J. Indian Inst. Sci.
A Multidisciplinary Reviews Journal
ISSN: 0970-4140 Coden-JIISAD

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LEAD ARTICLE

A Whirlwind Tour of Complex Systems

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1 Complex Systems Galore

What is common to you, bustling cities, traffic jams, economies, and pandemics like COVID-19? Or, can there be anything that is shared by these entities that are visibly so different from one other? A common factor, which you may say, is that all these are incredibly complex, and we do not fully understand them. Otherwise, why would governments and industries spend hundreds of crores of rupees on getting a better understanding their inner workings? There is also something which is not so obvious: all of them are composed of individual components, but they are radically different from the components that make them. In short, they are all *complex systems*.

Look at you, for example. You are made of a very large number of cells, but you are much more than any of them. What you perceive as *you*—your consciousness, your personality, your character— is something which cannot be described by the physicalities of a handful of organs and the countless number of cells that make your body. Of course, you would not exist without them, but they do not make you, *you*. Your sense of self-awareness is the result of trillions of cells operating in concert according to their own laws, without even being aware that they are part of you. Nor are they aware that their collective behaviour is resulting in something that is totally different from any of them. You, of course, are an ultimate complex system.

In fact, life in all its grandeur, is a complex system of astounding beauty— a beauty manifested in the form of elegant mathematical rules that apply to all life, ranging from tiny cells to gigantic blue whales that can weigh up to 200 tonnes.

Cities are also complex systems. Physically, cities are made of networks of roads, pipes and electrical wires transporting people, water, and electricity. They also have a large number of shops and offices, and inhabit millions of people. However, none of them make a city, because a city is a consequence of different components like physical infrastructure, government institutions, businesses, and most importantly, people, working in unison.

As Geoffrey West, a theoretical physicist who pioneered the complex system view of animals and cities, writes in his book *Scale*[25], "Cities are the crucibles of civilization, the hubs of innovation, the engines of wealth creation and centers of power, the magnets that attract creative individuals, and the stimulant for ideas, growth, and innovation." On the other hand, cities are also notorious for traffic jams, poor quality air and water, higher crime rates, and for being epicenters of disease outbreaks.

Unlike organisms, cities rarely die; instead, they grow at super-exponential rates. By 2050, more than 75% of the human population is expected to be living in cities due to what might be considered the largest human migration in the history of the planet[25]. Therefore, to ensure a sustainable habitat for the future generations, it is necessary to build sustainable cities.

1.1 Simplicity in Complexity

All complex systems, from animals to trees to cities, share some common properties. They are generally *nonlinear*, meaning that one quantity varies in a disproportionate fashion with respect another. For example, the metabolic rate— the rate at which energy is produced by an organism— increases slower than its weight. In other words, the metabolic rate of organisms is a function of the components of the animal's body. If the weight of an animal is doubled, then its metabolic rate does not double; it increases only by about 75%; this is true for trees and insects as well[25]. Cities too follow a similar rule: if the population of a city is doubled, then the number of gas stations increases only by 85%, not by 100%[25]. So do the lengths of roads, water pipes, and electrical wires.

Cascading electrical power grid failures are also nonlinear. Data suggest that larger blackouts are less frequent than smaller ones. However, since larger blackouts affect lakhs of people over large regions, they have more serious consequences than a number of smaller blackouts that are more frequent[5, 17].

Another universal characteristic of complex systems is that the collective is more than a simple sum of the individual components. In many

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cases, as in organisms, the whole takes a form that is too distinct from the form that can be obtained by the sum of contributions from constituent blocks. For example, a city is just not the sum total of roads, pipelines carrying energy, gas stations, and people; just as a brain is not the sum total of individual neurons. This behaviour, in which the collective develops characteristics that are more than the sum of the contributions from individual blocks, is called *emergence*[18].

1.2 It's All Networks

At the heart of every complex system is a network sustaining it. Just like the cardiovascular and other networks help us stay alive, a city is brought to life by a variety of networks, including the socioeconomic network of people— a network that has taken a new form with the advent of social media websites like Facebook, Twitter, and LinkedIn. These sites have removed the geographical barriers and enabled us to be connected with those in countries thousands of miles away. This is made possible by arguably the most revolutionary of all man made networks— the internet —a grand network of millions of computers, mobile phones, massive servers, and more recently, sensors. These devices connect to each other by a plethora of technologies— from long submarine cables connecting countries and continents to the humble wireless router through which you plug in to the internet. Sitting on top of this is the World Wide Web— another large network of documents, images, videos, and other artifacts that have changed the way we buy products, catch a taxi, and log our run in the neighbourhood park.

