ABSTRACT

Organizations are struggling to ensure business continuity without compromising on delivery excellence in the face of Covid19 pandemic related uncertainties. The uncertainty exists along multiple dimensions such as virus mutations, infectivity and severity of new mutants, efficacy of vaccines against new mutants, waning of vaccine induced immunity over time, and lockdown / opening-up policies effected by city authorities. Moreover, this uncertainty plays out in a non-uniform manner across nations, states, cities, and even within the cities thus leading to highly heterogeneous evolution of pandemic. While Work From Home (WFH) strategy has served well to meet ever-increasing business demands without compromising on individual health safety, there has been an undeniable reduction in social capital. With Covid19 pandemic showing definite waning trends, organizations are considering the possibility of safe transition from WFH to Work From Office (WFO) or a hybrid mode of operation. An effective strategy needs to score equally well on possibly interfering dimensions such as risk of infection, project delivery, and employee wellness. As large organizations will typically have a large number of offices spread across a geography, the problem of arriving at office-specific strategies becomes non-trivial. Moreover, the strategies need to adapt over time to changes that cannot be deduced upfront. This calls for an approach that is amenable to quick and easy adaptation. Our contribution in this regard is constructing a Digital Twin by leveraging various modelling techniques to realistically represent the above mentioned aspects of interest that can be subjected to what-if scenario analysis. We further demonstrate its efficacy using a case study from a large organization.

Keywords: Safe transition to work from office, Return to new normal, Enterprise Digital Twin, Modelling and Simulation for Covid19.

1 INTRODUCTION

The Covid19 pandemic has challenged society and organizations to make a trade-off between individual health safety and socio-economic progress. Organizations were forced to adopt WFH mode for all possible business-as-usual (BAU) activities. Since then, repeated waves with varying degrees of impact made return-
ing to normal a distant possibility. In early 2021, when organizations were looking for ways to open offices, a wave due to Delta variant caused a massive setback. Lately, another attempt to resume WFO had to be deferred due to the Omicron wave that started in December 2021. Throughout the pandemic, organizations have battled to ensure business continuity and delivery excellence in the face of uncertainty. The solution needs to consider various factors, such as evolving pandemic situation, scale of the operation, intricacies of office infrastructure, social capital.

Organizations are in a semi-perpetual uncertain situation about when, who and for how long will they be unavailable for work due to Covid19 infection (their own or their family member’s). Early information – say through reliable predictions – can help refine Business Continuity Plan (BCP) thus ensuring delivery excellence. Such predictions involve precise understanding of virus characteristics, vaccination status, job profiles and demographic variations of the employees, adherence to Covid Appropriate Behaviours (CAB) by employees and their family members, restrictions imposed by the local authorities and so on. Large size of the organization further exacerbates the complexity and computing burden.

In addition to the struggle towards delivery excellency and business continuity, a safe return to workplace is becoming a prominent need for organizations across the world (Galinsky 2022). Exploring effective and safe strategies to help transition from WFH to WFO, requires precise and critical evaluation about: when is the appropriate time to allow their employees to work from office? What would be the appropriate occupancy? What would be the change in infection trend when a certain percentage of employees start working from office? Are there any additional risks of infection for those who are coming to office? Can we reduce such risks by introducing appropriate interventions within offices? Such analyses require understanding of demographic factors of those who are returning to office, their vaccination status, comorbidity and Covid19 infection status, locality of office, office building layout, desk layout, various facilities within office building, allowed employee occupancy, interventions adopted within office building, details about office staff, etc. Moreover, all such details need to be correlated with the characteristics of the dominant variants, the infection situation of cities where offices are located, and interventions imposed by governments and city administrations for precise prediction. Large organizations have additional complexity about the size and wide heterogeneity.

Organizations primarily rely on city specific infection trends of their office locations to estimate infection risk for their employees and ripple effects thereof onto other risk parameters. This approach fails differentiate employee specific heterogeneity and socio-economic characteristics of employees from rest of the localities where employees are located. As result, the approach is neither accurate nor capable of analyzing the micro-level situations, such as the situation for a project, office or branch.

We adopted a simulation-based data-driven evidence-backed approach that has the idea of Digital Twin (Boschert and Rosen 2016) at its core. Our hi-fidelity purposive Digital Twin captures details pertaining to virus (the active mutant strains and their epidemiological characteristics such as infection transmissibility, extent of severity, and vaccine escape), individualistic characteristics of employees & their dependents (i.e., age, gender, comorbidity, vaccination status, typical movement patterns, adherence to CAB etc.), offices (size, layout, workspace per person, utility spaces etc.), locations (e.g., cities) of the employees and offices, and various pandemic control measures that are in effect and need to be explored. To capture these aspects of interest in a simulatable form, we adopt a hybrid modelling and simulation approach that meaningfully combines a) fine-grained actor/agent model to capture individualistic behaviours where precise information is available (i.e. information about employees, dependents, offices), and b) a coarse-grained stock-and-flow model where available information is partial (e.g. cities where employees are located). We leverage past macro-level data pertaining to pandemic evolution of different cities, states and countries to make our model faithful representation of the reality. Sito predict emerging situations for cities, branches and large projects towards refining BCP and exploring effective strategy for a safe return to office. In this paper, we present organizational digital twin and its simulation capabilities that help to understand possible
business disruptions due to Covid19 pandemic and explore strategies towards a safer return to office. This paper illustrates the efficacy of the proposed approach for a large organization.

