Halting Global Pandemics via the Commercial Air Route Network

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Abstract

How can a pandemic like SARS be halted in the modern age of air travel? This article argues that the classical mathematical models of epidemics are inadequate for describing the impact of air travel on the spread of contagions like SARS. Instead, the author proposes a modern model that incorporates air travel as the main vehicle or vector of disease spreading. The new model is based on network science instead of the traditional Kermack-McKendrick model *and its many derivatives*. The new model uses spectral radius ρ and blocking node analysis in place of basic reproduction number R_o as metrics for stopping pandemics.

This article compares three strategies for defeating pandemic spreading: 1) quick and effective removal by quarantine or inoculation of (n/R_o) people from a population of size n; 2) removal by quarantine or hardening of airports at the rate of $\Delta > \gamma\rho$; and 3) blocking by quarantine or hardening of approximately n/ρ blocking nodes in the air route network. The third strategy is illustrated for the airports and air routes in the OpenFlight commercial air route network. Symbols: n: population size in terms of people or airports; R_o: basic reproduction number; Δ: removal rate; γ: infectiousness; and ρ: spectral radius.

Stopping a Pandemic

The Black Death (Bubonic Plague) marched across Europe at a relatively slow pace of 3 miles per day. The worst of it swept westward from Eastern Europe over a period of 4 years beginning around 1347, killing approximately 1/2 of the inhabitants (75million). Outbreaks like Black Death and the 1918 Spanish Flu (100 million deaths) continue to fuel rational and irrational fear of global pandemics even though such disasters are few and far between.

Five hundred years after the Black Death pandemic, Kermack and McKendrick derived the first mathematical model describing the spread of an epidemic through contact.[1]

The Kermack-McKendrick model (along with its many derivatives and extensions) follows a logistics or S-curve whereby the number of cases in the early stages of an epidemic rises exponentially, reaches a peak, and then flattens out. Figure 1a shows a near-textbook fit to the S-shaped model for the spread of SARS in 2003.[2] Without countermeasures, an epidemic grows exponentially in its earliest stages and then tapers off as the number of potential victims is depleted.

More recently Althaus applied a modified form of Kermack-McKendrick model — the SEIR (susceptible-exposed-infectious-recovered) model – to the Ebola outbreak of 2014.[3] The equations and their solution are beyond the scope and purpose of this paper, however, the data used to validate the SEIR mathematical model are shown in Figure 2. This data and model were used to estimate the basic reproduction number R_o, defined as the average number of people who contract the contagion in order to spread it.

R_o determines the eventual size of the epidemic. Epidemiologists use R_o to predict the spread of the contagion:

$$R_0 < 1; \quad dies \quad out$$
$$R_0 > 1; \quad spreads \quad indefinitely$$
$$B = 1 - 1/R_0; \quad blocking \quad fraction$$

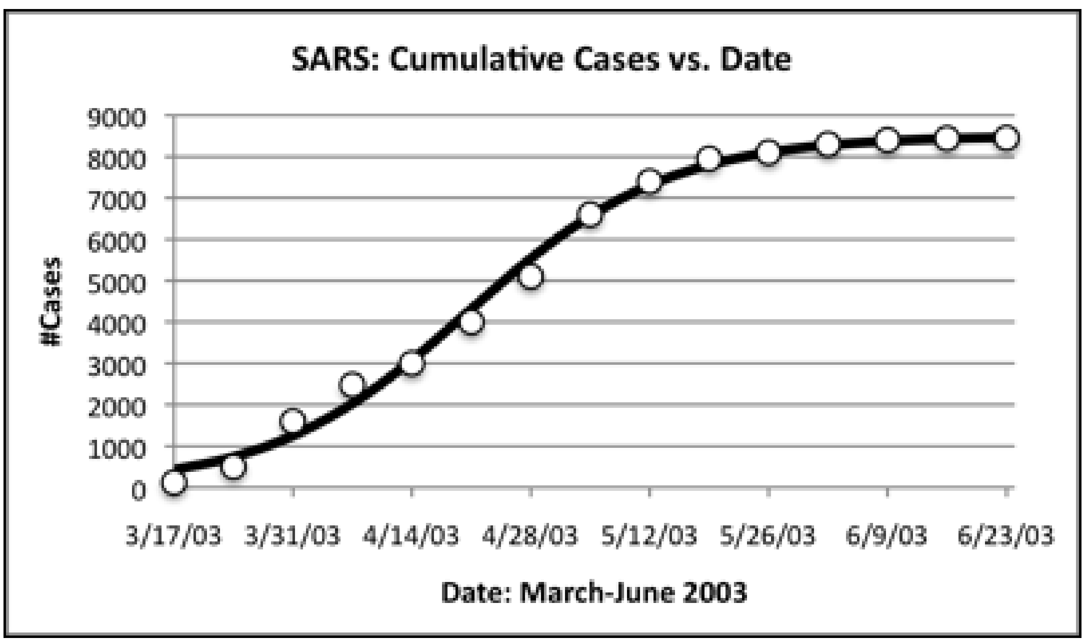
If R_o is less than one, the contagion dies out on its own. If it is greater than one, the contagion spreads as shown in Figure 2 for Guinea, Sierra Leone, and Liberia. Epidemiologists also use R_o to estimate $1/R_o$, which is the proportion of the population that must be quarantined or inoculated in a timely fashion to halt further spreading. R_o ranged from 1.51 for Guinea to 2.53 for Sierra Leone, which means that 66% - 40% of the population would have to be quarantined or inoculated in order to halt spreading.[4]

