Capturing complexity: Challenges in modelling COVID-19 in India

PRIYANKA NANDY1, SOHAM DIBYACHINTAN1, SAI VINJANAMPATHY2,* and MITHUN K. MITRA2,*

1 Department of Chemical Engineering, IIT Bombay, Mumbai 400 076, India
2 Department of Physics, IIT Bombay, Mumbai 400 076, India
*Corresponding authors. E-mail: sai@phy.iitb.ac.in; mithun@phy.iitb.ac.in

Abstract. In this article, we look at some of the challenges in modelling the spread of COVID-19 in a diverse country like India. In particular, we highlight the importance of incorporating the effects of mobility and of building granular models that take into consideration the social conditions in which the disease spreads.

Keywords. COVID-19; India; mobility; diversity.

PACS Nos 87.23.Cc; 89.65.Cd; 87.23.Ge

As the world reels under the onslaught of COVID-19, quantitative modelling has dominated the discourse of intervention design. Epidemiological models can provide policymakers with an invaluable tool to predict the course of an epidemic, thus enabling them to design intervention strategies to mitigate its worst effects. At the simplest level are compartmental models of the susceptible–infected–recovered (SIR) category and its generalizations, which help model the spread of a disease at a population level [1]. However while modelling such a vast, densely populated and diverse nation as India, it is imperative to allow further contextual factors to inform the basic model. Naturally, this poses certain challenges, but if we are to hope for accuracy, then understanding and integrating such complexities is essential.

In an incredibly diverse country of 1.3 billion people, one of the common constants of life is movement. Every day, over a billion people participate in the daily cyclical patterns of localised commute – from home to work, home to school, home to the market and common spaces, and back. And then there are seasonal, annual, or permanent patterns of internal migration, in which hundreds of millions of Indians cross local, district, and state barriers in search of work, for education, or for family. With increasing urbanisation and the erosion of locally-sustainable lifestyles, the latter number is steadily growing. In the intercensal decade between 2001–2011, internal migration grew 45%, from 305 million people to 450 million people [2]. Fine-grained micro-studies on population movement have suggested that the actual number is far higher, but it resists enumeration by National Sample Survey and census methodologies by being periodic yet short-term [3].

But how does the quantification of human movement impact the outcome of epidemics?

The answer is both simple and direct. Movement implies mixing. Infected people – especially those that are asymptomatic – can travel without raising an alarm, and bring the infection to previously untouched areas. Since the initial spread of the epidemic is exponential, just a few such cases can seed a new cluster. Secondarily, population movements are linked intricately to ‘essential’ employment in core sectors (manufacturing, construction, and a wide array of services), and thus to the health of the national economy. An abrupt halt in them – as happens in a lockdown sans public assistance to the populace – severely impacts both the economy and the well-being of these communities [4]. Further, since epidemic-control is a public health issue under the sole aegis of government institutions, an impacted economy may also impact its resource allocations and outcomes. It is thus imperative to quantify the effects of human and vehicular mobility when designing interventions for epidemic control and relief.

Interestingly, there is no evidence that this was part of the literature informing containment policy, nor that we attempt to characterise such movements in normal times. Limited attempts have been made to model aviation networks among major cities [5]. However, the bulk of the populace still use roads and trains to move between localities, districts, and states, and quantitative data on the nature of their movement has been sorely missing. This is a crucial exclusion. Without an estimate of these numbers, it is near-impossible to project how
closing or re-opening the transport networks – which is to say, imposing or lifting lockdown – will affect the spread of the epidemic. In the absence of real-world data, some attempts have been made to incorporate the effects of mobility via district-level surrogate measures, such as worker-population density and trip length estimates. This analysis illustrates the critical impact that transportation networks have on the spread of an epidemic [6].

It is not, however, a substitute for real-world data. Had such data been available, then ‘smart’ containment choices could have been made instead of adhering to a uniform shutdown, thus allowing life to continue (though at a reduced pace) while also keeping the reproduction rate $R_0$ of the epidemic below 1. This mode of intervention may have had rather different outcomes both economically and from a public health perspective than what we are seeing now. It would certainly have been beneficial for the most vulnerable amongst us – those who needed to continue to travel or commute while others stay home.

Having addressed the importance of modelling mobility – even (or especially, for purposes of benchmarking) during normal times – let us now look at the matter of granularity.

In the absence of interventions, there are two chief factors that determine the rate of spreading: the inherent transmissivity of the vector (which is an assessment of how many people one infected person can typically spread the disease to); and social conditions in which it is spread. Without accounting for these complexities, models designed to understand and predict the spread of disease are far likelier to break down and produce erroneous results, negatively affecting resource-allocation and intervention design at a time when the room for error is critically small. This is especially relevant in a country like India, which is exceptionally diverse not merely in terms of culture, terrain and environment, but in population profiles and the availability of institutional resources. The recent explosion of urbanisation [7] and rural-to-urban migration [8] has had an unfortunate effect of subsuming these localised nuances in quantitative representations, by drowning the patterns of individual blocks or districts under the much vaster populations of urban and suburban areas. Policy modelled on urban-dominated state-level data, therefore, has had rather unfortunate results for regions that do not conform to that dominant pattern, and have thus marginalised already underserved areas.

As an example, over the month of May, Mumbai, the epicenter of the COVID-19 epidemic in India, showed an increase in doubling time from 7 to 12 days approximately, indicating a slowdown in the spread of the epidemic. This was reflected in the state-wide behaviour for Maharashtra, which showed an increase in doubling time from approximately 10 to 17 days over this period. Over the same period however, the rural and infrastructurally underserved Ratnagiri, which recently had an influx of return-migrants from Mumbai after the lockdown, saw a decrease in doubling time from 20 days to roughly 3 days.

Localised, quantitative analysis such as these — whether at the district level or at the circle level — can help improve targeting of containment measures and infrastructural empowerment to treat emerging cases. In the absence of such fine-grained data, certain indicators may be helpful in directing intervention design. In general, areas with very high population density and high poverty indicators are unlikely to sustain basic containment measures, such as social distancing, self-quarantining, online shopping, or availing telemedicine. These areas also frequently overlap with localities where indoor drinking water and sanitation facilities are low, necessitating close-range interaction and exposure to common surfaces multiple times a day.

In urban centres, particularly, lower-income areas also overlap with employment in high-risk essential service industries, which makes residents vulnerable to a relatively faster spread as compared to areas where residents can afford to work from home. It is largely because of these concomitant factors that we have seen a sharp shift in COVID-19 as a disease of the privileged (that is, those that can afford air and foreign travel), to a disease ravaging the lower-income strata of densely-populated urban regions.

India entered the first phase of its national lockdown on 24 March, 2020. With increased vigilance, tightly controlled disbursement of testing and care via state-appointed bodies, enforced continuance of work in high-risk service-sectors, and the internment of citizens in their own homes, the nation entered a Foucauldian ‘frozen’ state [9]. However, this freezing seems to have had little effect on the disease’s spread. Despite nearly three months of lockdown, confirmed cases and COVID-19 fatalities have continued to rise, forcing certain regions (like Chennai) to go into renewed lockdown less than two weeks into unlock 1. It is vital, therefore, to abandon monolithic measures and focus on complex models sensitive to local social variables, such that the policies they inform have greater chances of success in the messy, overlapping, unpredictably interactive space of the real world.

References


