Unlocking Higher Education Spaces
- What Might Mathematics Tell Us?

Working Paper
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consisting of
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WARNING: this report contains preliminary findings that have not been peer reviewed. The findings are intended to provoke further study and policy discussion and should not be treated as definitive scientific advice in response to the SARS-CoV-2 epidemic. There may be some, possibly better, approaches to take, which have not been considered in this paper.

Whilst we expect these principles and illustrative calculations to help others formulate coherent and consistent guidelines, time has prevented accurate quantitative study of their effectiveness. This could be undertaken, but would require real data and time to build more detailed simulation tools appropriate on a case by case basis. Thus, we are not able to make specific recommendations from the principles, e.g. we cannot infer that it is safe to open university X if you follow principle Y.

Additionally, this report has been assembled in a short time frame, and while we have made every effort to ensure relevant references and links are present, where this is not the case, we apologise for the unintentional oversight. A **live document here** will collect any corrections and important supplementary information.

Briefing slides which summarise the report can be found **here**.

Contents

1 Introduction

Universities and the knowledge they create have been vital in the fight against the Covid-19 pandemic; we have seen innovation coming from the academic base inform policy in modelling pandemics, develop track and trace capability and fundamental work in clinical trials for a vaccine to name but a few.

In addition, universities support economic growth in their regions through direct employment and the many services and outlets connected to them. However, universities are suffering in the face of the pandemic with many still unopened, physical teaching courses suspended and ancillary staff furloughed. Universities are vibrant ecosystems which combine teaching, research and social activities; opening them back up to normal operation does pose significant challenges;

1. access and flow of people through buildings,
2. shared surfaces and bathrooms,
3. potential for aerosol transmission in indoor spaces,
4. operation of food outlets and leisure facilities,
5. interaction between the university, the wider local community, home communities of students and staff, public transport, to name but a few.

Previous work through Virtual Forum for Knowledge Exchange in the Mathematical Sciences (V-KEMS) discussed general mathematical principles which could be considered when unlocking the workforce [1], and to a certain extent, this problem builds on that foundation of knowledge with an application to university operation.

Having consulted with many in UK university leadership, V-KEMS developed a short, but by no means complete, list of topics we might be interested to discuss in a VSG format. These initial topics were:

- How much would grouping students into cohorts based on geography (halls of residence, residential streets) and using these to organise access to campus reduce transmission of disease compared to allowing everyone on at the same time?
  - Can students access social activities within their cohorts as well as academic ones.

  - What can we say about the benefits of cohorting and / or a less densely occupied campus.
  - How small would cohorts need to be to make a differece and consequently how much time on campus would they get?
  - How much could cohorting facilitate control of transmission through test, trace and isolate?
- How might some general principles apply to professional services and facilities staff such cleaners and security staff to reduce transmission on campus?
- What about transport to and from campus? How might one manage the interaction with local transportation routes?
- What can we say about the transmission of infection between a university, its local community and the wider home communities of staff and students?

The purpose of this report is to overview the work undertaken by a group of mathematical scientists (listed as contributors on page 2.) in response to the challenge above bearing in mind the warnings and limitations set out on page 3.

1.1 The VSG

Between 15 - 17 June 2020, a VSG was hosted by the Newton Gateway to Mathematics. During the first morning the problem as stated above was presented and short perspective pieces from various levels of university management were given. All delegates were asked then to suggest priority topics for the group to consider.

To manage the topics most effectively, the participants were divided into three teams; one team to look at the building level topics, one to look at campus level topics, and the third to look at wider community level topics. The initial topics per group are shown in Table. 1

Each group was asked to consider these topics and discuss using the collaborative software Mural[1]. These Mural boards allowed the groups to capture the specifics of the challenge, key assumptions which were being made, the linkage with other groups, and ultimately what mathematical modelling could be used to support the challenge.

[1] https://www.mural.co/

Table 1: Topics for VSG discussion

Building level (Group 1)	Campus level (Group 2)	Community level (Group 3)
Flow in buildings	Size, membership and leakage of student bubbles	Public transport flow and bottlenecks
Loading and unloading	Flow on campus	Freshers flu and community?
Small space management and scheduling	Difference between student / non-students / visitors	Employment – long range interactions

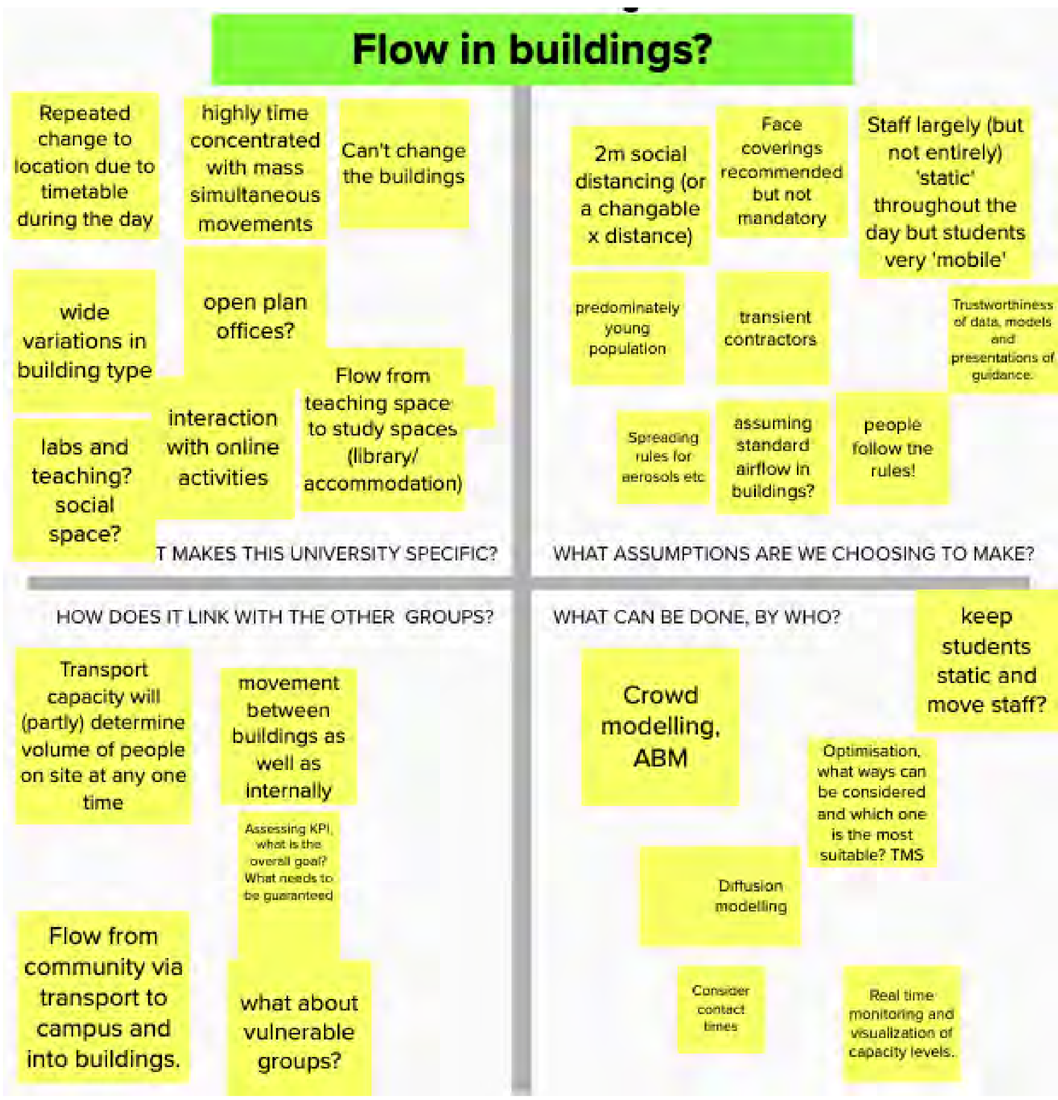


Figure 1: Example of mural exercise.

This report is structured around the three groups outlined above. Building level topics can be found in Section. 2, campus level topics can be found in Section. 3 and finally community level topics can be found in Section. 4.

1.2 Relative Risks for Staff and Students

First however, we review some important aspects of risk and relative risk to university staff and students. The challenges estimating absolute risk for September are significant, the numbers below look backwards and try to summarise relative risks. These may then remain similar whatever the status of the outbreak in the future.

It should be noted that most people who catch Covid-19 recover fully. The illness is however more likely to affect staff (because of age) more seriously which may generate significant reduction in service capacities during a semester. Controlling the virus will be important to maintaining service delivery.

Relative risk of death:

Most of the notes below summarise data for England from sample surveys in the community by the Office for National Statistics (ONS).

- *Age (grouped here as 15-24 students 25-44, 45-64 staff):* Chances of catching Covid-19 are not different with age, but depend more on your work (meeting people or not) and whether you leave home to go to work. [5]. During lockdown Mar 28 - May 29 the chance of dying went up with age [3]:
  - Age group 15 - 24 when compared with age group 24-44 by a factor of 6.35
  - Age group 15 - 24 when compared with age group 45-64 by a factor of 62
  - This continues approximately as a factor of 10 for every 20 years older.
- *Gender (grouped here as male or female):* During lockdown Mar 28 - May 29 Males in every age group had approximately double the risk of dying as females [3]. However there is no evidence of a difference between genders in who has had Covid-19 in the community [4].
- *Black, Asian, and Minority Ethnic (BAME):* The risk for BAME individuals of catching and dying from Covid-19 is about twice that of the rest of the population. Note, this relates to catching as well as dying. It may therefore be lower among students whose risk of catching Covid-19 may be lower than the average risk in the wider BAME population where occupation related exposure may be a factor.

Table 2: Infections and track and trace isolations in one university.

		As of June	
	Total	Infected	Uninfected
		8 %	
Univ N with 6,000 staff (all staff)	6000	480	5520
Univ N with 6,000 staff and 27,215 students	33,215	2,657	30,558

- *How is relative risk influenced by pre-existing health conditions?:* It is important to note that healthy people have much lower risks of dying than people with pre-existing health conditions, by a factor of about 5 for adults under 50. This suggests that the group of students (less than 20 %) with pre-existing conditions should be given the opportunity for entirely online learning experiences. Similarly for any teaching or non-teaching staff with pre-existing conditions.

- *How many people have or have had Covid-19?* The most recent ONS survey [4] suggests about 1 in 1,600 people in England currently have Covid-19, so all universities should expect to see some people on-site who are infected. Just four weeks earlier this was about 1 in 358, illustrating how dynamic a situation we are in. Other ONS data [3] suggests that about 8 % of the total population have had Covid-19. This is some way from herd immunity.

- *Estimates of impact on staff and students:* Infections and track and trace isolations in one university based on estimates of tracing outcomes are shown in Table. 2 [7]. Peak community infection rates up to twice this in April, but no data from ONS on April rates in the community. Track and trace contact estimates from [7].

2 Building-level Topics

Group 1 worked on three problems to do with building level topics in the context of Covid-19 and universities. Broadly speaking how to use teaching space and how to move between teaching spaces. The first problem involved modelling the risk in a single lecture theatre. The second on how do you allocate students to lecture theatre spaces using the constraints built in task one. The third on entering a room / lecture theatre from a corridor. There are two basic tensions which underpin the thinking in this task.

Small size *N* of class reduced infection $I = O(N^2)$ but reduces the student experience, causes timetabling problems, and increases risk to staff.

Keeping student together in the same room for a long time reduces movement, but can increase infection.