Rapid and effective public health response during the early stages of an epidemic can curtail uncontrolled spreading as shown in Figure 1b. This typically means isolation of infected people, timely inoculation of susceptible people if a vaccine exists, or removal of infected people through death or social space separation. In modern states, quarantine and inoculation are the primary tools of public health.

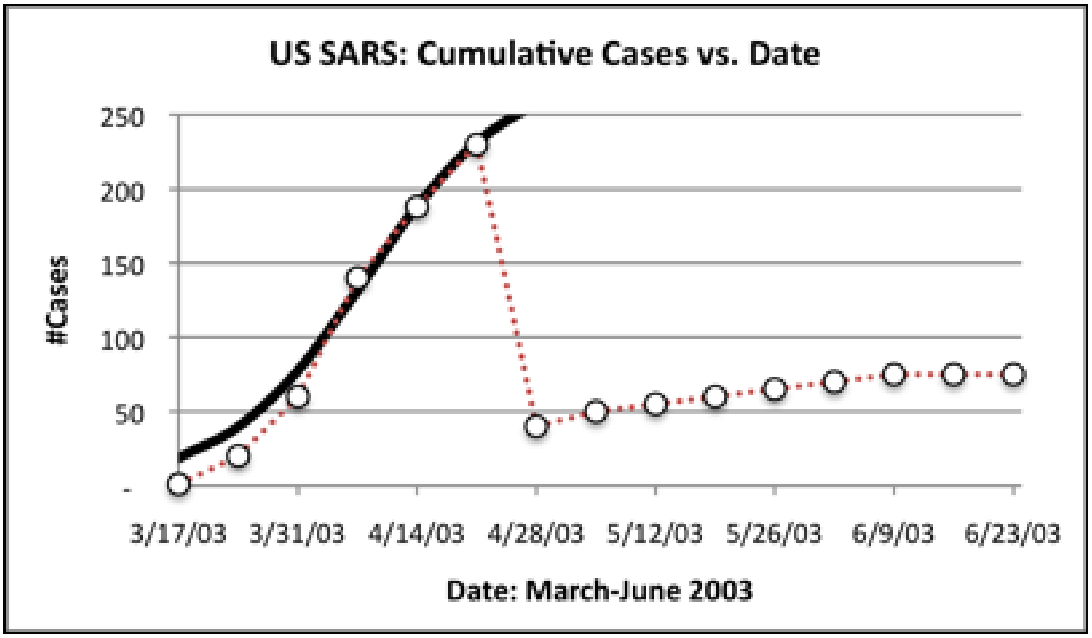
If we assume a conservative value of $(1.51+2.53)/2 = 2.02$ for Ebola, approximately 50% of the population would have to be quarantined or inoculated to halt uncontrolled spreading. Even if an Ebola vaccine had been available in large quantities, mass inoculation of millions of people on a timely basis would be difficult.

However, the threat of a global pandemic spreading through commercial air travel is the focus of this paper. When considering the commercial air routes as vectors of epidemic spreading, R_o no longer applies.

The SEIR model assumes uniform mixing of a population, and a fixed (average) herd infectiousness, γ. Uniform mixing means likelihood of contact with an infected person is evenly distributed throughout a population. Infectiousness, γ is the probability of passing the contagion from one person to another through contact. In addition, Δ is the removal rate, which is achieved through death, inoculation, or quarantine. Classical mathematical models such as the SEIR and other Kermack-McKendrick derivatives quantify how to stop an epidemic assuming narrow social spacing and uniform mixing. The model breaks down when spreading takes place through commercial air travel.



