Cohorting to isolate asymptomatic spreaders: An agent-based simulation study on the Mumbai Suburban Railway

Extended Abstract

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ABSTRACT

This paper studies cohorting in public transit systems and its usefulness in mitigating disease transmission. The Mumbai suburban railway system is used as a case study.

KEYWORDS

COVID-19; cohort; public transit; agent-based simulation

ACM Reference Format:

A.Talekar et al. 2021. Cohorting to isolate asymptomatic spreaders: An agent-based simulation study on the Mumbai Suburban Railway:Ėxtended Abstract. In *Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), Online, May 3–7, 2021*, IFAAMAS, 3 pages.

1 INTRODUCTION

The COVID-19 pandemic has resulted in over 103.2 million reported cases and over 2.2 million fatalities (as of 28th January 2021). Vaccines became available only recently, and almost all countries relied on social distancing measures to control the spread. An early lockdown in India significantly affected urban and regional mobility patterns [4]. Mumbai, a metropolis with 12.4 million inhabitants in the Brihanmumbai Municipal Corporation area (density $32,300\ people/km^2$), is India's economic hub. *Locals*, the Mumbai suburban trains, play a central role in the metropolis's economic and social activities. *Locals*, used by 20-40% of the population, had a pre-pandemic daily ridership of over 8.2 million. Resumption of normal service levels can potentially lead to a surge in the disease spread because the *locals* and the stations are densely packed during normal working hours. (See [2] for a study involving the New York City subway.) As of 28th January 2021, the operation of the *locals* continues to be restricted while policy makers search for safe ways to resume service. It is in this context that we explore and quantify the public health benefit of *cohorting* strategies on the *locals*.

Cohorting is motivated by two hypotheses. (*i*) Locally dense but globally weakly connected networks might help control the spread. This is the rationale for *social bubbles*. (*ii*) It is easy to contact trace, test and isolate [3] asymptomatic spreaders when travelers form cohorts. Asymptomatic spread is believed to be a key driver of COVID-19 transmission. The impacts of these two components is the focus of the paper. In this extended abstract, we show that cohorting, combined with targeted isolation of suspected asymptomatic spreaders, is beneficial in reducing the disease spread. For more details, see [7]. For a video describing cohorting, see [6].

The source code for the simulator is available from [5].

This work was partially supported by a Google Grant, the Centre for Networked Intelligence, National Institutes of Health (NIH) Grant R01GM109718, NSF BIG DATA Grant IIS-1633028, NSF DIBBS Grant OAC-1443054, NSF Grant No.: OAC-1916805, NSF Expeditions in Computing Grant CCF-1918656, CCF-1917819 & NSF RAPID CNS-2028004, NSF RAPID OAC-2027541. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the funding agencies.

Proc. of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021), U. Endriss, A. Nowé, F. Dignum, A. Lomuscio (eds.), May 3–7, 2021, Online.

2 METHODS

Agent-based simulator. We implement cohorting strategies on top of a city-scale agent-based simulator (ABS) with 12.4 million agents. The ABS models interactions in households, workplaces, schools, neighbourhoods, and transport spaces, instantiated based on Mumbai's demographic data, ward-wise population density data, and other mobility data from census and surveys. The ABS also models disease spread and interventions – testing and quarantining, home isolation, social distancing, graded containment, face cover usage, and varying levels of compliance to policies. See [1] for details.

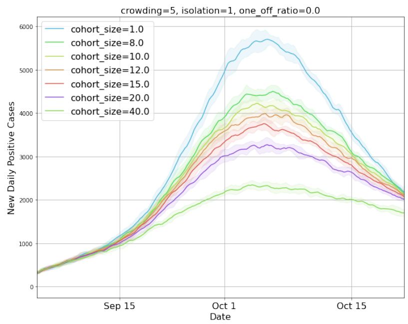
Commute model. For our study, we enhance the ABS's transport interaction space. We model the *locals* network of fifty-two stations inside the city limits of Mumbai and its suburbs, consistent with the number of agents generated. We then assign office-goers to either road or rail using a commute-time based choice model [7]. This results in 30% of the population using the *locals* for commute which is in line with the known ridership numbers on the *locals*.

Cohort formation. Cohorts are formed randomly among individuals sharing the same origin and destination stations. Agents in a cohort travel together twice everyday. Cohorts are assigned to coaches everyday, with new coaches added so that the seating capacity multiplied by a *crowding factor* parameter is not exceeded.

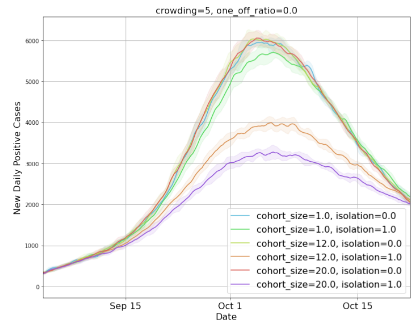
One-off travelers. These agents do not participate in cohorting, are assigned separate coaches, and are cut off from interactions with normal cohorts. The fraction of one-off travelers is a parameter.

Cohort interactions. The rate at which a susceptible individual gets infected is a combination of intra-cohort and intra-coach inter-cohort interactions. Cohorts assigned to different coaches do not interact. The intra-cohort infection rate is proportional to: (a) the cohort infectivity (the sum of the cohort members' infectivities arising from their disease states), (b) the travel time, and (c) an interaction strength parameter β_{coach}. The inter-cohort infection rate is proportional to (a) the other cohort's infectivity and (b) the overlap time for the interacting cohorts. See [7] for details.