Networks are connected in two levels: one at the level of *structure*, and the other at the level of *behavior*[6]. A consequence of this connectivity is that the behaviour of each individual in a network can affect everyone in the network. A classic case is the traffic jam, where the delays experienced by an individual driver depend a lot on the behavior of other drivers using the road network[10]. A more dramatic example is that of a stock market crash, where the behaviour of individual traders has a strong effect on everyone in the market— which is nothing but a network of buyers and sellers[10]. In fact, the behavioral component of network science is so universal and important that it has become an independent area of research. This research area, which uses ideas from social science and game theory, this has found applications in disparate fields like politics, biology, economics, education and computer science among other things.

2 Modeling Complex Systems

While studying complex systems, scientists often simulate the constituent entities using sophisticated software. Called *agent-based modeling*, this technique has become popular among transportation planners, economists, and more recently, epidemic modelers.

The roots of the technique date back to 1940s when Alan Turing— a computing pioneer widely considered as the father of computer science and artificial intelligence— was toying with interacting pieces of software to understand complex behaviour in physics and biology. However, agent-based modeling became popular only in the 1990s, after large scale computations became economically viable[24].

Agent-based models predict the collective behavior by simulating the behavior of the individual entities that make up a system. The individual entities, called *agents*, make their own decisions and behave accordingly. Depending on what is being simulated, an agent can mean different things: it could be a vehicle driver in the simulation of traffic flow, an airplane in a software system for optimizing airport operations, or a mosquito in the simulation of a malaria outbreak. In contrast to traditional mathematical models that take a top down approach, agent-based models take a bottom up approach and are considered good at predicting emergent behaviour. Now they help authorities in planning aircraft landing and takeoff in busy airports, deciding vaccine rollouts during an epidemic, and drawing out evacuation plans during a disaster[13, 23, 24].

2.1 Managing Pandemics

Infectious diseases are part of our lives, though, luckily for us, only few of them spread rapidly enough to become epidemics. While diseases like malaria spread via mosquitoes, human behaviour is the critical factor in spreading diseases like common cold, COVID-19, and AIDS.

Conventional epidemic models (also called *compartmental models*), segregate the population into different categories like 'susceptible', 'exposed', 'infectious', and 'recovered', and assume that all individuals are equally likely to encounter one another[8]. However, this assumption is unrealistic because a person is much more likely to meet someone closer to home than someone far away.

Since the prevalence of an infectious disease in a city is a direct consequence of interactions among people, a complex systems approach can be used to better understand the spread of an epidemic. In fact, agent-based models have proven to be quite handy in managing epidemics like Ebola, Zika, and of course, COVID-19[1, 2, 13, 22, 23].

The first step in modeling the spread of an infectious disease is creating a population of agents and the environment through software and data on a computer. An agent is a digital twin of a real individual, who goes to work, has her own opinions, idiosyncrasies, and irrationalities. The environment component of the model has digital analogues of important places like bus stations, markets, and important junctions where people congregate in big numbers, and also less crowded places like shops, hospitals, and parks. An article by Bissett et al. [3] in the current issue discusses the nuances of creating such artificial cities.

Once created, the agents are "set loose" to carry on with their lives, as if they have one. For example, a typical agent may talk to her neighbour in the morning, go to gym, and visit a local store to buy milk while returning home from work. She may also, without her knowledge, catch a virus or transmit one if she has already been infected. By simulating such mundane interactions of millions of people for weeks or months, researchers predict the likely number of infections, deaths, and load on local hospitals.

By leveraging location information generated by mobile phones and social media posts, agent-based models take a more realistic approach to modeling interactions between individuals. They also take into account ground realities like the probability of an individual wearing mask, maintaining social distance, and agreeing to take the vaccine.