Rest of the sections are organized as follows – Section 2 presents a brief overview of the state-of-the-practice and state-of-art prediction techniques for comprehending Covid19 pandemic and analyze situations. Section 3 discusses our approach. Section 4 highlights simulation results and findings of different strategy evaluation towards a safer return to office. We conclude this paper with our lesson learnt from this study and future potentials of using simulatable digital twin for wide range of socio-economic problems.

2 LITERATURE REVIEW

Modelling and simulation based approaches have been used to predict evolution of Covid19 for cities and countries. These approaches make use of coarse-grained model and fine-grained model with the former being the majority. They adopt one of the two techniques to predict the future – (a) statistical modelling supported by historical data (Agrawal et al. 2021, Mohan et al. 2022), including those based on AI (Fayyoumi et al. 2020); or (b) compartmental models (e.g., SEIR model) that capture epidemiological understanding or domain knowledge in the form of differential or similar evolution equations (He et al. 2020, Korolev 2021). While coarse-grained models are usually computationally efficient and explainable, they have several shortcomings which are particularly relevant in the context of predicting the progress of a pandemic. They either ignore the heterogeneity of the population or capture it notionally through select aggregated groups (Barat et al. 2021). Importantly, coarse-grained models fail to comprehend micro-causality and emergent behaviour within a cohort, e.g., super-spreader events from social gatherings. In addition to these generic limitations, the coarse-grained models are vulnerable to both internal and external threat to validities (Hayashi Jr et al. 2019). External validity becomes prominent during the early phase of a new variant as one needs to rely on data collected from different geographical region. For example, data from South Africa was used to understand the possible impact of Omicron variant in all other countries despite of wide variations in terms of vaccines and vaccine coverage, seroprevalence levels, administrative interventions and demographic heterogeneity. Internal validity is a concern for infection prediction as the observed cases in a given area are not an accurate representation of the reality as observations depend not only on actual infection but also on the ratio of asymptomatic cases and the scale of random testing. For example, analysis of infection spread of Omicron based on observed data might lead to inaccurate interpretation as asymptomatic cases are considerably high for Omicron (WHO 2022), testing uptake is low, and case reporting is a universal concern due to lower severity and wide use of home-testing facilities.

Fine-grained models, such as agent-based models, supporting emergent behaviour in a bottom-up manner are used to overcome these limitations (Kerr et al. 2021, Silva et al. 2020, Shamil et al. 2021). The key objective of these models is to capture the behaviour of micro-elements such as people, households and places (e.g., workplace, school, shops) to predict macroscopic emergent indicators such as the number of infected cases, cases that need medical infrastructure, deaths and so on. Such fine-grained models need to make a trade-off between richness and scale. The richness includes the ability to represent the heterogeneity of the people, households and places at a fine-grained level to take the model closer to the real context, i.e., city, state or country. Many of the agent-based models (e.g., (Silva et al. 2020)) consider high-level classifications of these entities as cohorts, where each cohort is internally modelled using aggregated equations, and represent the entire system as a connected network of a limited number of cohorts. These models address scalability by compromising granularity. Covasim (Kerr et al. 2021), on the other hand, uses an agent-based model to capture the individualistic behaviours of a wide range of micro-elements and their interactions. They linearly scale down the population (in the order of $10^2$) to make the simulation manageable. From a richness perspective, they capture demographic variations in the population, a wide range of places and interventions. However, the progression of infection in an exposed person and the combined effect of a specific variant and vaccine on the individual are encoded as predefined equations within person agents. This
limits the ability to understand the interplay of the effect of a vaccine and the characteristics of variant on an individual. Our previous work that proposes an agent-based digital twin of city for exploring the effect of non-pharmaceutical interventions (Barat, Parchure, Darak, Kulkarni, Paranjape, Gajrani, and Yadav 2021) follows similar approach as Covasim to represent people with demographic heterogeneity & professions, household architypes, place architypes, and interventions as agents. While these fine-grained models are capable of representing desired heterogeneity and individual behaviour, they merely scale to tens of thousands of population size. Therefore, we argue that they are at best suited for prediction situations of a city. We argue that comprehending infection situation and exploring strategies towards a safer return to office for a large organization is a harder modelling and simulation problem as compared to analysis/prediction of a city or country. The key reasons are: a) employees and their family members are socially connected with the rest of the city, b) the number of such cities where an organization has presence is not only large but unique in terms of infection spread and other pandemic characteristics, and c) relevant characteristics of employees of the organization under consideration are clustered together compared to the average citizens (considering job profile, age range, economic status and living standards). Essentially, need for analyzing a large number unique localities/cities, individualistic characteristics of employees, and non-deterministic social interactions of employees with rest of the localities make the existing approaches inappropriate and ineffective in this context.