2.1 Modelling a room

We are interested in the airborne transmission of Covid-19 in the particular lecture theatre shown in Fig. 2

Airborne transmission of Covid-19 in lecture theatres: stochastic analysis using a Monte Carlo model

The transmission can be modelled using the Gammaitoni-Nucci equation 1 which is the exact solution for an Susceptible, Infected, Recovered (SIR) model, which gives you the probability of infection in susceptible individuals using the parameters below. Importantly the measure ϕ of quanta generation - a recent study showed that this measure

p	pulmonary ventilation rate	m^3/h
I	number of infectors	N/A
ϕ	quantum generation rate	quanta/h
V	room volume	m^3
N	room ventilation	airchange/h
t	duration of class	h
S	number of susceptible individuals	N/A
$n = S + I$	class size	N/A

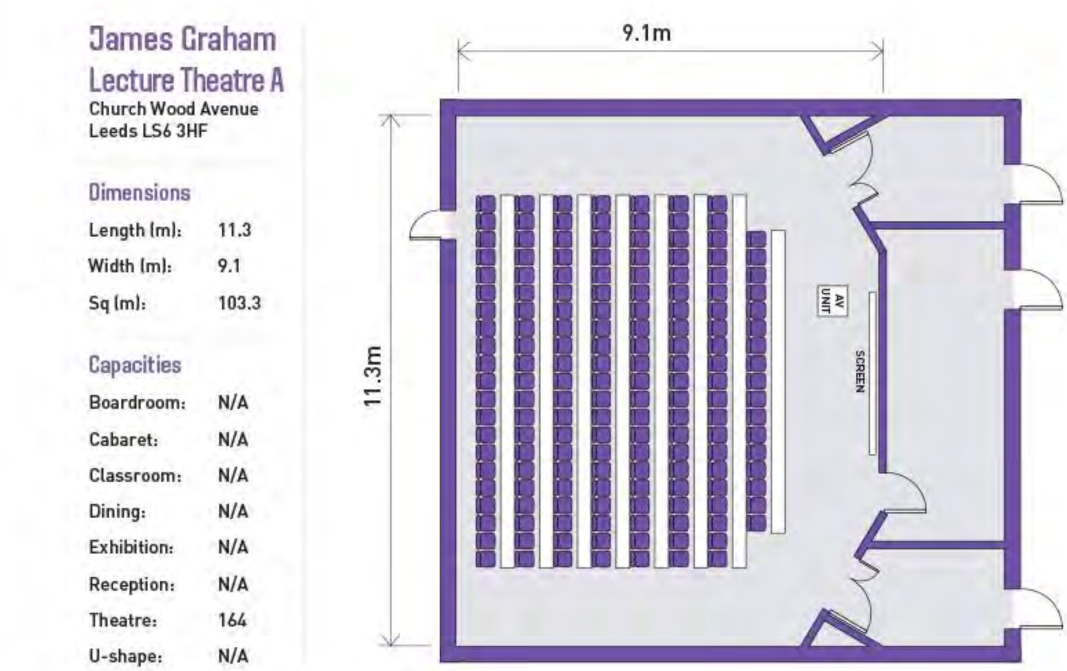


Figure 2: Example lecture theatre layout for consideration.

was around 10.5 quanta / hr breathing at rest, but when talking can be as high as 320 quanta per hour.

$$P = 1 - \exp\left\{ -\frac{pI\phi}{V} \left(\frac{Nt + \exp\{-Nt\} - 1}{N^2} \right) \right\}, \tag{1}$$

and the number of new infections C is given by $C = SP$.

The capacity of the lecture room considered in Fig. 2, given 2 m social distancing rules would be 16, and given 1 m distancing rules would be 32. The value of ϕ is taken from the study [9], where $\phi = 10.5$ quanta/h when breathing at rest, and $\phi = 320$ quanta/h when talking. The mean probability of infection as a function of class size is shown in Fig. 3, which also looks at the effect of ϕ.

How does this affect the problem of scheduling. Now assume that all students are to be given 2 hours of face to face teaching each week, delivered by the same member of staff. Given the presence of one infectious person initially, which schedule will lead to fewer infections:

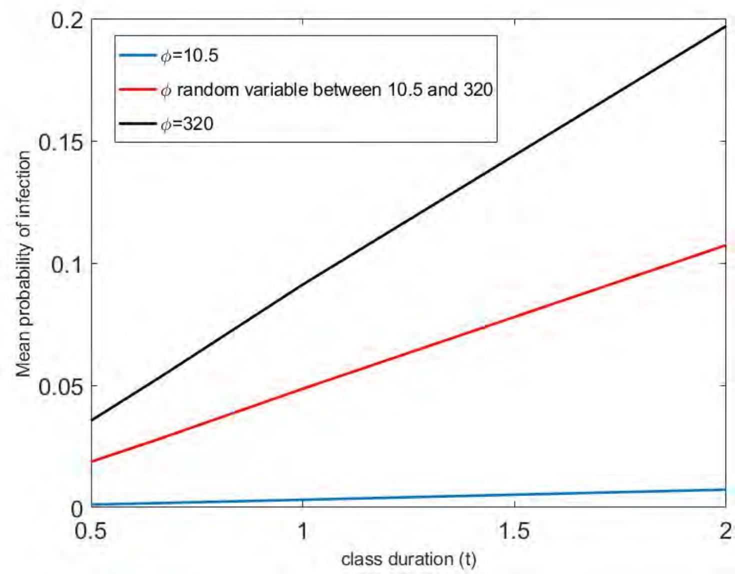


Figure 3: $I = 1$, $V = 300$ m^3, $N = 4$, p is a random number from the normal distribution with mean 0.48m^3/h and s.d.$= 0.2$m^3/h.

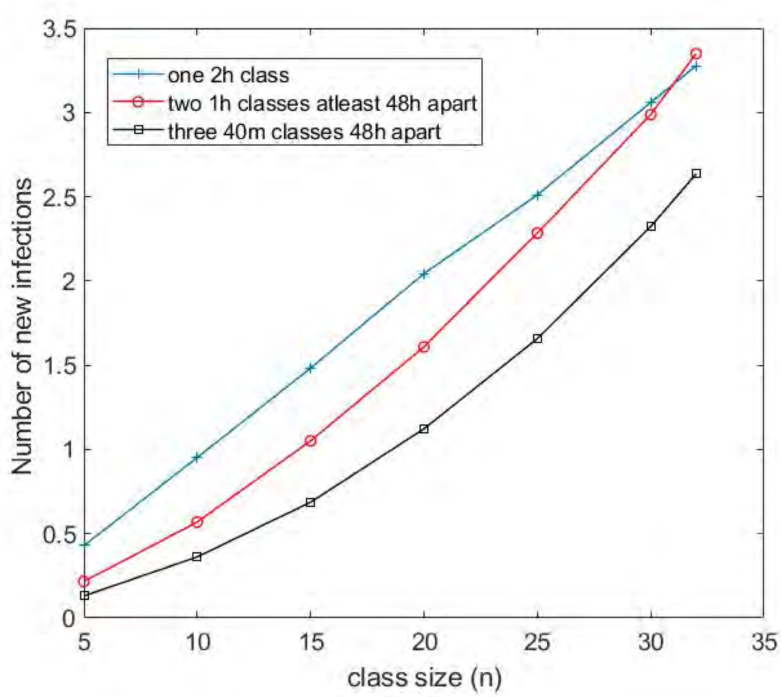


Figure 4: $I = 1$ initially, $V = 300$ m^3, $N = 4$, p has mean$= 0.48$ m^3/h and s.d.=0.2m^3/h, and ϕ is a randomly generated number between 10.5 and 320.

- one 2 hour session
- two 1 hour sessions more than 48 hours apart
- three 40 min sessions 48 hours apart ?

Given that the majority of people get symptoms within 5 days, and are contagious 2-3 days before the onset of symptoms, our own assumption has been made that susceptible individuals become infected after a period of 48 hours.

Fig. 4 possibly suggests that the mean number of infections as a function of class size for the different timetabling approaches. Note that social distancing measures of 2 m would allow for a capacity of 16, and 1 m distancing rules 32 for the room shown in Fig. 2.

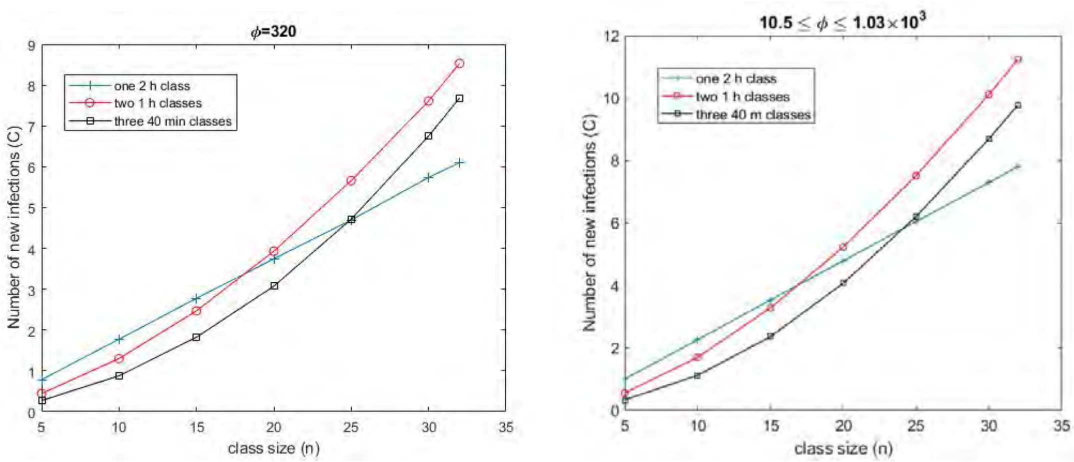


Figure 5: (Left) Model run with ϕ = 320. (Right) $\phi = 10.5 \leq \phi \leq 1.03 \times 10^3$

Fig. 4 suggests that three 40 min sessions are preferable to one 2 h session. However, this depends on ϕ (taken to be a random variable between 10.5 and 320 above) and the number of students in the class. In Fig. 5(left), With a 1 m social distancing (32 students) and assuming the students are talking constantly throughout the session (i.e. $\phi = 320$) then one 2 hour session would result in a lower number of new infections. This is also the case if we assume the students are engaged in light activity such as singing (i.e. $10.5 \leq \phi \leq 1.03 \times 10^3$) - Fig. 5 (right).

Issues around surface contacts

The next thing is to look at surface transmission, we did this with a stochastic model. There are two important basic facts from the Rapid Assistance in Modelling the Pandemic (RAMP) group.

1. Time-scales for decay are of the order of **hours** [10].
2. Cleaning is important to reduce C. However a cleaned surface should really be left for a couple of hours before it is re-used.

The basic model set-up is as before in Fig. 2, and of course any results will be room dependent. Here we make the following assumptions.