(a) Global spread of SARS.



(b). USA spread of SARS.

Figure 1. (a) Spread of the SARS virus in terms of the number of people who contracted the disease versus time, and (b). The spread of SARS in the USA was halted by fast and effective public health measures.

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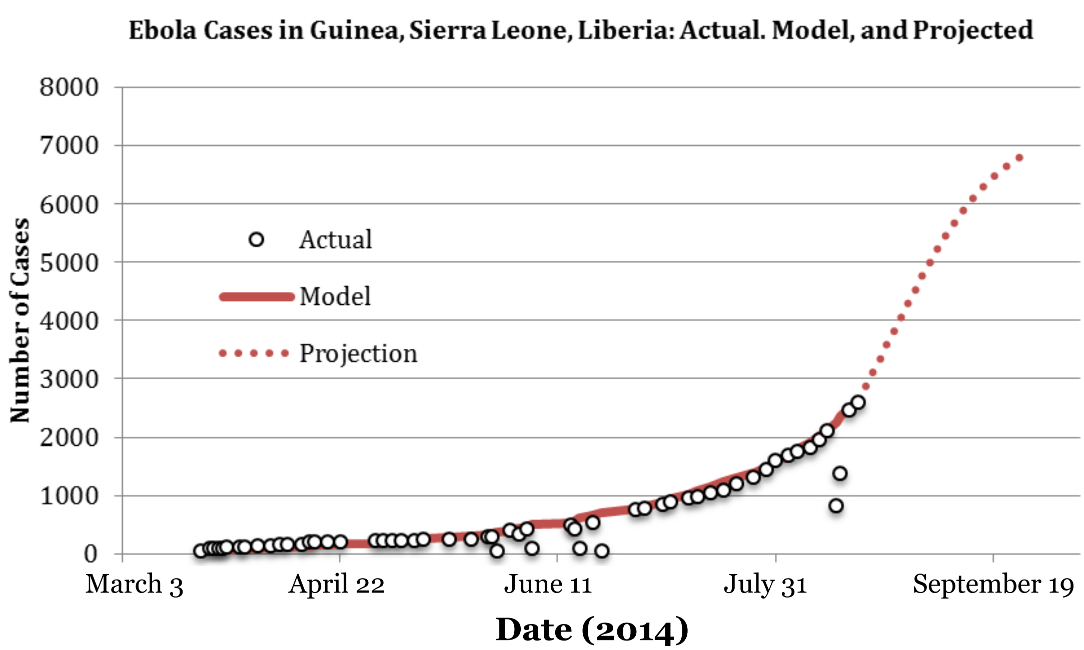


Figure 2. Ebola recorded cases for Guinea, Sierra Leone, and Liberia. Data points are shown as open circles. Solid and dotted lines are from a mathematical model.

Air Travel

An epidemic becomes a pandemic if it crosses regional boundaries. Left unchecked, a contagion with $\gamma R_o > \Delta$ slowly marches across a continent until it either exhausts the supply of susceptible people or reaches an ocean or other natural barrier. Ebola became a pandemic when it left West Africa and spread to the U.S. and Spain. SARS spread to 29 other countries before it was stopped. The Black Death ignored borders.

The commercial air route network partially shown in Figure 3 is the principle mechanism of pandemic spreading beyond the origin of a disease. Nodes represent airports and links represent routes. Epidemiologists hypothesize that infected passengers transmit contagions by traversing one or more links in this network. Hence, the air route network replaces the "flat world" model of Kermack and McKendrick with a social network "complex world" model. Air travel restricts (and extends) the uniformly mixed human social network, because air travel spreads the seeds of destruction by following links in a network. Hence, uniform mixing cannot be an underlying assumption of the "complex world" model.

The spread of contagions in networks is a well-understood and heavily studied topic of network science.[6] In place of basic reproduction rate R_o, network scientists use a network parameter called the *spectral radius* ρ, and in place of the removal rate equation of Kermack-McKendrick, we use the Wang et al. relationship below. Spectral radius is a measure of self-organization.[7] It depends on the density of air routes and the number of routes into and out of airports. It is obtained from the connection topology of the network.