3 SIMULATABLE ORGANIZATIONAL DIGITAL TWIN

We propose a novel configurable and extensible Organization Digital Twin (ODT) to explore and understand the strategies to mitigate risks that Covid19 pandemic may potentially pose to the employees, their dependents, and projects of an organization. ODT acts as a faithful virtual environment to enable in-silico simulation-led experimentation of different strategies for defining/refining new business normal and evaluating the likely impact on business as well as health & safety of the workforce. Conceptually, ODT captures four aspects of interest – virus characteristics, workforce details, localities of interest where employees stay and offices are located, and office & office interventions as shown in Figure 1.
We adopt a multi-model simulation technique that combines data-centric statistical approach, coarse-grained compartmental model, fine-grained agent-based model and probability model to faithfully capture four aspects of interest and establish a meaningful interoperability between them. We use coarse-grained model augmented with statistical model where domain understanding is low and information is partial (e.g., information about cities and states where employees are located). We use fine-grained model where understanding is precise and complete information is available. We use probability model to represent non-determinism in agent behaviour to represent known unknown scenarios where the information is partial and/or there exists a degree of ambiguity, e.g., probability of an employee to meet with other employees during their business-as-usual activities in an office. We capture all four models in an interoperable simulatable form to help understand future trends through exploration of scenarios. Key model components of ODT that capture aspects of interest and their interoperability are described below:

**Virus characteristics:** We conceptualize infection spread dynamics of covid19 pandemic by comprehending established facts and peer-reviewed literature on SARS–CoV–2 family including all major variants (WHO 2022). For modelling and simulation purpose, we focus on two aspects: a) infection stages and their transitions, and b) virus transmission from one individual to other. Existing literature (He et al. 2020, Korolev 2021) considers four prominent infection stages of a covid19, namely Susceptible, Exposed, Infectious and Removed (SEIR), as shown in Figure 2. Entire human population (irrespective of age, gender and other demographic characteristics) was Susceptible at the beginning of the pandemic. A susceptible person (target) can be Exposed to a variant through close contact with an infectious person (source) for a specific duration. An exposed citizen becomes infectious after a time delay – typically after 2–3 days. In this stage, an individual can remain Asymptomatic or may develop Mild symptoms. Subsequently, some mild symptomatic individuals may become Critical depending on age, comorbidities and vaccination status of the individual. An infectious person (i.e., Asymptomatic, Mild or Critical) can be detected through testing – a symptomatic person is typically tested (and isolated) within couple of days from the onset of the symptoms whereas a part of asymptomatic people get detected through contact tracing. All asymptomatic and mildly symptomatic people move to Recovered stage after a time delay – it is a virus characteristic. Critical people may move to either Recovered stage or Deceased stage depending on age, gender, comorbidity, infecting variant and vaccination status. As shown in Figure 2, Recovered people may become Susceptible again after a delay due to waning of vaccine-induced immunity or reinfection possibility.

Transmission of virus from an infectious person to susceptible person can happen when the susceptible person is within the proximity of an infectious person for a specific time span. In our problem statement, a person (i.e., employee, dependent or office staff) can get infection from household, locality or office. The household transmission is primarily a factor of the number of infected family members and household secondary attack rate (Tibebu et al. 2021) of infecting variant(s). Infection from locality depends on the movement of the individual, tendency towards complying with covid related interventions and compliance with CAB, and normal infection trend of the locality (discussed in locality model). Office induced infection
is typically the factor of desk arrangement, possible contacts with colleagues and typical attack rate of the variant in a closed space (discussed in office model).

**Workforce model:** Workforce model captures relevant characteristics and behaviours of employees, their dependents, and support staff of an organization. As shown in Figure 3, it captures the demographic details (i.e., age and gender), health information (i.e., pre-existing comorbidity and vaccination status), and Covid-19 infection status where we consider five infection states (i.e., *Susceptible*, *Exposed*, *Asymptomatic*, *Mild*, *Critical*, *Recovered* and *Deceased*) as recommended by majority of the Covid19 pandemic models (He et al. 2020). Workforce model also captures the family structure of the employees that includes dependents, household location (i.e., the city where the employees are living), office of the employees & support staffs (i.e., city where office is located), and project details of the employees.