Rooms with 8 rows, 21 seats per row, 1 in 5 seats in 5, alternate rows.	Students go in / out following shortest path to their seat.	Students can touch any seats along their way.	Students clean their seat at the beginning o the lecture

Effect of lecture length

The first example to consider with this model is to look at the effect of lecture length. We use the following parameters as an example when developing our model, but note that these are just our own assumptions, and not based on any evidence:

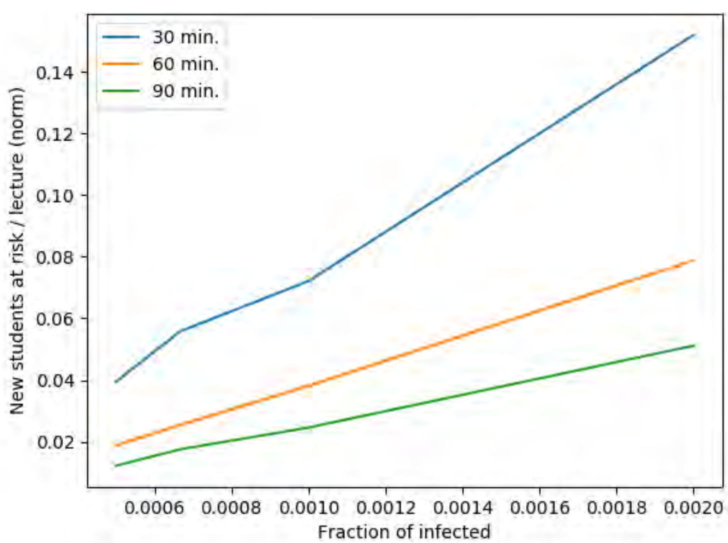


Figure 6: New students at risk from transmission via surfaces in lecture theatre for different lecture lengths.

p_{clean}	0.90	Probability of student cleaning
p_{trans}	0.1	Probability of infection from touching an infected surface
p_{move}	0.5	Probability of student touching seat on the way to their seat
		Room cleaning every 8 hours (end of the day)

What we see in Fig. 6 is new students at risk as a function of the fraction of infected population (1:2000 to 1:200). The longer the session the better it is, as there is less movement and touching of surfaces. Interestingly, but unsurprisingly this goes as counter to the airborne transmission shown earlier.

Hot-seat and cleaning strategies

The second example is to look at the effect of cleaning strategies and "hot seating"; having colour coding of seats so that for example students in consecutive sessions would not be sitting in the same place. Parameters we have assumed are as below:

p_{clean}	0.90	Probability of cleaning
p_{trans}	0.1	Prob. of infection from surface
p_{move}	0.5	Prob. of touching seat on the way
T	60 mins	Lecture length

Fig. 7 shows again new students at risk as a function of infected population. The control line shows students always in the same rows. The dashed line is for the case of odd then even rows for consecutive lectures which has a strong effect. The dot-dash line considers if a student cleans at the end of the lecture as well as at the beginning, and the dot-dot line is when cleaning staff come and clean in the middle of the day.

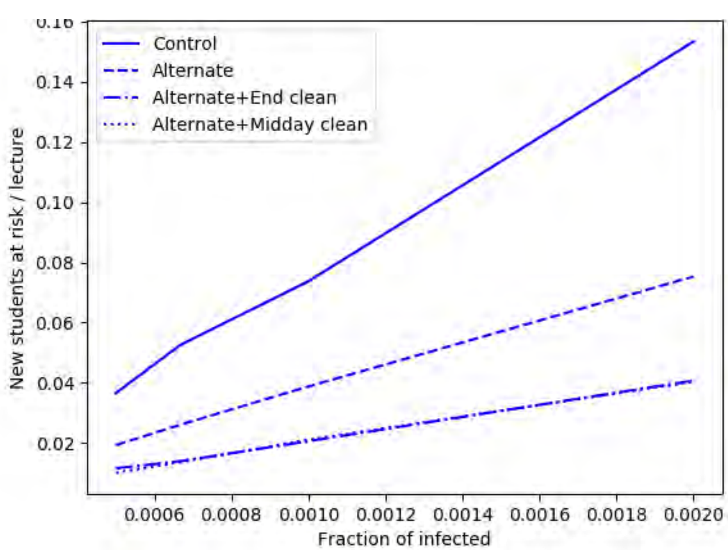


Figure 7: New students at risk from transmission via surfaces in lecture theatre for different cleaning strategies and seating protocols.

Possible conclusions for this specific case: airborne transmission increases with lecture length and risk of transmission fro Surface transmission decreases with lecture length. Requires estimates for parameters for each specific set up. Cleaning strategies have a significant impact.

2.2 Static room allocation

This task considers the question *is there room capacity to give every student a face-to-face session a weekly for each of their modules?*

For this section the VSG had data for 1 week of teaching sessions and teaching room size at Warwick University. The data shows there are 682 modules with module sizes ranging from 521 to 1 student and 256 rooms with sizes from 500 seat lecture theatre to small flat floor rooms for 3 students.

Assumptions we are making are based on a 2 m distancing driven capacity reduction; 10 % capacity for a tiered lecture theatre and 30% for flat floor as a safer occupancy.

We also decided to put a limit of a maximum of 25 people in each room (in fact after reducing the capacity of each room this upper limit of 25 only affects 14 of the 256 available rooms). Such additional limits can be motivated by the increased risk of airborne infection with number of people in a room.

Modelling assumptions: largely driven by the modellers choices, augmented with discussions with university management.

To allocate just one face-to-face session for each module

To assume the teaching day is extended from 9 am – 8 pm for all 5 days. This increases the hours available from 40 –o 55 a week.

To assume a maximum of 25 students in an room (then testing maximum student numbers of 15 and 10 students.)

The current modelling makes no assumptions about

Numbers of teaching staff available

The desirability of scheduling of modules into blocks for a group of students to reduce the number of times coming into campus and entering and leaving a teaching space

The actual timetable would also need to make sure a students sessions are not in the exact same time slot. As there will be a number of equivalent sessions (unlock scheduling lectures) this should not be too big a constraint.

If there is a slight shortage of space, it might be possible to partition some of the larger rooms, e.g. those of capacity >25, if access ways permit, to give more teaching rooms. Dividing the rooms into 1st year only rooms, second year only rooms etc. Reduces the number of students using the same space.

To reduce the movement of students ideally a group of students would remain in the room for several sessions and be wiping their desks on entry and exit. There is some evidence [11, 12] that if you clean a work space then you should leave that space vacant for two hours before using it. This scenario was not possible for the Warwick data. This can be mitigated in part for large rooms by having different spaces that are used at different times e.g.colour coded.

Table. 3 shows the nine scenarios modelled heuristically and the percentage occupancy of available space in each scenario. For example, assuming a 55 hour week, and maximum occupancy of 25 students, the capacity of available space would be 48 %. However, in another scenario, using a 30 hour week with a maximum of 15 students, there was no solution found within available capacity.

Table 3: Capacity of available space under different working scenarios.

Weekly hours	Max 25	Max 15	Max 10
55 hours	48 %	54 %	65 %
40 hours	48 %	76 %	90 %
30 hours	90 %	N/A	N/A

2.3 Dynamics

This task considers the movement between rooms, and movement into a room, including students, staff, less mobile people, etc.

In Ref. [1], fast movement in "corridors" was shown in some circumstances was shown to be *relatively* safe. But *bottle necks* e.g. at lecture room entrances are much less safe. A key paper from the Fire Safety Engineering Body [2] is used to form a model. With the following definitions;

$J =$	the flux of the students
v	the mean speed of the students
ρ	the density of the students
b	the width of the bottle-neck

Then

$$J = b\,\rho\,v, \quad J_S = J/b \tag{2}$$

If we have N students entering a lecture theatre through a gap of width b then the time T it takes to do this is given by

$$T = \frac{N}{J} = \frac{N}{b\,J_S}. \tag{3}$$

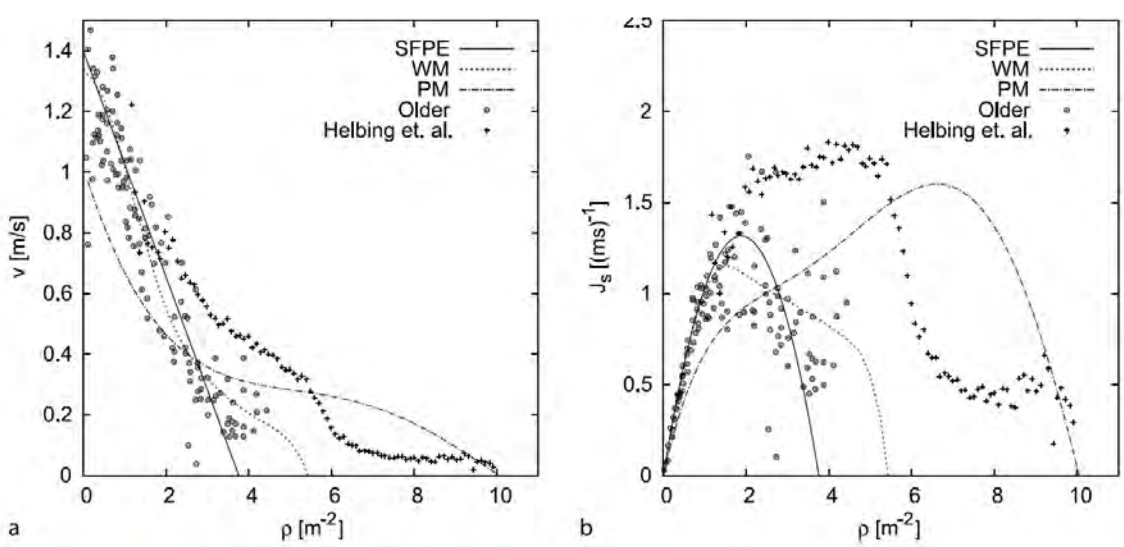


Figure 8: Fundamental diagrams for pedestrian movement in planar facilities. The lines refer to specifications according to planning guidelines. References contained within Ref. [7]

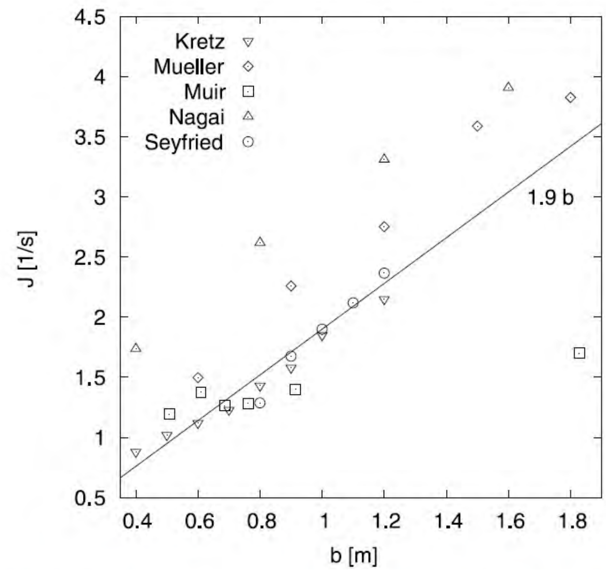


Figure 9: Influence of the width of of a bottleneck on the flow. Experimental data of different types of bottlenecks and initial conditions. All data are taken under laboratory conditions where the test persons are advised to move normally.(Taken from Ref. [7] inc. further references.

Fig. 8 shows some *fundamental* diagrams for pedestrian movement in planar facilities. Fig. 9 shows the influence of the width of a bottleneck on pedestrian flow.

Suppose that we have strict 2 m distancing rules, then each student will occupy a area of the order 2 m $\times$ 2 m. Therefore we have

$$\rho = \frac{1}{4} m^{-2}. \tag{4}$$

In this case from Fig. 9 $J_S \approx$ 0.25. So a room of 25 students with b = 0.6 will take $T =$ 166 seconds to enter.

3 Campus-level Topics

Group 2 considered two problems related to campus level topics in the context of Covid-19 and universities. The first problem involved modelling student bubbles. The second considered flow of students and bottlenecks around campus.