Lewis found empirical relationships between the fractal dimension of contagion spreading, infectiousness, and spectral radius.[8] His set of relationships is based on the observation that network epidemics obey a long-tailed exceedence probability density closely matching a power law with fractal dimension q.[9] Parameters b and k are determined by simulation and fitting a power law of the form C^{-q}, where C is number of infected nodes and q is the fractal dimension of the resulting exceedence distribution obtained by simulating the spread of a contagion from a single node to other nodes within a connected network. The relationship between fractal dimension, infectiousness, and spectral radius is:

$$\log(q) = b - k\gamma\rho; \quad b,k : constants$$
$$q : fractal\dim ension$$
$$\gamma : \inf ectiousness$$
$$\rho : spectral radius$$

A critical point exists when log(q) = 0, resulting in the following relationships for network epidemics.

1. Spectral radius ρ determines the removal rate needed to halt further spreading [Wang 2003]:[10]

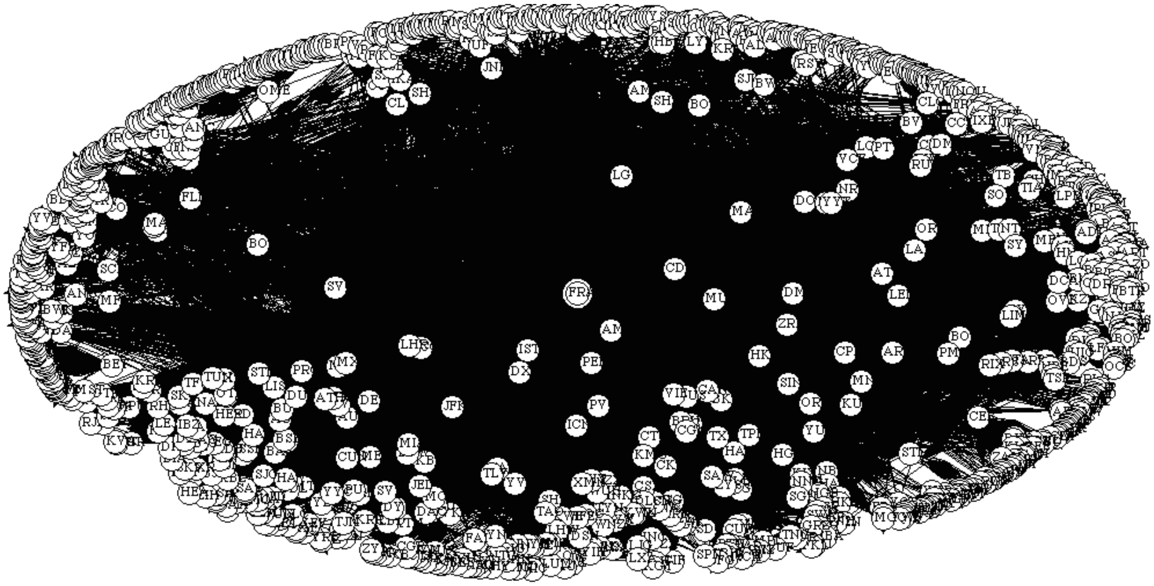
$$\gamma\rho < \Delta; \quad removal \quad rate$$

2. The relationship between spectral radius and infectiousness determines risk (and severity) of spreading. Constants b and k are parameters determined empirically for each network .[11]

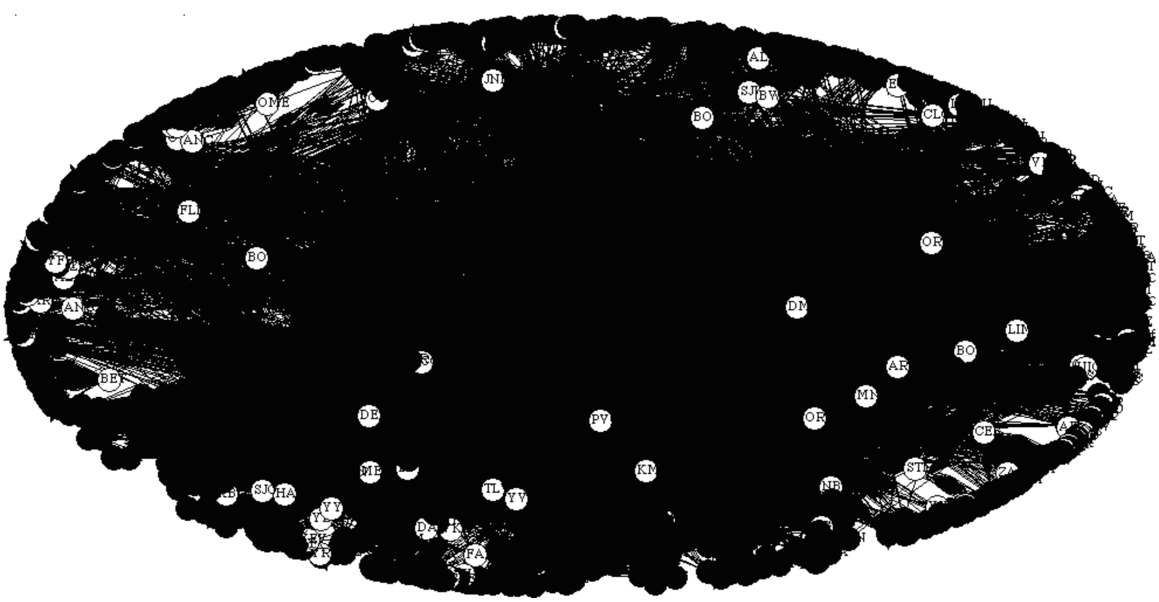
$$\gamma\rho < \frac{b}{k}; \quad removal \quad rate$$
$$\gamma\rho > \frac{b}{k}; \quad high-risk$$
$$\gamma\rho >> \frac{b}{k}; \quad catastrophic \quad risk$$

