spectrum of fixes that can be applied in a timely manner.

Looking at the computed results, it is easy to identify several fundamental conclusions that led to the crisis. Today the underlying factors that created the 2007-2208 economic crisis still exist and may create a future crisis that may differ in the initial conditions and stating point, but lead to the same conclusion, because:

- The interdependencies among economic functions favor the pandemic through intercommunication
- The severity is caused by the rarefication of supply (e.g. money supply, availability or timely facing the local to prevent the global)
- Regulations and rules of engagements at each function separately
- The immaturity of risk determination and the inability to continuously test change scenarios to predict risky configurations
- And finally, the inefficiency of current economic monitoring methods.

Algorithmic Management: The Future of Financial Engineering

Continuously computing the value of dynamic complexity at any point in time is one of the most important dimensions of using dynamic complexity as the metric to identify, anticipate and cure economic imbalances. This requirement necessitates moving to a robotic cognitive approach that can be applied quasi instantaneously to identify and eventually heal any imbalances that may lead to an undesirable outcome (see Figure 19).

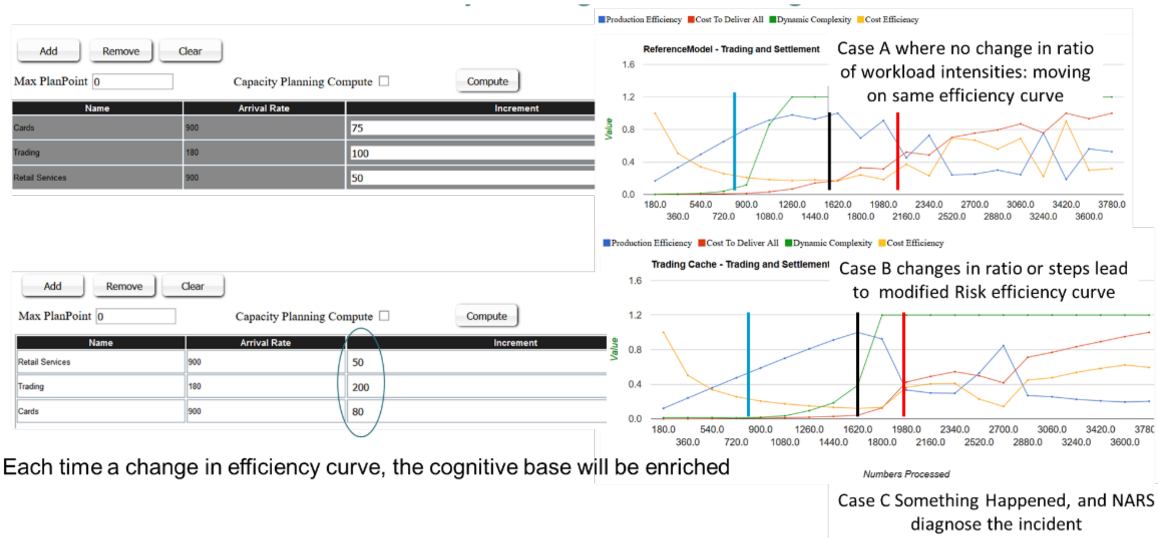

Figure 19. Automation of financial engineering, risk evaluation addresses the variations in workload intensities and continuously feeds the automatic cognition

By starting with a few computed, validated cases, the robot can compute all other possible cases. With human validation, the thresholds that must be monitored in real-time so that right actions can be employed ahead of a crisis (see Figure 20). Any change in initial conditions—processes, structures, infrastructure or dynamics—will restart the computation process with a new emulation/new matrix.

Process/ Increments	Process 1	Process 2	Process 3	Process 4	Process 5	Process 6
Workload increment by 10%	🔴	🔴	🔴	🔵	⚫	🔴
Workload increment by 20%			🟡		🟢	
Workload increment by 30%	🟡	🔵		🔴		🔵
Workload increment by 40%	🟢		🟢		🔴	🟡
Workload increment by 50%		🔴		⚫	🔵	
Workload increment by 60%	⚫		🔵			🟢

- 🔴 Computed from real characteristics of initial conditions and planned increments—validated
- 🔵 Robot Computes from real characteristics of initial conditions and other increments—validated and possible
- 🟢 Robot Computes from real characteristics of initial conditions and increments—not validated
- ⚫ Robot computed from planned characteristics of initial conditions and planned increments—not Validated
- 🟡 Robot computes from other characteristics of initial conditions and other increments—not validated

Figure 20. Supervised machine learning for automatic identification of risk scenarios

Voice technology and voice-controlled computers will provide real time status updates and detailed information—like efficiency curves, critical analysis of the point in the curve, diagnosis, detailed SMV and cognitive conclusions that recommends the right financial engineering to address current financial issues as well as to devise new and innovative financial products. Using supervised machine learning algorithms, the robot will determine risk through the 4 metrics and qualifying each as high, medium or weak. Humans will be freed to more deeply interpret the provided diagnosis as well as the plausibility of the recommended curative actions (see Figure 21).