3.1 Social bubbling

This task looks at the impact social bubbles could have on the impact of an epidemic on a campus, how this could be feasibly implemented. First we limited the scope by only considering freshers. It is more feasible to impose and enforce bubbling of a typical subgroup [2].

Live on-campus in university-owned accommodation

Taught undergraduate students – already share timetables and small-sized classes

First-years ("freshers") ay benefit more from direct guidance than senior students, no existing relationships.

Available data supports that this subgroup is a sizeable proportion of the university population.

Infeasible to bubble atypical subgroups

Live off-campus

May / may-not live with peers

Teach overlapping cohorts.

Assumptions made by the modellers which may be very different to other scenarios.

Freshers are predominantly age 16 - 18

Campus-based university (as opposed to city-based)

Bubbles can be based on degree course:
- Shared timetables and small-sized classes
- Only one elective per student – additional electives must be studied remotely
- Each bubble housed together on-campus – sufficient capacity, no varying / atypical living requirements.

Infectious population will be difficult to identify
- -Young people are more likely to be asymptomatic
- Symptoms may be confused with common 'freshers flu'

[2] We realise that this means some students will be excluded, or adversely impacted, by any such suggestions generated from this modelling

Bubbles containing infected individuals will immediately be locked down, preventing further spread

Most leakage is controlled where possible

- Food is delivered to residences
- Students must use on-campus shops and clubs

There will still be an amount of illicit interactions

- Bubble to bubble
- Bubble to on-campus society
- Bubble to off-campus society

Notable limitations

- Atypical subgroups have been excluded – unmanaged leakage may cause the bubble system to breakdown
- Students restricted to spending their work and social time with the same cohort

Two-Model Approach

Dividing between the expertise present in our group, we have developed two separate models using comparable parameters. The first generation-based model considers the impact of different sizes of bubbles on the final size of epidemics within the student population, whereas the second discrete timestep Susceptible, Exposed, Infected, Recovered (SEIR) simulation model considers how social bubbling impacts disease testing.

Model A: Generation-Based Model

We also adapted the methods in Ref. [18]

- Disease model (SIR) - As the model was designed to consider the final size of epidemics, not their temporal dynamics, there is no explicit exposed class. This may effect the success and impact of tracing and isolating social bubbles.
- Network contact setup
  - Number and size of bubbles - initial settings 128 bubbles of size 12, alternative setting 64 bubbles of size 24, 32 bubbles of size 48
  - Individuals interact with the student community at large via mean-field transmission at a rate ϵ

We find, unsurprisingly, the benefit of social bubbles diminishes as the chance of infection from the student population increases. Note that it would not be possible to eliminate this - even under the current lockdown the chance of infection from the community is not 0.

Smaller bubble sizes can withstand larger rates of community infection, Fig. 10. However, if bubbles are too small this would likely impact adherence, hence increasing community transmission.

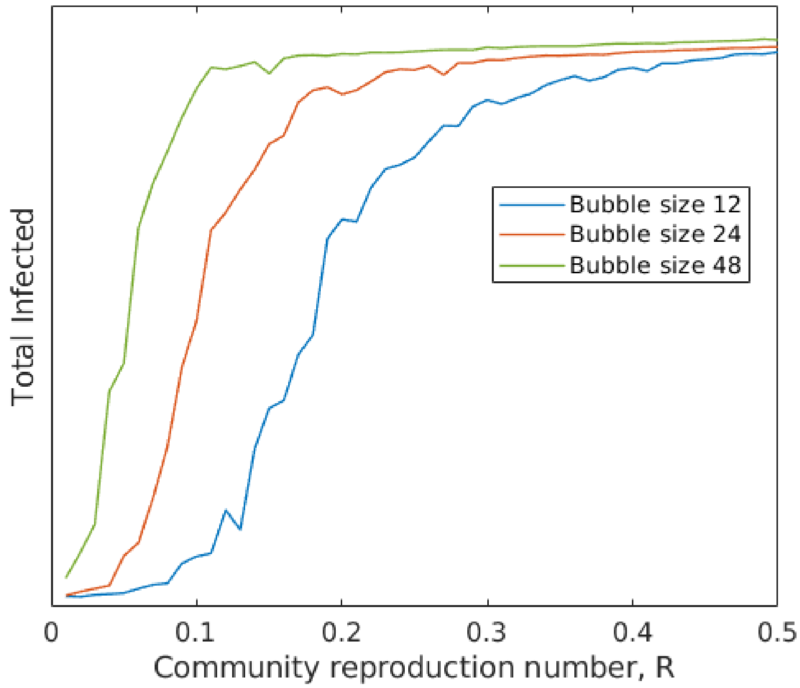


Figure 10: y-axis values are omitted, as the exact impact of bubbling scenarios depends on the underlying parameters. This initial analysis should be seen as exploratory and providing qualitative results, not an accurate quantification of the relative benefits of different bubble sizes. Results are averages over 50 simulations.

Model B: Discrete Timestep SEIR Simulation Model

A timestep SEIR disease model was also undertaken with the same parameterisation as above so as to be comparable. The timestep method is necessary to understand the effect testing might have. Only includes bubbled students. Ignoring possibility of serious infection or death:

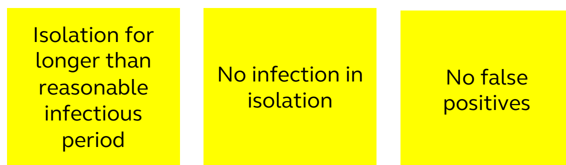
- Per-day infection probability over a bubble contact
- Per-day infection probability for an extra-bubble contact
- Rate of movement from exposed to infectious
- Rate of movement from infectious to recovered

Network contact setup:

- number and size of bubbles initial settings - 128 bubbles of size 12

- number or rate of extra-bubble infectious contact (in person, via staff, fomites, etc)

Testing and Isolation:



- Rate of detection of a true infection per day

A few sample outputs (mean plots over 50 runs only no individual models runs or uncertainty shown) are shown in Fig. 11 - 13. All y-axes are at different scales, and are number of infectious students in bubbles - y-axis labels have been removed so that the (very uncertain) numerical outputs here aren't used inappropriately. In addition, Fig.14 - 16 show the same as Fig. 11 - 13 on the same axis scale.

Tentative conclusions based on our chosen scenario and assumptions are that there would either need to be a very low amount of interaction between bubbles or a very high rate of testing in this student context.

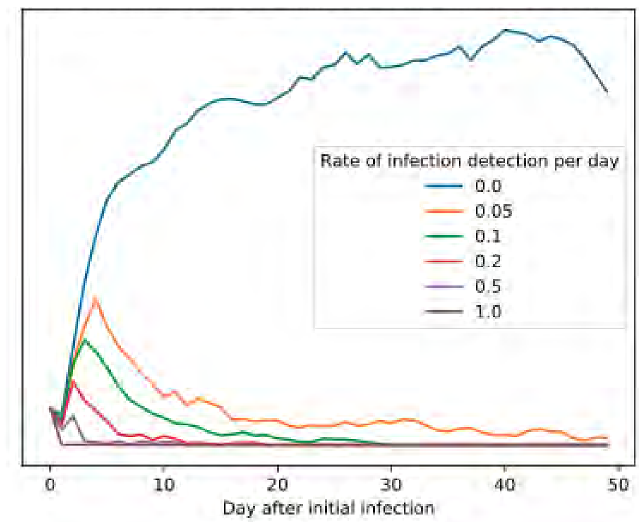


Figure 11: 128 bubbles of size 12 with 100 extra-bubble contacts

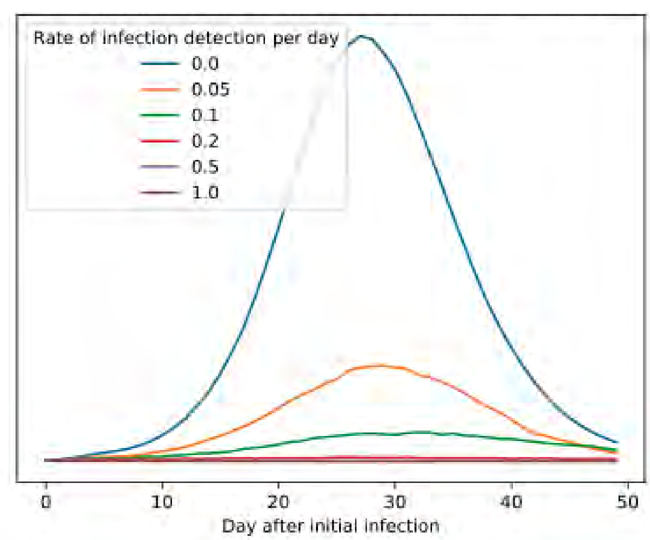


Figure 12: 128 bubbles of size 12 with 500 extra-bubble contacts

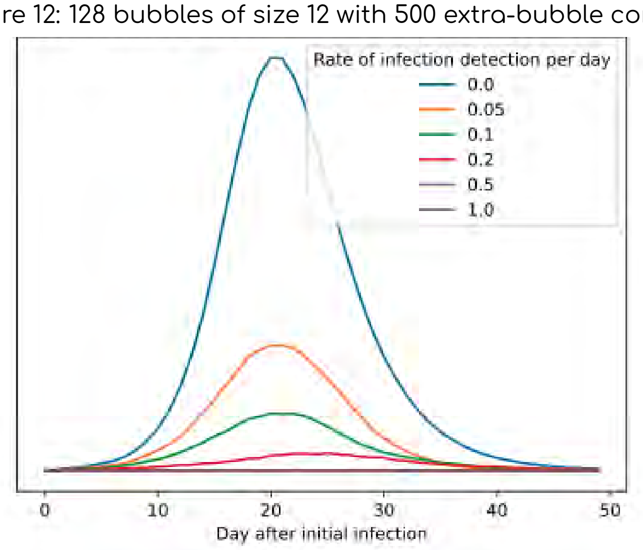


Figure 13: 128 bubbles of size 12 with 1,000 extra-bubble contacts.