If the product of infectiousness and spectral radius is less than removal rate, the contagion can be controlled. That is, if the health care system removes susceptible passengers from the air route network at a rate greater than γρ, the network contagion dies out. For the OpenFlight1000 network of Figure 3, we have ρ = 55.8. Then, Δ > 55.8γ only if γ < 0.0179, or 1.79%, because Δ cannot exceed 1. The OpenFlight3340 (the complete commercial air route network) contains 3,340 airports and 18,277 routes. Its spectral radius is estimated to be approximately 68; b = 0.64, k = 0.35, so the critical point γ is (0.64)/(0.35*68) = 2.69%.

Indeed, the OpenFlight network is subject to massive spreading unless a contagion's infectiousness is less than 1%. Even if infectiousness turns out to be relatively low, the requirement that $\Delta > \gamma\rho$ may be difficult or impossible to achieve if resources are spread across 3,340 airports and 180+ countries.



(a) OpenFlight1000 contains the most-connected 1,000 airports and 14,384 routes.



(b). OpenFlight1000 with 84 blocking nodes shown in white and non-blocking nodes shown in black. The spectral radius of this network is 55.8.

Figure 3. Top 1,000 airports and routes obtained from open source data available at http://openflights.org/data.html. (a). Nodes are airports and links are routes. (b). Blocking nodes are white and the non-blocking nodes are black.

Blocking Strategies

Halting the global spread of any contagion through air travel may require a different strategy, because OpenFlight is large, and so is its spectral radius. What alternatives do public health practitioners have? This section explores a network blocking strategy that identifies critical airports as blocking nodes, and critical routes as links essential to the continuity of the air route network. The blocking strategy is to identify blocking nodes and either inoculate or isolate them to halt further spreading.

Lewis defines a *critical link* as a link that separates the network into isolated components if it is removed.[12] That is, removal of a critical link divides the network into separate sub-networks such that it is impossible to reach nodes in one sub-network from nodes in other sub-networks. Similarly, a *critical node* is a node that separates the network into isolated "islands" if removed. Critical links and nodes are essential to the continuity of the network. On the other hand, their removal blocks transmission of a contagion from one region to another. Hence, critical nodes are also *blocking nodes*.

There are 84 blocking nodes in Figure 3, thus, 84 of the 1,000 airports hold the air route network together. Removal, isolation, or hardening of 84/1000 = 8.4% of all airports prevents a global pandemic in OpenFlight1000. On the other hand cancelation of all routes or isolation of 1,000 airports is unlikely to be economically allowed. So, hardening of 84 blocking node airports is both practical and feasible.

The full OpenFlight network contains 3,340 airports and 18,277 routes. Approximately 11% of the 3,340 airport nodes are blocking nodes. Isolation or hardening of these nodes divides the entire air route system into sub-networks separated from one another. The "air gap" between airports halts the spread of a contagion across sub-networks. However, the contagion may still spread throughout a large sub-network.

Levy Flights

Blocking node (airport) strategies appear to be attractive, especially if the number of blocking nodes is low. However, there is some evidence that air travel actually reduces consequence (illness and death) rather than aggravating it due to the Levy flight pattern of most contagions. For example, Hu et al. argue that long-tailed Levy flights reduce the virility of a contagion and lead to its eradication if the fractal dimension of the Levy flight power law is less than 2.0.[13] Other researchers have not confirmed this theory, but if true, it offers an unorthodox and controversial alternative strategy.