In our workforce model, an employee continues WFH in their respective home city unless they are instructed to return to office. During WFH, an employee may get exposed to Covid19 virus from household infection and/or as they interact with rest of the population (termed as *locality induced infection*). We model household (shown in Figure 3) to understand the probability of an employee (or a dependent) getting exposed through household infection. We borrowed the concept of household transmission discussed in lancet research (Allen et al. 2022) and realized in our earlier work (Barat, Parchure, Darak, Kulkarni, Paranjape, Gajrani, and Yadav 2021) to compute the possibility of a household infection. The locality induced infection is considered in location model.

After getting exposed to a specific variant of Covid19 virus, each individual goes through different stages of infection starting from *Exposed* to *Recovered* or *Deceased* state (as shown in Figure 2). An infected employee stay away from work (i.e., takes leave) after detection (due to symptoms, contract tracing, household testing) till they move to Recovered state – and the same with dependents. We consider an employee is impacted (and may take leave) if their dependent is infected (we term such employees as *impacted employees*).

Organization may send communication to employees (a strategic intervention) about resuming WFO for number of days in a month/week (e.g., twice in a week) starting from a specific date. Employees who have
moved out of their work location city need to return on receiving this communication. In office they will use the desks and other facilities made available by office administration (a strategic intervention consideration to allow specific facility). An employee may receive infection from asymptomatic (and/or undetected) infectious office colleagues. We term this type of infection as office induced infection. We also consider support staff coming to office and mixing with employees when office is open. Dynamics of office induced infection for employees and office staff is considered in office model.

Here, we adopt a fine-grained simulatable agent/actor model to precisely represent individualistic characteristics and behaviours of the employees, dependents and office staffs as a set of interacting agents. We combine stochastic model along with agent model to consider realistic assumptions where precise data is not available and/or to replicate uncertain scenarios. For example, pre-existing comorbidity of employees, dependents and support staffs might not be known to organization – there we use city/country specific comorbidity distribution. Similarly, vaccination status for dependents might not be updated in employer record – there we use vaccine adoption rate of the located city. Uncertain scenarios where we use stochastic behaviours includes: probability of an employee going to office in a given day, movements within the office, and employees using office facility at a given moment and so on. Key rationales for considering fine-grained representation of workforce are: a) analysis is cognizant of the unique characteristics and heterogeneity of the workforce, b) it helps to understand the situations at multiple levels, e.g., for organization, branches, and projects and c) organizations have workforce related data to construct a fine-grained workforce model.

**Locality of interest:** This model is for understanding the possibility of locality induced infections. A person getting exposed to Covid19 virus from their respective locality on a given day largely depends on two factors: a) movement of the individual and other characteristics such as adherence to CAB and compliance of local protocols, and b) current rate at which the locality is exposed to Covid19 virus, i.e., Susceptible to Exposed (S2E) rate. This rate may vary from locality to locality and computing it for a locality requires precise information about - a) number of people in the locality that are susceptible (serosurvey reports provides only an indicative value), b) number of actively infected individuals (existing Covid19 dashboards indicates detected active cases, which is a subset of actual active cases), and c) possible contact rate of individual. Comprehending future trend of S2E rate of a locality requires consideration of additional influencing factors that include - dominant variants of concern and their characteristics, non-pharmaceutical interventions, CAB. Here, knowing precise distribution of dominant variants in a locality is not possible and possible noncompliance of interventions by the residents can only be vaguely estimated from anecdotal evidence.

We model locality of interest using a configurable coarse-grained stock-and-flow model (SnF4L) to understand the overall infection spread dynamics in a locality and derive the trend on S2E rates. Conceptually,
## I. STOCKS AND ASSOCIATED DIFFERENTIAL EQUATIONS

<table>
<thead>
<tr>
<th>Stock</th>
<th>Initial Value</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. ( P_s ) (Susceptible)</td>
<td>( P_{sus} = (P_0 - P_3) \times f_{sus} )</td>
<td>( \frac{dP_s}{dt} = \phi_1 - \phi_2 )</td>
</tr>
<tr>
<td>2. ( P_e ) (Exposed)</td>
<td>( P_{exp} ) (Initial Detected Active Cases) ( \times \tau )</td>
<td>( \frac{dP_e}{dt} = \phi_1 - \phi_2 )</td>
</tr>
<tr>
<td>3. ( P_i ) (Infected)</td>
<td>( P_{inf} = \tau )</td>
<td>( \frac{dP_i}{dt} = \phi_2 - \phi_1 )</td>
</tr>
<tr>
<td>4. ( P_r ) (Recovered)</td>
<td>( P_{rec} ) (Initial Detected Recoveries) ( \times \tau )</td>
<td>( \frac{dP_r}{dt} = \phi_1 - \phi_2 )</td>
</tr>
<tr>
<td>5. ( P_c ) (Critical)</td>
<td>( P_{crit} ) (Initial Reported Critical Cases)</td>
<td>( \frac{dP_c}{dt} = \phi_3 - \phi_4 )</td>
</tr>
<tr>
<td>6. ( P_{de} ) (Deceased)</td>
<td>( P_{death} ) (Initial Reported Count)</td>
<td>( \frac{dP_{de}}{dt} = \phi_4 )</td>
</tr>
<tr>
<td>7. ( P_{on} ) (Onset)</td>
<td>( P_{onset} ) (On Day 0 of Simulation)</td>
<td>( \frac{dP_{on}}{dt} = \phi )</td>
</tr>
</tbody>
</table>