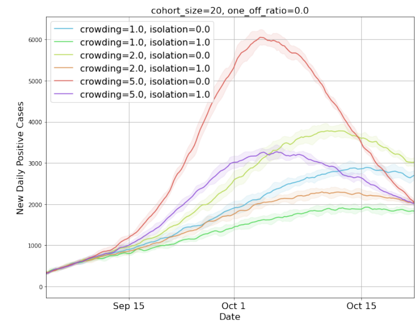
Intervention modelling. A member of the cohort may be identified as positive due to screening at the station's entry (detection probability 0.4), contact tracing, hospitalisation, etc. Alternatively, the



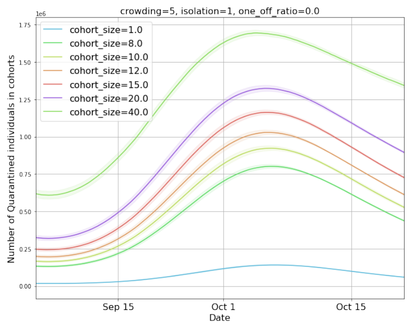
(a) Cohort size



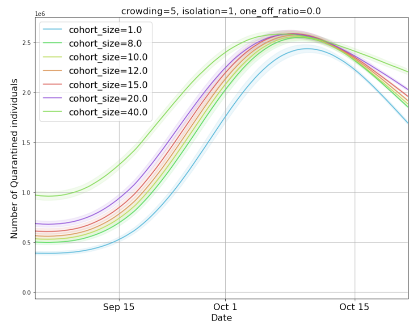
(b) Cohort intervention policy



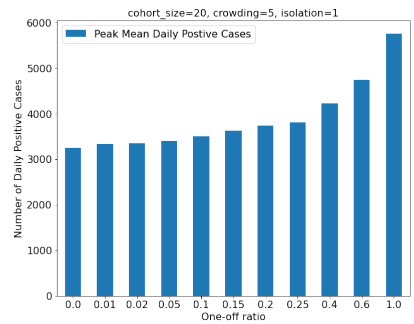
(c) Crowding



(d) Quarantining due to cohorting in locals



(e) Quarantining in the city



(f) Peak daily +ve cases vs one-off ratio

Figure 1: Subplots (a)-(c) and (f) show daily reported cases due to all interaction spaces, not just the *locals*. These are averages of five runs each on two synthetic city instantiations. Shaded regions in subplots (a)-(c) denote one standard error. Subplots (d)-(e) show the number quarantined. Parameters that vary in a subplot appear in the legend while those held fixed appear above. Parameters: crowding = crowding factor (limits coach occupancy); isolation = 1 for active cohort isolation, isolation = 0 for no isolation; one_off_ratio = one-off fraction.

member may voluntarily self-isolate upon recognition of symptoms. In all such cases, the entire cohort is placed under home quarantine for 14 days. This will likely reduce transmission in the transport space, but we recognise that home interactions increase.

3 RESULTS AND DISCUSSION

All simulated scenarios begin on 07 September 2020, which is taken as the start date for *locals* service. The initial states account for prior interventions and relaxations from the start of the pandemic in January 2020 (testing strategies, contact tracing, quarantining, lockdown, its graded relaxations, etc., see [1]).

1. Impact of cohort size. Figures 1a and 1b show the change in infection spread dynamics for various cohort sizes. Without isolation, all cohorts have similar dynamics. Isolation reduces disease spread because potential asymptomatic spreaders are quarantined. Larger cohort sizes lead to greater reduction in disease spread. (Due to practical considerations like coach capacity utilisation, enforcement of policies, cohort sizes of 12-20 may be appealing.)

2. Impact of crowding factor. Figure 1c plots daily positive cases for different crowding factors. We observe that the disease spread is sensitive to the crowding factor. A crowding factor of 1 without isolation has a lower daily maximum than a crowding factor of 5 with isolation, suggesting that reducing crowding in trains by a factor 1/5 is better than enforcing isolation of cohorts on crowded trains.

3. Number of quarantined individuals. Figure 1d shows that the number of people quarantined due to cohorting alone. It increases with increased cohort sizes. Figure 1e shows the total number quarantined in the city. Interestingly, the increase in quarantining due to cohorting is small. We attribute this to smart testing and isolation: cohorting with reasonable cohort sizes reduces the daily positive cases substantially by quarantining potential asymptomatics well before testing and contact tracing mechanisms take effect.

4. Impact of one-off travel. Figure 1f shows the impact of allowing one-off travel. Comparing the bar heights for 0.4 and 1.0 (no cohorting), we see that, even with as many as 40% one-off travelers, cohorting results in significant reduction in disease transmission.

In conclusion, cohorting can significantly reduce disease transmission due to targeted testing and isolation. Larger cohort sizes are more effective at reducing disease transmission. Due to practical considerations, cohort sizes of 12-20 are appealing. One-off travel up to 10% shows only marginal increase in disease transmission, and even at 40% one-off travel, disease transmission can be significantly reduced by cohorting. There is thus benefit in incremental implementation of cohorting. Disease transmission is sensitive to crowding which should be effectively managed. While managing crowding on train coaches, care must be taken not to crowd the stations, which is an aspect that needs further study. While our study focused on the Mumbai *locals*, the findings are generally applicable to other public transit systems (like metros, buses).

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