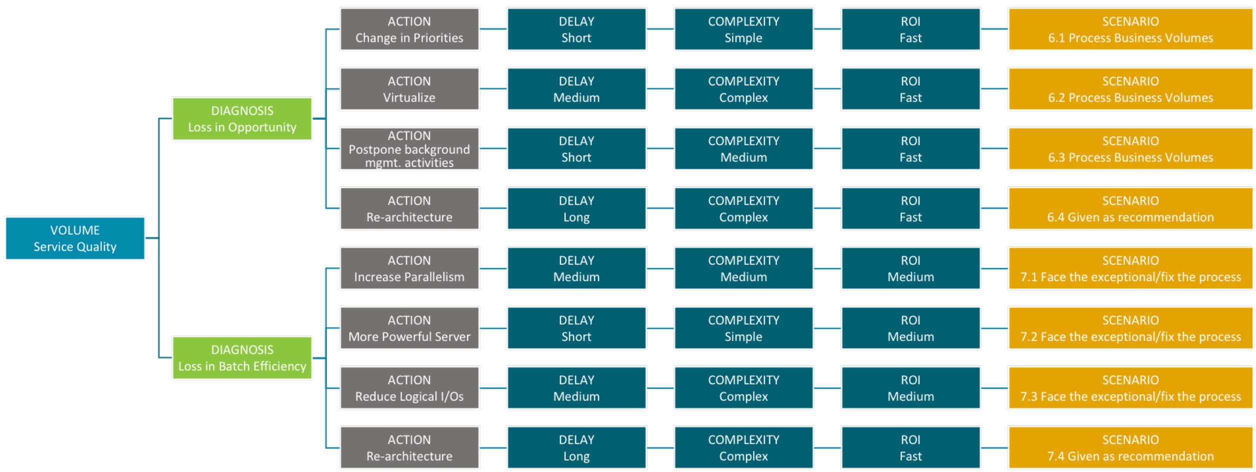

Figure 21. Example of automated algorithmic cognitive diagnosis/action monitoring for 4IR implementations

Pairing human perception and decision making capabilities of supervised machine learning with the scientific disciplines of dynamic complexity and perturbation theory will create a systemic and iterative collection of knowledge that will become the right synthesis for economic progress.

Conclusion

The approach presented in this paper has been successfully applied in multiple cases to support critical government decisions. The postal services in France used the NARS model for strategic planning and to identify opportunities to reduce costs and efficiently manage declining mail volumes without impacting service quality, as well as prepare for privatization and deregulation. It was also used to automate the tax system in France with the goal being to optimize the timely surveillance and inspection of tax returns. Further the NARS model was instrumental to building an employment system that would offer the best service at a controlled and predictable cost.

In each case, the objective was to minimize the continuous build-up of dynamic complexity from planning to the architecture and implementation stages and inform strategic decisions in order to fix a risk in time to avoid a singularity. These capabilities have become considerably important to manage automation and real time services of different criticality.

The significance of the approach becomes increasingly convincing as more economic models are built and additional decision support to government leaders is provided. Clearly, complexity will be always a concern, but dynamic complexity is the real threat to continuity and efficient management of the subsystems that support the global economy.

From our experience, it is clear that new tools and methodologies that offer both certainty and accuracy are needed to augment traditional risk prediction and management practices. This is the only way that governments, policymakers and other key stakeholders can take back control of financial systems. Dynamic complexity and economic mathematics that cover systems with a high level of interdependencies is the privileged way to build long lasting econometrics ephemeris. This will make it possible to guide rather than react to market fluctuations in ways that yield the desired outcomes, including improved economic growth, prosperity and sustainability in the 4IR.

About the Author

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Dr. Nabil Abu el Ata is an inventor and scientist with over 15 patents, co-founder of URM Forum and author of *Solving the Dynamic Complexity Dilemma, The Tyranny of Uncertainty* and *Leading from Under the Sword of Damocles.* In the late 1970s, Dr. Abu el Ata's mathematical discoveries provided the predictive accuracy necessary to support innovative space exploration missions. By solving a dynamic complexity problem that was previously defined as unsolvable, Dr. Abu el Ata set the foundation for a new era of risk management, which today enables organizations to predictively expose and prescriptively treat risks caused by dynamic complexity. For the last two decades, he has worked with global leaders in financial, telecommunications, retail, entertainment, services and government to help them control risk and take strategic actions to improve business outcomes.

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URM Forum is bringing together a collaborative global network of individual thought leaders that will work across industry and government segments to identify solutions that are vendor neutral and non-competitive in nature. By interacting and collaborating on shared risk management objectives, URM Forum is committed to developing the best practices and technology frameworks that will allow business and government stakeholders to make smarter decisions in times of uncertainty, maximize future opportunities and mitigate dynamic complexity related risks associated with the Fourth Industrial Revolution. URM Forum members must be invited and qualify based on their ability to contribute towards a meaningful solution, which is part of what makes this forum unique and our work impactful. Executive, technology, academia and government experts and practitioners interested in joining URM Forum are encouraged to apply at www.urmforum.org.