## II. FLOWS

<table>
<thead>
<tr>
<th>Flow</th>
<th>Description</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>11. ( \phi_1 ) (Susceptible to Exposed)</td>
<td>( P_s \times \omega = P_e )</td>
<td>( \phi_1 = \phi_1 )</td>
</tr>
<tr>
<td>12. ( \phi_2 ) (Exposed to Infected)</td>
<td>( P_s \times \omega = P_i )</td>
<td>( \phi_2 = \phi_2 )</td>
</tr>
<tr>
<td>13. ( \phi_3 ) (Infected to Critical)</td>
<td>( P_i \times \tau = P_c )</td>
<td>( \phi_3 = \phi_3 )</td>
</tr>
<tr>
<td>14. ( \phi_4 ) (Critical to Recovered)</td>
<td>( P_c \times \tau = P_r )</td>
<td>( \phi_4 = \phi_4 )</td>
</tr>
<tr>
<td>15. ( \phi_5 ) (Critical to Deceased)</td>
<td>( P_c \times \tau = P_{de} )</td>
<td>( \phi_5 = \phi_5 )</td>
</tr>
</tbody>
</table>

## III. AUXILIARY VARIABLES

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( v ) (Vaccinated)</td>
<td>( \phi_3 ) (Recovered to Eligible) = ( R_{death} = \phi_6 )</td>
</tr>
<tr>
<td>( \phi_6 ) (Vaccinated to Waiting)</td>
<td>( P_v \times \delta = P_w )</td>
</tr>
<tr>
<td>( \phi_7 ) (Vaccinated to Waiting)</td>
<td>( P_v \times \delta = P_w )</td>
</tr>
</tbody>
</table>

## IV. DELAYS

<table>
<thead>
<tr>
<th>Delay</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \delta_1 ) (Exposed to Infected)</td>
<td>( 43. \delta \times \tau = P_{on} )</td>
</tr>
<tr>
<td>( \delta_2 ) (Critical to Recovered)</td>
<td>( 44. \delta \times \tau = P_{rec} )</td>
</tr>
<tr>
<td>( \delta_3 ) (Critical to Deceased)</td>
<td>( 45. \delta \times \tau = P_{death} )</td>
</tr>
</tbody>
</table>

---

SnF4L extends established compartmental model, precisely SEIR model (He et al. 2020), where we consider six sequential cohorts representing infection phases, namely \( P_s \) (Susceptible), \( P_e \) (Exposed), \( P_i \) (Infected), \( P_c \) (Critical), \( P_r \) (Recovered) & \( P_{de} \) (Deceased), and an additional feedback loop from \( P_r \) to \( P_s \) to represent loss of immunity and possibility of reinfection. Cohorts are represented using Stocks, and movements of aggregated number of people from one cohort to another are represented using Flows (indicated with \( \phi \)) as shown in Figure 4. Flows are mostly governed by a set of factors, which are represented as auxiliary variables, and time delays (indicated using \( \delta \)). Stocks, flows, auxiliary variables and time delays are summarized in Table 1. As shown in Figure 4 and described in Table 1, flows \( \phi_1 \) (\( P_t \) to \( P_c \)), \( \phi_4 \) (\( P_s \) to \( P_r \)), \( \phi_5 \) (\( P_c \) to \( P_{de} \)), \( \phi_6 \) (\( P_c \) to \( P_{death} \)) depend on vaccine adoption and vaccine efficacy. We comprehend vaccine (and booster dose) adoption and its impact on infection dynamics using a simplistic interconnected SnF4L model. It contains three stocks: \( P_{EL} \) (for eligible population), \( P_v \) (vaccinated population) and \( P_W \) (population who are waiting for next dose) and infers the proportion of population in a locality that – a) is vaccinated recently and possibly has high vaccine induced immunity \( (f_i) \), and b) was vaccinated long back and possibly has less vaccine induced immunity \( (f_w) \). Term \( p_c \) is the probability of coming in contact with infected people (the ratio of infected people contributing to infection spread, to the total living population) and parameter \( \alpha \) is a multiplier we use to tune this probability. To derive \( S2E \) rate of a locality (i.e., city, state or country), we use a four-step process:

1. **SnF4L model** is first contextualized using locality specific net initial population \( (P_0) \), reported critical cases \( (P_{crit}) \), reported deceased count \( (P_{death}) \), detected active cases \( (P_{active}) \), detected recoveries \( (P_{rec}) \),
and tentative susceptible percentage \( f_{\text{Sus}} \) from census records, government dashboards, authentic media bulletins, and published sero-surveys.