A Levy flight is a biased random walk in 2-dimensional space (surface of the earth) such that the size of displacements between waypoints obeys a power law. Levy flights occur in nature, especially in animal behavior.[14] They are a form of foraging and diffusion, e.g. the pattern of movements to various rides and amusements in Disneyland, foraging at stores in shopping malls, and the diffusion of wealth through a society. The power law of frequency versus distance traveled suggests a pattern containing many short bursts and rare giant strides. Levy flights are frequent bursts of short steps and rare bursts of long steps. Lewis examines the Levy flight of SARS in detail,[15] and expands on the idea of viruses as objects obeying Levy flights.[16]

The nature of a Levy flight is completely determined by the fractal dimension (exponent) of the power law distribution obtained by observation. The tail of this distribution gets longer and heavier as the frequency of long steps increases. The fractal dimension increases in the opposite direction. For example, a large fractal dimension such as 3.5 corresponds with a short-tailed distribution while a fractal dimension of 1.5 corresponds with a long- or fat-tailed distribution.

Fat-tailed distributions have small fractal dimensions and thin-tailed distributions have large fractal dimensions. A Levy flight with fractal dimension equal to 1.6 is "fatter" than a Levy flight with dimension 2.0. The expected length of a step is larger for 1.6 than for 2.0.

According to Hu et al., longer is better, when it comes to controlling a disease, suggesting that small jumps are more dangerous than large jumps.[17]

Lewis analyzed the Levy flight of SARS and estimated the fractal dimension of its power law as q = 1.6, which is less than 2.0.[18] Hence, Hu et al. would expect SARS to die out. SARS actually did die out after 6-9 months of spreading to 29 countries.[19] Quick-actions and long-distance air travel may have stopped SARS.

An intuitive explanation for Hu's conclusion is that putting out a large forest fire is more easily done if pieces of the fire are picked up and moved far away, before the fire gets too large. Then, each "sub-fire" can be more readily extinguished – none of the sub-fires gets too big or out of control. Similarly, dispersing infected people long distances apart via air travel makes it easier to eradicate the contagion, assuming quick action by public health organizations.

Similarly, longhop air travel disperses the contagion and isolates infected individuals simply by separating them spatially. Dispersion of dense clusters of contagion to remote areas, with fast and effective quarantine, may be more effective than fast and effective quarantine alone. This provocative idea needs more testing.

Conclusion

Network models are not meant to replace classical models that assume uniform mixing and narrow social spacing between and among populations. Rather, network epidemic models apply when populations are sparse or exhibit non-uniform social structure found in commercial air travel, "hot spots" of high-density populations, and other social networks exempt from the uniform mixing hypothesis.

This work extends previous network models of epidemic spreading using an empirically-derived model that relates fractal dimension to infectiousness and spectral radius. It proposes methods for stopping global pandemics that may spread through non-homogenous populations and therefore are not accurately modeled by classical models. This is the first report on the effect of blocking node isolation on contagion spreading through a network.

About the Author

Theodore "Ted" G. Lewis *is an author, speaker, and consultant with expertise in applied complexity theory, homeland security, infrastructure systems, and early-stage startup strategies. He has served in both government, industry, and academe over a long career, including, Executive Director and Professor of Computer Science, Center for Homeland Defense and Security, Naval Postgraduate School, Monterey, CA. 93943, Naval Postgraduate School, Monterey, CA., Senior Vice President of Eastman Kodak, President and CEO of DaimlerChrysler Research and Technology, North America, Inc., and Professor of Computer Science at Oregon State University, Corvallis, OR. In addition, he has served as the Editor-in-Chief of a number of periodicals: IEEE Computer Magazine, IEEE Software Magazine, as a member of the IEEE Computer Society Board of Governors, and is currently Advisory Board Member of ACM Ubiquity and Cosmos+Taxis Journal (The Sociology of Hayek). He has published more than 35 books, most recently including Book of Extremes: The Complexity of Everyday Things, Bak's Sand Pile: Strategies for a Catastrophic World, Network Science: Theory and Applications, and Critical Infrastructure Protection in Homeland Security: Defending a Networked Nation. Lewis has authored or co-authored numerous scholarly articles in cross-disciplinary journals such as Cognitive Systems Research, Homeland Security Affairs Journal, Journal of Risk Finance, Journal of Information Warfare, and IEEE Parallel & Distributed Technology. Lewis resides with his wife, in Monterey, California.*

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