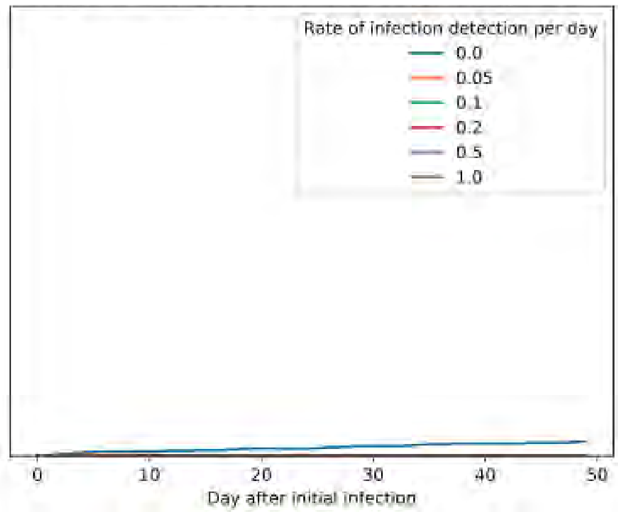


Figure 14: 128 bubbles of size 12 with 100 extra-bubble contacts

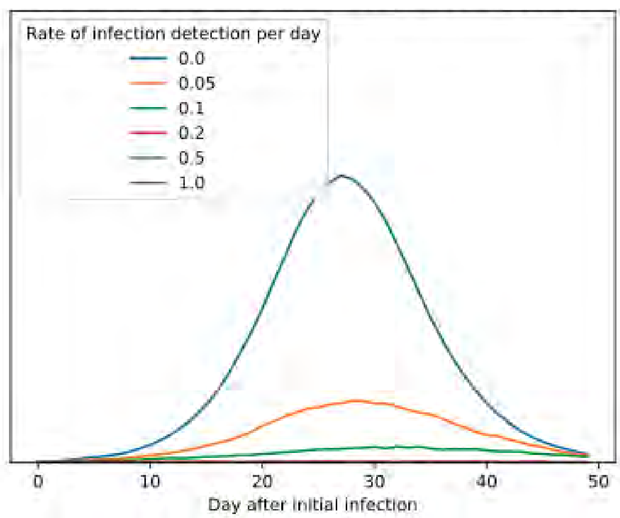


Figure 15: 128 bubbles of size 12 with 500 extra-bubble contacts

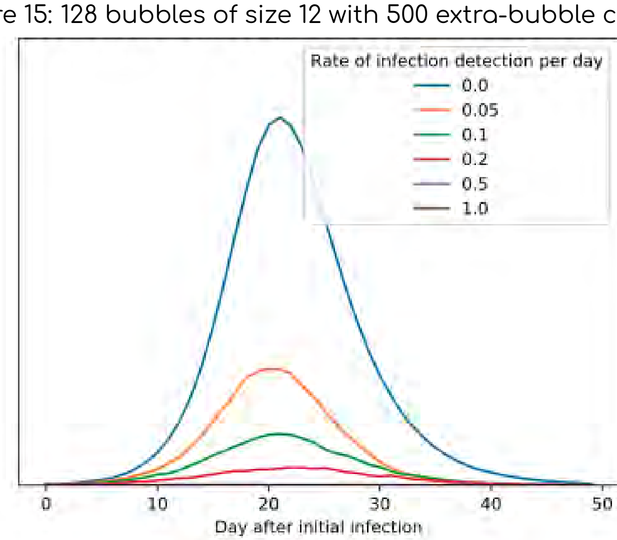


Figure 16: 128 bubbles of size 12 with 1,000 extra-bubble contacts.

Further Work Summary

To extend this work we would want to life the assumption that we are only looking at students who live on campus and model higher-year undergraduate students, taught postgraduate students, research postgraduates who may also teach junior students, intersections of typical and atypical subgroups both living on-campus.

We also consider hierarchical bubbling; allowing students to be in larger bubbles. Consider different transmission rates across contacts. Acceptable practice during low disease-prevalence which could then be restricted should the disease spread increase. This would have the advantage of offering a more varied student experience, but has the isolating structure in place in the event of an outbreak.

Incorporate interaction with / leakage from wider society in particular where students are accessing society resources such as food shopping, healthcare, social activities, etc. Additionally, would need to consider non-university visitors to campus. This is particularly important as the adverse health impact of an epidemic on a campus would be worse for the staff population and the wider communities through their interaction due to the age demographics.

Testing could be Incorporated into the generation-based models, and we could extend how we test in the discrete timestep model to consider fixed disease parameters, fixed compliance, varied bubble size.

We suggest a couple of plots which could be looked at - Fig. 17, how the size of bubble affects the rate of testing and also how the level of outside bubble transmission affects the size of bubble possible.

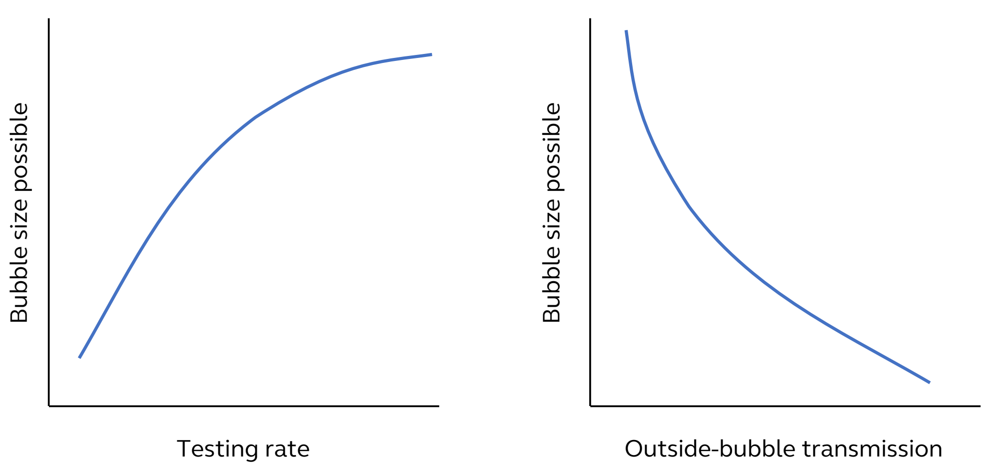


Figure 17: (left) Fixed disease parameters, fixed compliance, varied bubble size (right) Fixed testing regime, varied non-bubble contact

Future work concerning university social bubbles should keep in mind:

- The adverse health consequences of an epidemic on campus would not be felt most by students, but by the university workforce and the general population around the university, because of the age demographics of students.
- Size and stringency of bubbles will have an impact on adherence.
- Decisions surrounding the implementation of social bubble policies should be well-founded in research based on well-founded sets of epidemiological parameters.

3.2 Flow around campus

The issue considered here is the timing of scheduled activities in different buildings and whether this creates bottlenecks either at the entrance or exit to buildings or at various choke points around campus. After consulting with pedestrian flow experts and a quick literature search the group found that this problem (i.e. scheduled flows) is not usually considered in pedestrian flow models because the main focus there is usually evacuation.

Two broad approaches that could be used are continuum models (gas dynamic-like Partial Differential Equation (PDE)s) and microscopic discrete event simulations.

The group consulted with a crowd flow expert and decided that coming up with an optimiser is probably a distant goal, rather the group should try to solve the forward problem so that sensitivities to parameters can be tested, inputs etc.

A useful simplification between discrete event and continuum models are Ordinary Differential Equation (ODE) models on a flow network. Here we can use a meta population model where at each node there are continuous variables which model separately the populations x_i of students who are trying to enter that node and y_i of those that are trying to leave.

The group considered as a toy model the simplest possible geometry (for now) of four nodes. These you can think of as two buildings (with lecture theatres) connected by a choke point (which is modelled by separate nodes for its left and right boundaries). Alternatively it could be a building and the bus station. We choose to assume that it is in our gift as planners to schedule the start and end times of lectures (or bus journeys). These are modelled as given flows; $a_i(t)$ for anticipated arrivals, and $l_i(t)$ for anticipated departures. This simple model is shown in Fig. 18.

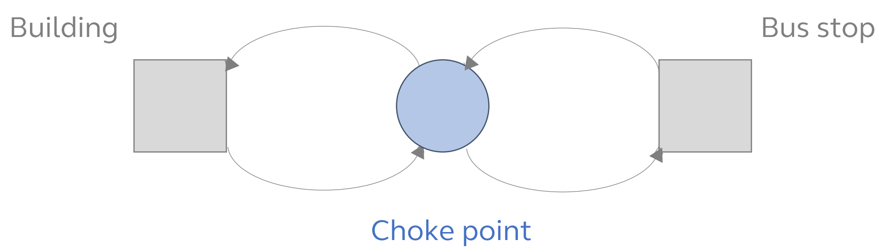


Figure 18: Diagrammatic depiction of toy model.

The key idea is to have some form of congestion function such that the flux through each node $X_i \sim dx_i/dt$ and $Y_i \sim dy_i/dt$ depends on the total population $(x_i + y_i)$ at that node in a nonlinear way.

Finally, the inputs $a_i(t)$ and $l_i(t)$ can be explored assuming they are Gaussian's centered on times that we choose.

Whilst the group did not have time to compute the model, it is felt that this could be a promising approach to modelling possible congestion with further development. It is possible to extend this to different meta populations i.e. different bubbles and different forms of nodes i.e libraries, cafes, sports centres etc.

In this toy model, we have a lecture hall, a bus station and a choking point. Every building entry and exit is a node in this graph. Let's assume that nodes represent doors to a building or crossing points. Let's also introduce two variables at each node:

X_i for inflowing density and Y_i for outflowing density. Let X be the vector $\{X_i\}$ and $Y = \{Y_i\}$, we also need O and I for desired outflux and influx which can be a function of the nodes to which each node is connected in the graph. We also have variables at each node for people who are waiting to enter or leave lets call these $x = x_i$ and $y = y_i$.

$$\frac{dx_i}{dt} = f_{\text{in}}(I_i, X_i, x_i, Y_i)$$
$$\frac{dy_i}{dt} = f_{\text{out}}(O_i, X_i, y_i, Y_i)$$

where

$$I_i = A_{ji}Y_j + l_i(t)\mathrm{e}_i, \quad \text{and} \quad O_i = A_{ij}X_i + a_i(t)e_i$$

with A_{ij} being an origin-destination matrix and $l_i(t)$ and $a_i(t)$ being extrinsic populations leaving and arriving (sources and sinks) such as scheduled flows at the start and ends of timetabled lectures.

$\frac{dX_i}{dt}$ = = actual outflux. $\frac{dx_i}{dt}$ = desired outflux - actual outflux. Similarly for Y_i and y_i.

For the simple network in Fig. 18 we would have with node 1 being building A, node 2 building B and 3 and 4 being the left and side and the right-hand side of the choke point:

$$A = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix}.$$

In principle the matrix A will not be symmetric if you have one way systems. There also needs to be some conservation principle at the choke point.

Properties we desire of $f_{\text{in/out}}$:

- if both densities are low then the flow is precisely $\hat{I}$ and $\hat{O}$
- if there the opposing flow is low enough there is a high upper threshold before conjestion (aka nonlinear saturation) kicks in.
- try 1D out flow to begin with
- flow $= O$ if $X < \kappa$
- less than O if $\kappa < X < \gamma$
- reaches some flowmax if $X > \gamma$

In time Δt:

C	capacity of the door
O_i	people arrive wanting to leave
X_i	actually leave
	so x_i increases by $X_i - O_i$

$$\frac{dx_i}{dt} = g(X_i, O_i)$$
$$X_i = x_i f_{\mathsf{congest}}(x_i, y_i, C_i)$$

I_i expected number of people whom we have made the capacity to arrive entering so y_i increases by $Y_i - I_i$

$$\frac{dy_i}{dt} = g(Y_i, I_i)$$
$$Y_i = y_i f_{\mathsf{congest}}(x_i, y_i, C_i)$$

$$f_{\mathsf{congest}}(x, y, C) = \exp(-(x+y)/C)$$

For simplicity lets try taking $C = 1$ and $g(X_i, O_i) = (X_i - O_i)H(x_i)$ where H is the heaviside step function. Alternatively you can take a smoothed $\tanh$ function e.g. $H(z) \approx (1 + \tanh(z/\epsilon))$ where $\epsilon \ll 1$.

It remains to specify the fixed demands $a_i(t)$ and $l_i(t)$. As a first run we choose to try

$$a_i(t) = \sum_{j=0}^{N} p \exp\left(-\frac{1}{2}\left(\frac{t-\alpha_i^{(j)}}{\sigma}\right)^2\right)$$

with

$$\alpha_1^{(j)} = jB, \quad \alpha_2^{(j)} = (j+1/2)B,$$

where B is some kind of of typical length of a lecture plus travel time. This above assumes that:

- the lectures in A and the buses in B are timed to be precisely out of phase.
- optimal spread by letting

  $$l_i(t) = \sum_{j=0}^{N} p \exp\left(-\frac{1}{2}\left(\frac{t-\lambda_i^{(j)}}{\sigma}\right)^2\right)$$

  with

  $$\lambda_1^{(j)} = (j+1/4)B, \quad \lambda_2^{(j)} = (j+3/4)B$$

  to have the ends of lectures (or arrivals of busses) optimally spaced out to not coincide with lectures or bus journey start times.