2. Estimate parameter \( \alpha \) by simulating \( SnF4L \) with different \( \alpha \) values and comparing simulated trends of detected infected cases \( (P_I) \), detected recovered cases \( (P_R) \), critical cases \( (P_C) \) and number of deceased \( (P_D) \) with the actual trends.

3. Adjust \( \alpha \) for prospective future scenarios, such as best case scenario, scenario for complete movement relaxation, emergence of new variant with higher infectivity than known variants.

4. Finally, the \( S2E \) rates are computed for all possible scenarios using \( s2e \) equation defined in equation 26 of Table 1.

We repeat this process for all localities where employees and offices are located. However, this \( S2E \) rate provides an aggregated estimation about locality specific trend at which common population is getting exposed to Covid19 virus. We then feed the results obtained in this step to a transformation function \( TF_{\text{Org}} \) to introduce organization specific movement requirement and socio-economic differences from rest of the locality. We observed two categories of employees: a) employees who have the provision to avoid contact if required (e.g., employees from IT organizations) – essentially job profiles that do not demand high movement, can use online shopping for most of their needs, can afford to stay in modular household, b) employees who do not have such provision, i.e., not economically strong enough to afford modular residences, their job profile needs extensive contacts with people, and so on. Former category often isolate themselves from rest of the city when there is a surge in infection. Relationship is defined as follows:

\[
TF_{\text{Org}} = S2ERate \times (1 - \text{decayRate})^x, \quad \text{where decay rate is associated with the infectivity/panic factor of the dominant variants in the locality and } x \text{ is typically 5–7 days (a weekly update).}
\]

We use historical infection data of employees to fine tune this transformation function.

**Office and office interventions:** The key objective of office model is to identify efficacy of candidate WFO strategies to minimize office induced infection. Here, the key aspects of an office are office desks and their proximity, typical BAU movements of employees and support staff, and possible utilization of available facilities, such as canteen, meeting rooms, executive cabin, and gymnasium as shown in Figure 3. For WFO scenario, a percentage of employees and office staff visit office (an office intervention) during the business hours of the organization. In office, employees mostly spend time at their desk and use facilities based on certain pattern of movement with some randomness. Essentially, the transmission of infection from office colleagues depends on virus characteristics (as discussed in virus characteristics model), desks layout and employee congregation during business and casual activities within office - and similarly for support staff.

We use a fine-grained agent-based model to represent relevant office places as agents and allow employee and support staff agents to visit offices to simulate the candidate WFO strategies. Our agent-based formulation helps to define different fine-grained intervention, such as: different occupancies from a specific date (e.g., 25% employees from April 1, 2022) for all or specific office, opening/closing facilities in a specific office (e.g., Gymnasium should be closed till June 31, 2022), restricting occupancies within different facilities (e.g., 50% occupancy for Canteens and 30% occupancy for meeting rooms).

**Simulation led experimentation:** In an ODT simulation, workforce model decides the localities of interest by navigating cities where employees and offices are located as shown in Figure 3. Locality model is then contextualized and \( S2E \) rates are computed for all localities of interest. These locality specific \( S2E \) rates are then normalized for organization using \( TF_{\text{Org}} \). Transformed \( S2E \) rate is used in the workforce model instantiated with anonymized employee data to understand the emergent infection spread. Scenarios pertaining to WFO and hybrid setup are experimented by combining office & intervention model.
Simulation of a contextualized ODT helps to understand trends about KPIs of interest that include number of employees who will be unavailable due to Covid19 infection, employees who might be impacted (and thus may take leave) for infection of their dependents and number of office induced infections in case of WFO as shown in Figure 1. Appropriate navigation of employees relationship with the project, office, city and branch (as shown in Figure 3) also helps to understand unit levels infection trends.

ODT simulation led experimentation with various possibilities of opening offices (i.e., interventions to represent opening office with varying capacities, with limited facilities vs all facilities from specific date) and observation of simulated KPIs help to understand their consequences/impact over time. Moreover, experimentation can be conducted for different hypothetical scenarios such as situation if all Covid19 restrictions are lifted or population is not complying with any Covid19 norms (i.e., a worst case scenario), or extreme scenario when a new variant emerge in a locality, and so on.