While kick-starting vaccination campaigns, public health officials in the state of Iowa, USA, had a perplexing question to answer: with limited number of vaccine doses at their disposal, they wanted to know which regions to vaccinate first: locked down regions where the transmission rates are already low, or regions that are more open with higher transmission rates? Focus on dense urban areas that are hotbeds of transmission or on the outskirts bustling with commuters, who potentially carry the virus to far off places? To answer this question, the researchers at the University of Pittsburgh, Pittsburgh, USA, ran an agent-based simulation, and suggested that dense urban areas of the state should be vaccinated first. The model also helped public health officials to optimally distribute the vaccine doses among hundreds of vaccination centres across the state[13]. As part of the COVID-19 response, a number of other agent based modeling studies have been very influential in guiding public health policies, e.g.,[9, 14].

Agent-based models can also provide insights that look counterintuitive at first. For many outbreaks, the best way to protect older people from infections is to vaccinate the younger people first, e.g.,[15]. Researchers at the Biocomplexity Institute and Initiative, University of Virginia, USA, found that vaccination based on the number of contacts a person has is much more effective than other strategies being discussed, e.g., based on demographics[4]; the benefits hold even when the estimates are noisy.

This is not the first time that a complex system approach has helped authorities in managing an epidemic. In October 2014, when Ebola was raging across West Africa, the US government decided to dispatch a consignment of mobile Ebola treatment units to Liberia, a small country along the western coast of Africa. Just days before the departure, the officials wanted to know the ideal places for placing those clinics. Researchers at Virginia Tech, Blacksburg, USA, ran agent-based simulations to generate recommendations for the locations of mobile clinics. Their model considered, among other things, the quality of roads leading to the clinic— a factor that can't be included in a conventional epidemic model. Agent-based models also provided valuable inputs to in devising the strategy for field-trial of Ebola vaccines[23].

In late 2015, just when Ebola was beginning to abate in Africa, another virus started spreading rapidly in Brazil and neighboring countries in South America. Called Zika, this virus transmitted mostly via mosquitoes, but also through unprotected sex, and blood transfusion. While there have been no new outbreaks after 2016, Zika remains a matter concern as no vaccine or treatment is currently available.

Researchers at New York University and John Hopkins University, USA, are building an agent-based model to simulate an outbreak of the Zika virus in New York city. The model includes a set of 8.5 million agents representing New York city's entire population, and another set of agents representing the City's mosquito population. It simulates different factors affecting mosquito population including the availability of breeding grounds like old tires and empty cans that can hold standing water, and also elements of human behaviour influencing the spread of the disease[23].

2.2 Framing Policies

Well before the application of complex systems concepts to epidemic modeling, researchers were looking at some problems in public policy through the lens of complex systems. In fact, one of the early successes was in the area of road traffic management when researchers at the Los Alamos National Laboratory, USA, developed Transportation Analysis and Simulation System (TRANSIMS). The tool allowed traffic planners to include a mix of vehicles like cars, trucks, and buses and simulate their movement individually. Conventional modeling techniques, on the other hand, saw traffic as a *collection* of vehicles, and lacked the granularity required by city authorities. The bottom up approach used by TRANSIMS, novel at that time, fared better in predicting traffic jams and pollution levels than the conventional models that relied on equations of fluid motion. Today, traffic planners use TRANSIMS-like software tools to create digital analogues of entire cities, complete with intersections, roundabouts, pedestrian crossings, and thousands of vehicles to understand traffic behaviour in particular cities[19, 24].

In big cities, airports also experience congestion. In Europe and North America, about a quarter of flights are late either because they could not take off or land on time. During rush hours, flights often wait for minutes for their turn to take off, and towards the end of the journey, go in circles up above the airport while waiting for permission to land. With more than fifty flights either taking off or landing every hour in busy airports[12], air traffic controllers use sophisticated software for managing take offs and landings. This software uses agent-based models to accurately determine landing times and recommends a sequence of aircraft to land so as to minimise the total delay[21].

A systems approach to framing policies is gaining traction in economics too. In that community, there is a growing realisation that big events like financial crises are a consequence of interactions between the constituent elements— broadly the people, financial institutions like banks, and the regulatory environment— of the economy. Economists are now beginning to view economy as a complex system, and are using tools that are commonly used in complex system analysis. An agent-based model developed by the researchers at the Bank of England simulates the interactions between numerous actors and is indeed better at mimicking market fluctuations in the real world. Not surprisingly, the central banks around are embracing methods that take a bottom up approach to understand the economy[23].