It remains to specify the demand functions of leaving and entering. For our simple example we can take

$$I_1 = Y_3 + l_1, \quad O_1 = X_3 + a_1$$
$$I_2 = Y_4 + l_2, \quad O_2 = X_4 + a_2$$

people want to arrive

$$I_3 = Y_1 + x_3, \quad I_4 = Y_2 + x_4$$

people want to leave

$$O_3 = X_1 + y_4, \quad O_4 = X_2 + y_3$$

8 ODE's. the dynamic variables are $x_i, y_i \quad i = 1 \dots 4$. Intermediate variables called X_i and Y_i, and we have four input functions of time $I_i(t)$ and $O_i(t)$ just for $i = 1, 2$. Parameters B, p, C, and σ.

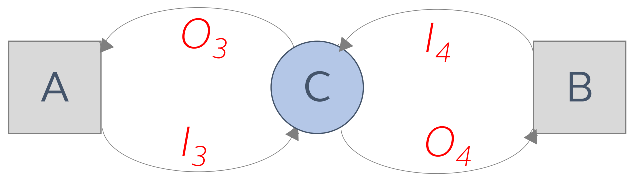


Figure 19: Simple model with labelled nodes.

We have also implemented a discrete event simulation version of the toy problem. First experiments show that staggering can have effects, but as they can be both positive and negative, it is important to simulate the specific situation of each Higher Education (HE) institution.

4 Community-level Topics

This section considers two problems to do with the interaction of universities with their surrounding communities in the context of Covid-19.

The first problem was about transmission of Covid-19 between university members and the surrounding community, exploring how this interconnectedness makes Covid-19 a corporate social responsibility issue for universities. The second problem considers transport for university students and staff, both from the point of view of modelling supply and demand and from the point of view of transport as a locus of viral transmission.

4.1 Understanding university contact networks, community contacts and infection monitoring

Covid-19 and Corporate Social Responsibility for Universities

Risk from Covid-19 increases dramatically with age, and the vast majority of UK fatalities have been of people over retirement age. A university could be the location of a substantial outbreak with relatively few serious cases and perhaps no fatalities among university members. However, there is essentially no chance of containing a large outbreak on a campus because university communities are strongly connected with their surrounding communities, even in the case of campus-based universities.

Although universities have a legal health and safety duty to their students and staff, they surely have an equally important corporate social responsibility to their surrounding communities. This responsibility is to limit the probability of hosting a large outbreak which then spreads to a fatal outbreak in the host community. There is an implied responsibility to work to understand this probability and how it is affected by the control and testing measures that the university takes, both through modelling and data collection.

At the VSG we explored this issue through

- surveying some relevant models in the literature,
- gathering relevant statistics from public sources,
- conducting interviews with several university planners and a former student union president, and

- building a simple mathematical model to study how quickly outbreaks within a university will spread to their surrounding communities, and how this depends on sizes of social bubbles.

Universities as potential propagation hubs.

Universities are large, complex systems with many people present, often together in large groups and in close proximity. Thus, the chance of a Covid-19 outbreak within a university is of serious concern.

The UK has already experienced numerous Covid-19 outbreaks in the care home sector. This was devastating for the residents, and also produced some "disease leakage" back into society. Since care home residents tend not to leave their homes very often, it was easy to think that each care home could be considered as a closed system. However, due to care home staff having contacts outside of their workplaces, agency staff working at multiple care homes, and recovering infected cases being moved from hospitals to care homes, this assumption was sadly very far from true in practice.

Universities are structured very differently. In particular, a single university is much larger than a care home, and almost all university members will enter and leave the university each day. They will need to travel to, and from, university, sharing transport methods with the general population, as well as visiting shops and other public places. On public transport university members may be enclosed in close proximity with members of the public for prolonged periods, thus giving a significant opportunity for Covid-19 transmission, should anyone be infectious.

Within the student population under ordinary circumstances there are many opportunities for viral superspreading events at social events and at teaching events, and these types of contacts are not in aligned cohorts. It appears from early serology testing results that young people in the age groups accounting for the majority of students may be more likely to be asymptomatic or to experience only mild symptoms: although a similar or even larger proportion of 10-30 years olds have been infected to other age groups (see ONS infection survey data [8], they are much less likely to have reported illness or to have tested positive [14]. A new chain of infection seeded into a hall of residence could potentially survive for several generations without causing any reported symptomatic cases. Thus in the absence of randomized testing a large outbreak could quickly arise within a university before the university leadership becomes aware of it and can take action to suppress contacts.

Meanwhile, the risk from such outbreaks, while having an impact on vulnerable members of the university community, is mostly borne by vulnerable members of the surrounding community, particularly those over the standard retirement age. Some statistics illustrating who bears the risk are given in the section "Differential impact of epidemic by age group" below.

Any reasonably large outbreak inside a university would lead to an outbreak in the surrounding community, and it is likely that the great majority of serious cases and fatalities would not be among university members, even if university members accounted for the majority of total cases. Fixing a particular size of outbreak within the university, we might expect the total outbreak size in the surrounding community to be related to the number of cases outside the university that it seeds. The timing of an outbreak is unpredictable. Shared transport, shared use of shops and food outlets, faith groups, and staff households may be the key transmission opportunities between university members and the surrounding community, so it will be worthwhile to take steps to minimize these interactions where possible. An existing example is dividing supermarket opening hours into periods during which only vulnerable and elderly people may shop, and general opening hours. The hours could be further separated by asking university students to shop only after 2pm, say.

In short: not only may universities become outbreak hubs of Covid-19, but they are also likely to propagate any outbreaks to the wider community, which bears the majority of the risk.

The importance of good communication

- Effective communications could increase the number of people following the guidelines in place. It has been reported widely that less than 50% of under 30's are sticking to lockdown rules [15]
- Universities must be smart in incentivizing and normalizing Covid-safe behaviour among students and staff, especially when it comes to behaviour off-campus.

Initial schematic model of contacts involving university members

Some existing papers model contacts within large US universities, treated as isolated systems. We don't have contact matrices specific to UK university communities, but we can still draw a *schematic* contact network illustrating interactions that members of a university community have with each other and with members of the surrounding community, plus long-range interactions, e.g. from students travelling either for tourism or home to their family, and from staff going on holiday or to conferences. Many of these long-range interactions happen at predictable times, and we choose to assume for the time being that the risk of imported infection from any other countries that have a higher Covid-19 prevalence will be managed for the time being by government-mandated quarantine for arriving travellers.

Such a schematic diagram would be a useful starting-point for thinking about which kinds of contacts a university or a local community has control over and which are unavoidable. Universities should be mindful of the fact that through their operations they can introduce contacts that become unavoidable for the local community. An example schematic diagram is shown in Fig. 20. Categories of people are on the left, and activities where they interact on the right. Blue links are under the control of the university and green links are not. Notice that the links where students and staff are most likely to interact with people in vulnerable age categories are mostly green, e.g. transportation, shopping, healthcare and faith groups.

We could not find an empirical contact matrix from a university community. Is a university contact network more clustered than the general population? Could it be arranged so? Increased clustering could allow for more effective Test, Track & Trace (TTT), perhaps allowing isolation of contacts of contacts without quarantining a large proportion of the university community.

Known versus unknown contacts - this is an important distinction for effective contact tracing. Here extramural contacts occurring on public transport or in shops differ from contacts through social activity or faith groups. Unknown intramural contacts might occur on campus at food or retail outlets.

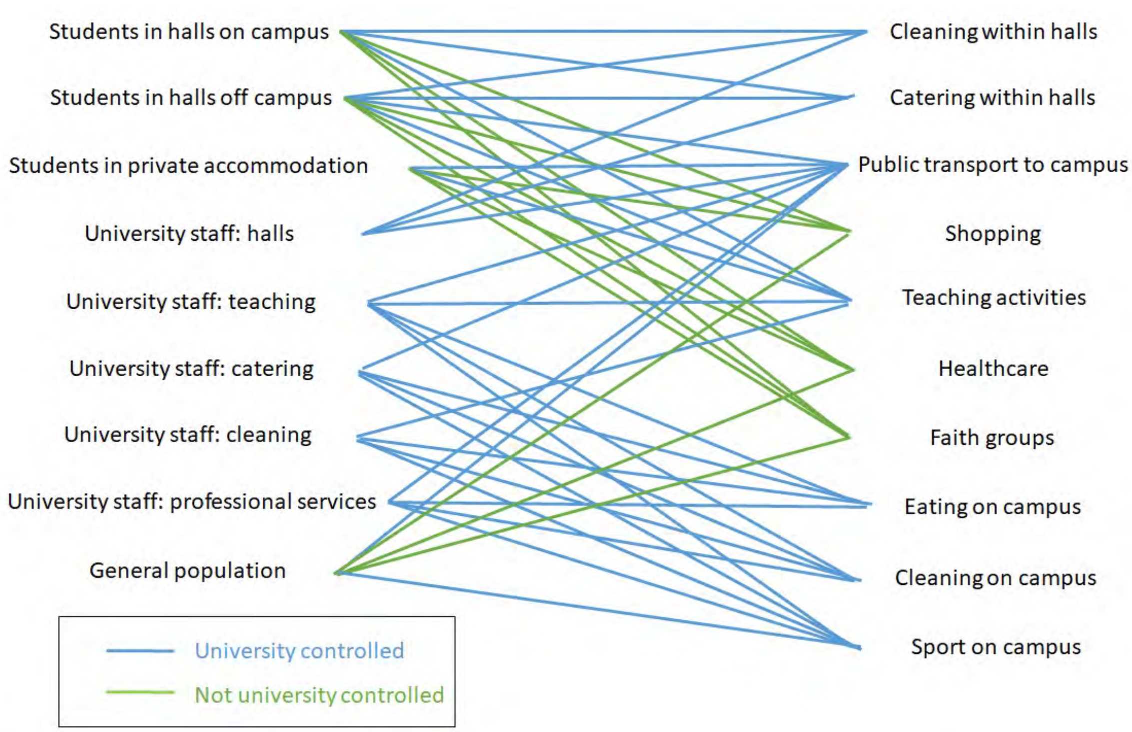


Figure 20: Schematic contact network

Monitoring infection - how quickly can university leaders know there's an outbreak?

How can university leaders and local healthcare systems become aware of campus outbreaks and respond to them quickly before they become large and spread to the surrounding community? How much testing does this require and how should this be targeted? Is it feasible? How should a university respond if there is an outbreak in its local area? Should universities do their own testing where possible? Modelling is required to answer these questions. A preprint addressing this problem by Gressman and Peck [16] is discussed in a later section.

The section below on in-house testing considers one way in which universities can act to reduce the probability of a large outbreak on campus.

Data about university sizes and student and staff characteristics

Higher Education Statistics Agency (HESA) data on staff and student numbers:

- Broken down by job type, sex [3]
- Ages of Academic staff per department [4]
- University student numbers by university [5]
- The HESA figures say that in 2017/18 there were 2.34 million students in HE in the UK (77 % undergraduate, 13 % taught masters, 10 % other postgraduate). 16 % of the undergraduates and 53 % of the postgraduates were overseas students. There were 211,000 academic staff and 217,000 non-academic staff employed in UK universities. 19 % of academic staff and 16 % of non-academic staff were aged 56 or over. 3.5 % of academic staff and 1.4 % of non-academic staff were aged 66 or over.