To improve confidence level of our trend analysis/prediction, all simulation scenarios are repeated multiple times (N) and KPIs are estimated based on an average of all simulation runs. Multiple runs for same scenario helps to converge KPI values that emerge from a combination of deterministic and stochastic behaviours of ODT. We decide N based on the below method:

Run simulation 5 times and compute average of all KPIs ($KPI_{Avg}$)
while All KPIs have not converged do
    Run simulation and compute new average ($KPI_{new}$) from all simulation runs.
    for all KPIs do
        if deviation of ($KPI_{Avg}$) and $KPI_{new}$ is under tolerable range then
            Converged := True
        else
            $KPI_{Avg} := KPI_{new}$
        end if
    end for
end while

Figure 5: Prediction and validation.
4 CASE STUDY

We contextualized ODT for TCS India and predicted infection trends since March 2021 while it continued its business-as-usual operation mostly as WFH mode. ODT is also exploited to explore a wide range of strategies towards a safer WFH to WFO transitions.

**Contextualization:** To carry out our experimentation, ODT is instantiated to represent virus characteristics of known prominent variants (i.e., Alpha, Delta and Omicron) (WHO 2022). Hypothetical variants are considered by varying infectivity, severity, fatality rate and reinfection possibilities to explore worst case and extreme situations. Workforce model is contextualized with anonymized data of its 425K+ employees who are living with 600K dependent across 1800+ cities in India during WFH mode of operation. Age range (as opposed to specific age), gender, vaccination status, infection status are also considered. Employee project, city, offices are mapped to anonymized employee agents for all large projects, cities and offices. These information are generalized and mapped to a set of archetypes of projects, cities and offices for small projects, cities and offices – this helps to maintain anonymity without compromising the analysis precision. Missing comorbidity information is adjusted to country/city level distributions. We reduced localities of interest from 1800+ cities to 36 localities that include 25 cities, 10 states and a country for predicting S2E rates. This simplification is done in accordance with the organization data – around 60% employees are staying in 24 cities and these cities include location of all major branches and offices. Reflecting on job profiles and other socio-economical characteristics, we applied transformation function $T_F^{Org}$ to normalize $S2E$ rates for employees and their family members. Location specific $S2E$ rate is directly used to compute infection possibility of support staffs. Office model is instantiated with its 140+ offices across 30+ branches and close to 100 large projects. Number of desks are matched with Admin data and facilities are instantiated using prominent architypes of facilities derived from Admin data of the organization (e.g., $X_1$ number of large canteens of capacity more than 500, $X_2$ number of small canteens with capacity 50, and $X_3$ medium meeting rooms with capacity 20 associates, and so on).

**Validation:** We started our experiment by contextualizing a small branch with 5K employees who were operating from home. Simulation is conducted for January to June 2021 and compared simulated KPIs with reported cases. Next, we considered a larger branch with 50K+ employees with multiple offices to establish the faithfulness of ODT and finally the entire geography of TCS India with 425K+ employees is considered for experimentation. Our predictions and their refinement considering emerging information about virus characteristics are presented to stakeholder bi-monthly basis starting from May 2021. Our prediction in the month of September 2021 is shown in Figure 5. As shown in the figure, our prediction about employee infection trend closely matches with weekly reported case from March 2021 to August 2021 (i.e., for the wave due to Delta variant). The distribution of genders and age groups are also comparable with the reported cases (other trends such as projection about project, city and branch level weekly infection counts are closely predicted but not included in this paper due to confidentiality). Our predictions also include future trends for three scenarios: a) optimistic scenario (i.e., if Covid19 specific restrictions continues and no emergence of new variant), pessimistic scenario (i.e., significant movement relaxation and noncompliance of CAB but no new variant), and extreme scenario (pessimistic scenario + a new variant with high infectivity).
Figure 7 shows a comparative analysis of three illustrative scenarios: a) 25% employees returning to office (occupancy) from March 2022, b) 25% occupancy from April 2022, and c) 50% occupancy from April. In these scenarios, we considered canteens are open with 50% capacity, medium to large meeting rooms are open with 50% capacity, labs are open and rest of the facilities are closed. Our experimentations indicate opening office with 25% occupancy from April is safer than opening office with same occupancy from March. Allowing 50% occupancy from April may cause surge in infection count – mainly to those offices where number of desks are more than 5K and number of meeting rooms and canteen capacity are less. Moreover, instances of office induced infection will be significantly high for 50% occupancy.

**Business Impacts for TCS India:** Our ODT led experimentation findings are used by stakeholders of TCS India: risk & compliance unit used predictions for refining BCP during the Delta and Omicron waves of Covid19. A potential surge of infection for TCS India during December 2021 was predicted 3 months in advance. Possible consequences for potential strategies towards a safer return to a new normal are experimented in advanced and shared with decision-maker to make a trade-off between % of WFO vs employee health safety, and refine branch & project level BCP. We argue that our experimentations helped TCS India to improve: i) operational efficiency and resilience as many alternatives are evaluated and consequences are shared in advance, ii) operational cost for two reasons: a) cost effective test environment, and b) validated course of action has less chance for failure and business loss while dealing with Covid19 related uncertainties, iii) agility in change management. It also helped to improve employee safety and customer satisfaction (with advance communications about potential delay in deliverables).