However, agent-based modeling is not new to economics. In fact, one of the early successes of agent-based modeling was Sugarscape— a tool that simulated social interactions on a desktop computer in the 1990s. In this tool, agents moved in search of "sugar"— the analogue of resource in the real world— which was unevenly distributed. With this simple model, the researchers could simulate complex collective behaviours like migration[7, 24].

Researchers at the World Bank are using agent-based models to understand climate change. However, climate change affects the poor across the globe. With agents representing more than million households from about hundred countries, the model simulates how climate change would affect the poor. While the results showed that the poor are at greater risk than the rich, they also showed remarkable variation. For example, if a country's poor are farmers living in rural areas, they would actually benefit from the expected rise in global food prices. However, the poor living in cities would be hit hard by rising prices. Such studies have helped policy makers estimate the human cost of climate change[24].

2.3 Modeling Emergencies

While agent-based models have blossomed into reliable tools for predicting collective behaviour, experts in the field have realised the importance of continuously calibrating the models with real world data. Modelers also try to incorporate findings from studies in human psychology to make agents' behaviour as close as possible to that of humans. This is a tricky endeavour because under normal circumstances, human behaviour is very complex. However, it becomes quite predictable in emergencies when primal tendencies take over.

Psychologists have found that, in a crisis situation, instead of fleeing to safety, people tend to look for their friends and family first. After incorporating this behaviour in their agents, researchers at the Biocomplexity Institute at Virginia Tech, USA, found something very interesting: right after an explosion in a busy place, people do not stay in safe zones, but rush back to ground-zero looking for their friends or family members. They might also cause traffic jams while rushing in a frantic attempt to pick up their children from schools[24].

These results are part of a bigger study aimed at understanding the emerging situation in the event of a nuclear attack near the White House in

Washington, DC. Called National Planning Scenario 1, this model includes more than 700,000 agents mimicking the actual population in terms of attributes such as age, sex, and occupation. The model also includes elements of physical infrastructure like roads, hospitals, power lines, and mobile phone base stations. The paper by Parikh, Marathe and Swarup [16] appearing in this special issue shows how machine learning techniques can be applied to the data generated from the simulation of a nuclear attack to produce a ranked list of behavior recommendations to agents (e.g., seeking medical help before trying to locate family members).

3 Future Directions

One of the major drawbacks of agent-based modeling is that it is a computationally expensive process. Simulations with a reasonable number of agents can take many days to complete on large computers with hundreds of processors. However, in crisis situations, the decision makers want information quickly. To address this, the leaders in the field envision what is called the Petabyte Playbook— a library of digital twins of large cities with precomputed models of a multitude of hazards. Such models, running on the cloud, and accessible from laptops via a simple interface, would give decision makers all the information they need with the click of a few buttons.

The modeling community is already making strides in this direction. Computer scientists at the Virginia Tech have built a prototype of a web-based tool that enables public health officials to simulate pandemic situations on their own. The tool can easily be extended to simulate other crisis situations like cyclones and cascading disruptions in electrical power networks[24]. Researchers are also applying machine learning algorithms to data collected from real complex systems[20]. A team of researchers from China took a large volume of traffic data to predict times of traffic congestion using algorithms based on artificial neural networks (ANN) [26]. In another study, researchers made a group of student volunteers to drive a car in a simulated environment, and looked at their brain signals for an hour. By analysing their brain wave data using ANN algorithms they detected the onset of mental fatigue in the drivers with greater accuracy[11]. Such studies can potentially help in the development of reliable drivers fatigue detection systems, and help prevent a number of accidents. As mentioned earlier, the article by Parikh et al. [16] appearing in this special issue shows how machine learning techniques can be used to generate behavior recommendations for agents in the event of a nuclear disaster. These and other similar studies indicate that machine learning techniques will significantly enhance the capabilities of agent-based models.

With advanced systems like Petabyte Playbook and new machine learning techniques, researchers hope to build tools that help not just bureaucrats, but individuals too. Who knows, one day you might be able to access them from your phone!

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Accepted: 19 September 2021
Published online: 7 October 2021

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