A socially structured model for SARS-CoV-2 transmission on campus including community seeding

We consider a stochastic SEIR model for transmission of SARS-CoV-2 for a given scenario and assumptions. All hosts are initially susceptible (*S*). Exposed hosts (*E*) become infectious (*I*)after a latent period and recovery. Distributions of times to infectiousness and recovery are assumed to be lognormal and gamma distributed respectively, in line with recent data on SARS-CoV-2 transmission dynamics [24]. We adopt a model that captures some of the social structures that govern transmission between n_C staff and

[3] https://www.hesa.ac.uk/news/24-01-2019/sb253-higher-education-staff-statistics
[4] https://www.hesa.ac.uk/data-and-analysis/staff/table-21
[5] https://www.hesa.ac.uk/news/17-01-2019/sb252-higher-education-student-statistics/location

students on campus and their households; assuming that hosts mix in households in groups (see below) and randomly within the community. We assume that all hosts are initially susceptible and simulate epidemic trajectories using the Gillespie algorithm. Incorporating up-to-date estimates of the proportion already immunised via infection from serology reports would be possible.

We assume that everyone regularly on campus is part of a household. A fraction of (students) live only with other students. The size distribution of these households may depend on both the accommodation infrastructure and University guidelines for interaction within halls (for example, asking students to form households within a corridor). For simplicity we assume that the remaining members of the University are the only member of their household that attends the University, and they have a household size distribution approximately governed by 2011 UK Census data [?]. The force of infection on host j due to infections within its household of size n_h is given by $\lambda_H \Sigma_{i,i\neq j}^{n_H} I_i$.

For demonstrative purposes only, we assume that members of the University mix in randomly assigned groups of approximate size n_G. Mixing within the group is chosen to be frequency dependent with force of infection of individual j in a group of size n_G given by $\lambda_G \Sigma_{i=1,i\neq j}^{n_G} I_i/n_G$. We expect that group size and clustering may have a large impact on rate of transmission within a University. Groups could be defined based on building use, transport use, and/or social contacts. Social contact groups could be as small as the 'bubbles' under consideration in some contexts or as large as year levels. Building level groups could be tailored to capture expected usage and any cohorting or 'firebreak' principles being implemented within a building. Data on student and staff accommodation, building use, transport use, and social contacts on campus could be used to inform staff/student membership of different social or close-contact groups on campus. Scenario analyses with such a model could inform the potential benefit of strategies for reducing mixing on campus on the size of newly detected outbreaks on campus and, for e.g., the number of infections already seeded into the community when an outbreak on campus is detected. Use of randomized testing for detection of an outbreak on a campus is discussed below.

Finally we assume the force of infection has a term due to random mixing between all members on campus $\lambda_C \Sigma_{i,i\neq j}^{n_C} I_i/n_C$. This term could be interpreted as akin to the 'untraceable' contacts modelled by Gressman & Peck [16] and / or transmission via fomites outside of group or household settings. The representative value of λ_C could be influenced by social distancing measures including ensuring that campus facilities are operating within the capacity that allows for this.

As a toy example, we simulate this model in a University with 25,000 members, of which 30 per cent live on campus or in accommodation with other members of the University.

We have assumed $\lambda_H = 0.3$, $\lambda_G = 0.1$ and $\lambda_C = 0.05$, and infection is seeded by a single exposed host (Fig. 21).

The threshold number of cases for detection on campus is unknown, and could be high given many young adults experience asymptomatic infections [25]. We expect that group size the parameters $\lambda_H, \lambda_G, \lambda_C$ may influence the number of cases in the non-University household members, and the time-elapsed, prior to an outbreak reaching the threshold for detection. Below we show the number of seeded cases at detection (left panels), and the time until detection (right panels), as a function of the detection threshold (in terms of an absolute number of cases on campus) for models with different approximate group sizes (Fig. 22) and strength of community mixing (Fig. 23).

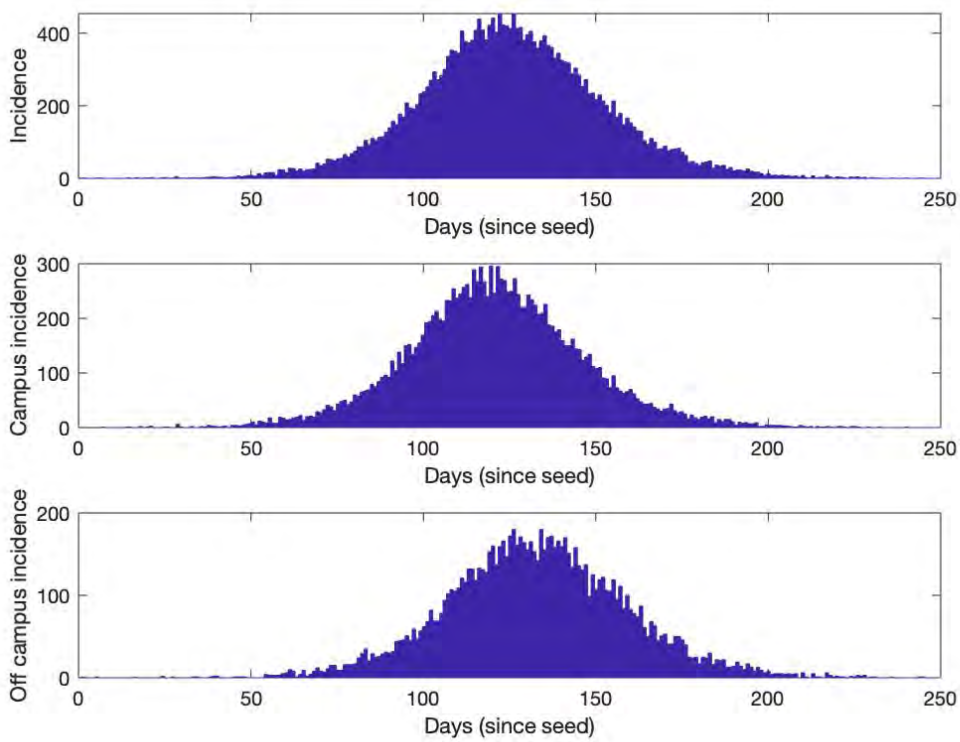


Figure 21: Realisation of epidemic in households of 25,000 University members according to our model. Daily incidence for all University households (top panel), University members (middle panel), and non-University members (lower panel). Note that the outbreak in non-University household members peaks after that of University members, and has a lower overall attack rate (44 per cent compared to 62 per cent), which is unsurprising given we ignore other sources of infection for these hosts.

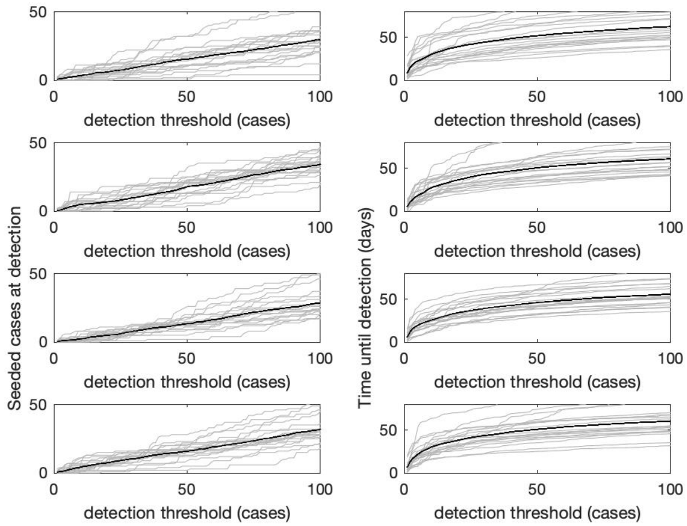


Figure 22: Cases in non-University household members (left panels) and duration of outbreak (right panels) as a function of detection threshold according to our model. Results for stochastic realisations (grey) with mean (black) for approximate group sizes varying from 5 (top panel), 10, 20, 50 (bottom panel). Note we have selected stochastic realisations which yield sizable outbreaks. Results may vary with population size and different prescriptions for mixing within a group.

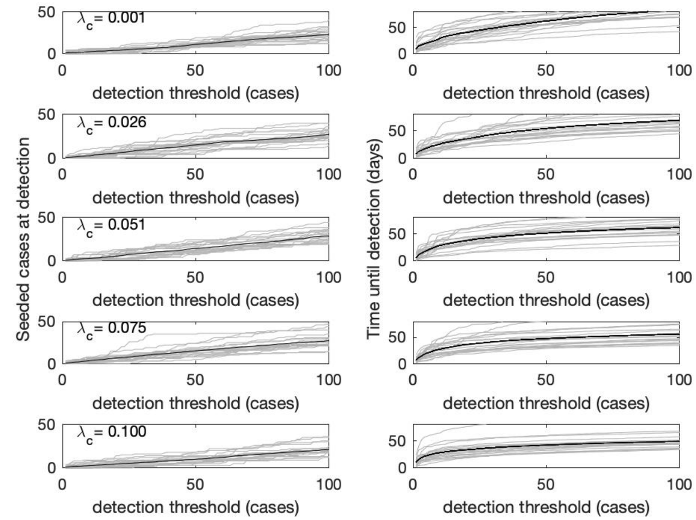


Figure 23: Results for stochastic realisations (grey) with mean (black) for average group size of 5 and community level mixing λ_C varying between 0.001 and 0.1 as indicated in the legend.

In our toy model, the proportion of cases in non-University members at detection does not vary significantly with group size n_G or the strength of community mixing λ_C. This may be because we have assumed that transmission probability is much larger amongst household members and there is significant community mixing. Indeed larger values of λ_C correspond to more rapid outbreaks which could influence ability to react / contain these in a timely manner. Results are likely sensitive to choices of $\lambda_C, \lambda_G, \lambda_H$ and the choice of group membership. Further exploration is warranted to explore the impact of mixing on campus on outbreak size and community impact.

We could / should also include a background rate of infection in the surrounding administrative region. This is particularly important for capturing the other sources of infection for household members that are not University members. It may be worth having multi-level background infection rates that depend on the nature of student's part time jobs and the occupations of non-University household members in the model, particularly given observations that infection-rates vary widely depending on the nature of a workplace [28].