### 5 CONCLUDING REMARKS

Covid19 pandemic put us into a situation demanding business continuity with delivery excellence without compromising employee health and wellness. Given the scale and multi-city nature of our operation, one-size-fits-all kind of a solution was not an option. Instead, a specific set of strategies needs to be devised for each office building. Moreover, the strategies need to adapt over time to changes that cannot be deduced upfront. This called for a rigorous approach that is amenable to quick and easy adaptation. We presented one such approach that: (i) Leverages pure data-centric statistical model, coarse-grained system dynamic model, and fine-grained agent-based model, (ii) Helps human experts arrive at pragmatic strategies to effect WFH
to WFO transition keeping the key stakeholders satisfied, and (iii) Easily adapt the strategies over time. We validated the approach with a large organization and the results are encouraging. Having proven the value of digital twin centric simulation-based approach to decision making in one socio-techno-economic context, we are now planning to address the decision-making problem in other contexts such as sustainability, critical disease control and health safety.

REFERENCES


AUTHOR BIOGRAPHIES

SOUVIK BARAT is Principal Scientist at Tata Consultancy Services Research. He holds a PhD Computer Science and his research interests include digital twin technology, modelling and simulation of complex systems, agent and actor technology, enterprise modeling, and business process modelling. His email address is souvik.barat@tcs.com.

DUSHYANTHI MULPURU is a Researcher at Tata Consultancy Services Research. Her research interests include modelling and simulation of complex systems, digital twins and artificial intelligence. Her e-mail address is dushyantithi.mulpuru@tcs.com.

ABHISHEK YADAV is Researcher(System Engineer) at Tata Consultancy Services Research. He holds a master degree in software engineering. His research interests include digital twin technology, modelling and simulation of complex systems, agent and actor technology and machine learning. His email address is y.abhishek1@tcs.com.

ANWESHA BASU is a Researcher at Tata Consultancy Services Research. Her research at TCS includes digital twins and modelling and simulation of complex systems. Her email address is anwesha.basu1@tcs.com.

VINAY KULKARNI is a Distinguished Chief Scientist at Tata Consultancy Services Research. An alumnus of Indian Institute of Technology Madras, Vinay is a Fellow of Indian National Academy of Engineering. He is a Visiting Professor at Middlesex University London. His research interests include Digital Twins, Adaptive Enterprises, Model Driven Engineering, Artificial Intelligence, and Software Engineering. His e-mail address is vinay.vkulkarni@tcs.com.

SAVITHA SAMUDRALA is a Senior Consultant at Tata Consultancy Services and heads the Delivery on Procurement Products. She holds a Master Degree from Indian Institute of Science. Possess strong Customer Relationship Management, Solution Design & Implementation for Fortune 500 & Global MNCs in Insurance, Financial, Banking & Telecommunication domains. Her email address is savitha.samudrala@tcs.com.

AVINASH BHIDE is an Enterprise Risk Officer at Tata Consultancy Services (TCS) and Member of RIMS India Advisory Board. He has been actively involved in TCS in the APEX COVID-19 committee for business continuity and emergency response support for last 2 years. He is very active in external networking through participation in various Risk forums thus bringing in the Outside-in perspective. His email address is avinash.bhide@tcs.com.

PRABHA THOMAS is Vice President and Chief Risk & Compliance Officer at TCS. She heads Enterprise Risk Management and Regulatory Compliance. She has rich experience covering program management, large account management, enterprise quality management, business process management, governance, risk and regulatory compliance. She chairs the COVID-19 Apex Committee in TCS. Her email address is p.thomas@tcs.com.

KEERTHI KRISHNA working as Product Manager at Tata Consultancy Services, Extensive knowledge in design and development of parts from concept to production, Agile Practitioner and interested in Digital twins, Artificial Intelligence and Machine Learning. His email address is keerthi.k@tcs.com.

ARUN YADAV is Global Head of TCS IT Infrastructure Technologies. An alumnus of Indian Institute of Technology, Kanpur, he is responsible for end-to-end solutions for Infrastructure Services & Administrative Services for TCS. His interests include IoT, Mobility, Cloud and Digital Twin technologies. His e-mail address is arun.yadav@tcs.com.

ABHIJIT MAZUMDER is the CIO of TCS. He is currently responsible for TCS Corporate IT Strategy & Technology operations, and leading effective digital transformation on the pillars of Agile, Cloud, Automation, Machine Learning, and Artificial Intelligence. He brings with him multi-dimensional experience though various portfolios he has led for 27+ years. His e-mail address is abhijit.mazumder@tcs.com.