Parameters of this model could be tuned as new information about the disease dynamics emerges. For example, analyses of contact tracing data have recently provided estimates of the relative risk of transmission for household and non-household contacts [26]. While we do not know how quickly SARS-CoV-2 would spread unmitigated within a University, we could compare estimates of the population level reproduction

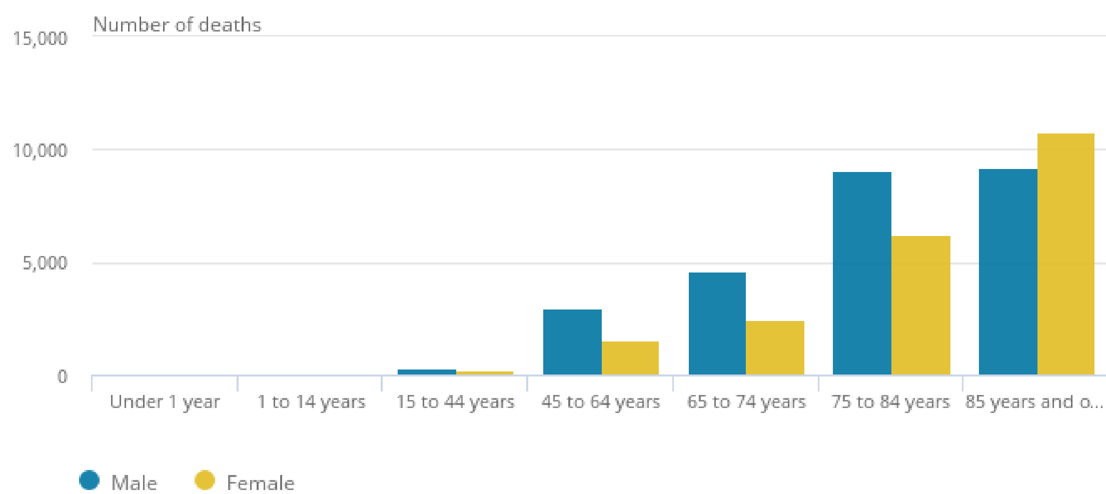


Figure 24: The number of deaths involving Covid-19 was highest in makes across the majority of age groups. Deaths involving Covid-19 registered in Week 1 and Week 23 of 2020 by sex and age group. England and Wales [29].

number $\mathcal{R}$ for SARS-CoV-2 with the reproduction number for a population with this mixing structure [27].

It may be desirable to couple a model for campus transmission with a dynamical model of the outbreak in the surrounding administrative region. This would enable tailored assessment of the risks seeding from the University to the community and vice versa. Extensions to the model could also consider age-structure which would allow estimates of the health burden of outbreaks within, and externally to, the University as a result of a University's activity. The impact of other principles discussed in the previous VSG such as the "poorly-exclusion" mode of working, that may have differential impact on campus and community transmission could also be considered within such a framework.

Differential impact of epidemic by age group

The differential impact of Covid-19 by age group in England and Wales is clearly illustrated in this dynamic ONS page [29], and shown in Fig. 24.

The demographic characteristics of a typical university are likely very different than those of its surrounding community, and this will lead to differential impacts of an epidemic on the university and wider communities.

As an example, consider the impact of age demographics in Southampton, Table. 4.

Table 4: Southampton age demographics

Age (years)	Percentage of population [30], P	Infection fatality rate [31], I	Deaths per 1000 total infected people if infection risk were independent of age, 1000*PI
0-9	12.27%	0.00161%	0.00
10-19	11.53%	0.00695%	0.01
20-29	22.80%	0.0309%	0.07
30-39	13.93%	0.0844%	0.12
40-49	10.96%	0.161%	0.18
50-59	10.69%	0.595%	0.64
60-69	8.12%	1.93%	1.57
70-79	5.98%	4.28%	2.56
80+	3.71%	7.80%	2.89

We can begin to grasp the potential for differential impacts of an outbreak on the university community and on the wider community by looking at the ratio between deaths in the 10-29 or 20-29 age groups and those in the 30+ age group:

- Deaths in 30+ age group : deaths in 10-29 age group = 101:1
- Deaths in 30+ age group : deaths in 20-29 age group = 113:1

In practice infection risk would not be independent of age, owing to varying contact patterns between and within age groups, different risks of contracting Covid-19 by age, and many other factors. More detailed modelling would be needed to understand the impact of an epidemic on campus on the wider community.

Benefits of in-house testing

Firth *et al* [32], full reference below) models the proportion of the population typically in isolation at any time due to contact tracing. Would tracing and quarantining contacts of contacts lead to such a high proportion quarantined within a university community (i.e 1/3 of the community at any one time if contacts of contacts are quarantined)? One issue is that some people inevitably have a lot of contacts due to their roles, (e.g. porters, security staff) and these people are likely to be made to self-isolate frequently. How does the number of people in quarantine depend on the local prevalence of infection (presumably linearly, for the range we are interested in) and how does it depend on the turnaround time for testing? One reason for universities to do their own in-house testing is to get much reduced turnaround times, with two potential benefits:

- faster release from quarantine for contacts of negative cases (depending on sensitivity of test over time, tests may not be sensitive very early in infection or later on when less replication in upper respiratory tract.)
- option of testing 1st generation contacts of positive cases, rather than simply enforcing 14-day isolation.

Another reason for universities to do their own testing would be to give university management the ability to know quickly about an outbreak on site and respond to reduce transmission until the outbreak is controlled.

Work on bubbles in group 2 indicated that screening would need to be frequent to control transmission. Informal communication from Carl Bergstrom (University of Washington) suggests that batch testing of the whole university community twice a week would be necessary to prevent outbreaks for a particular US university. This information should be revisited when a preprint is available to assess its relevance to UK universities.

Some existing literature relevant to modelling university contacts

1. *Simulating Covid-19 in a University Environment* [16]: Stochastic agent-based model of classes at a university (treated as an isolated system). Studies required rates of randomized testing, tracing and quarantining, as well as lecture sizes. They model a typical large US research university (liberal arts system, in which students enrol separately for many small courses, not possible to separate students by subject, unlike a typical UK university). But joint honours courses still make this kind of separation difficult in most UK universities.

   > *It is extremely important that students refrain from all contact outside of academic and residential settings.*

   This seems directly at odds with what was said in the initial study group presentation by Amanda Chetwynd (former pro-VC for student experience, Lancaster), about the *central importance of social networks to students' experience of university as their home.*

   Gressman and Peck's study did not model a range of parameters for Covid-19. They assumed 3 % of the university community is tested at random each day but assume a great reduction in contacts compared with normal university life. They write in detail about the false positive rate and its effect on the number of unnecessarily quarantined individuals. They assume 75 % of infections are asymptomatic and asymptomatic infections are half as likely to transmit. Estimates of the benefits of interventions based on identifying symptomatic individuals could be sensitive to these assumptions.

2. *A new method of exercising pandemic preparedness through an interactive simulation and visualization* [17]. The paper is based on a US university and describes a table-top exercise for decision-makers to take part in that uses a simulation model to show how their interventions affect disease spread, etc. This is an interesting way for mathematical modellers to assist university leaders, which could also be useful at UK universities.

3. *The effectiveness of social bubbles as part of a Covid-19 lockdown exit strategy, a modelling study* [18]. Looks at the effect on R of allowing two-household bubbles in a fairly locked-down scenario. Possibly not very relevant to our problem? But it looks as though it informed the recent rule change in the UK allowing people who live alone to form a bubble with another household.

4. *Modelling testing frequencies required for early detection of a SARS-CoV-2 outbreak on a university campus* [19]. An SEIR model with varying: testing regimes combining symptomatic and asymptomatic; transmission rates; rates of presentation to health services; rates of immunity. They find high rates of background screening are typically necessary, but high rates of presentation of symptomatic people at health services can compensate in part. This model does not include contact tracing.

5. *Effectiveness of isolation, testing, contact tracing and physical distancing on reducing transmission of SARS-CoV-2 in different settings* [20]. Looks at the effect of isolation, testing and tracing, social distancing on transmission rates. Uses the BBC Pandemic Haslemere data set. Finds testing and tracing approaches combined with other measures are most effective. Estimates that 10,000 new symptomatic cases per day implies 140,000-390,000 contacts newly quarantined per day.

6. *Combining fine-scale social contact data with epidemic modelling reveals interactions between contact tracing, quarantine, testing and physical distancing for controlling Covid-19* [32]. Investigates the interaction of disease dynamics with testing and tracing, using the BBC Pandemic Haslemere dataset. Found that tracing contacts of contacts reduced size of outbreaks, but one third of the population quarantined simultaneously.

7. *Mathematical modeling of the spread of the coronavirus disease 2019 (COVID-19) taking into account the undetected infections. The case of China* [21]. This discusses the development of a model for the local spread of Covid-19. This is based on research and tracing in China. Their keys aims are to: estimate cases, considering different scenarios, deaths and the number of beds needed. They produce a θ-Susceptible, Exposed, Infected, Hospitalised, Recovered, Dead (SEIHRD) which is based on Be-CoDiS. This model was initially used to model, successfully, Ebola in the Democratic Republic of Congo in the years 2014-2016 and 2018-20. They provide a useful link for epidemic modelling [6]. Many assumptions are made on page 3. To solve these they use a Runge-Kutta method.

8. *The small-world network of college classes: implications for epidemic spread on a University campus* [22]. Constructs networks based on subject enrollment. Suggest that students *are connected through multiple independent paths* and both large (> 100) and medium classes need to be taken online to reduce connectivity of student population.

9. *Epidemic Spreading on Preferred Degree Adaptive Networks* [23]. Study the standard SIS model of epidemic spreading on networks where individuals have a fluc-

[6] `https://www.ucm.es/momat/epidemics`

tuating number of connections around a preferred degree κ. They let κ depend on the fraction of infected individuals, they model the behavioural adaptations in response to epidemics. They model *Reckless*, *Typical* and *Nosophobia* behavioural patterns, whereby we have individuals who are oblivious, cautious and avoiding all contacts. They go on to discuss the *Blind and Selective Adaptation* whereby a person does not know if their contact is infected. Their results include a 'fear factor'.

10. *Age-dependent effects in the transmission and control of COVID-19 epidemics* [14]

    > *We find that those aged under 20 years are roughly half as susceptible to infection as those over 20 years of age, and that 79% of infections are asymptomatic or paucisymptomatic (that is, subclinical) in 10- to 19-year-olds, compared with 31% in those over 70 years of age.*

11. Interesting Carl Bergstrom Tweet thread on university testing [7]. Includes a link to a paper not available from the EU, with screenshot [8] that describes outcomes after quarantining of 640 new US Army recruits: despite isolation of 4 initial cases, 22 % were infected after 22 days. Perhaps a military bootcamp has relevant similarities with a 1st year university intake.

4.2 University Transport

This section still needs significant editing to extract the key points from the interviews.

The transport problem for universities

Many UK universities rely on public or university buses, trams or trains to get a large proportion of people on and off site every day. This causes several problems in the context of Covid-19:

- Public transport presents a big source of opportunities for infection between members of the university community and the surrounding community. Both airborne and surface transmission must be considered.
- Public or university-specific bus, tram and rail transport demand has to be reduced, the number of services increased, or both, in order that the existing services can meet demand with 25-30% of the seats occupied.

7 https://twitter.com/CT_Bergstrom/status/1272310035016605697?s=20
8 https://twitter.com/CT_Bergstrom/status/1272310662773915648/photo/1

- Car-sharing may not be possible for most staff due to social distancing requirements. This could cause problems for car park capacity at sites where too few staff can work at home.
- Individuals in vulnerable categories who would normally travel to campus by public transport may have to find alternative modes of transport.

The transport problem for students is quite different from the transport problem for staff, but they overlap. The severity of the transport problem under Covid-19 varies greatly between universities.

We did not conduct mathematical modelling of the transport problem during the study group, but rather conducted a scoping exercise. We learned that transport capacity is already fairly well estimated, but that there is an urgent need for simple predictive modelling of how transport demand depends on the choices that universities are currently making about their on-campus activities in the coming year, particularly the teaching timetable.

Modelling objectives

It is valuable to propose solutions or frameworks to universities of what might work. But it would also be useful to explain what won't work. It's important that universities understand what the consequences of certain strategies may be, and who would be affected. Well in advance of the 2020/21 academic year it is valuable to be able to model transport supply and demand for individual routes to within say 10% error in order to know whether a university's teaching and operating plan is incompatible with its transport constraints. Demand modelling is also important where a university relies on a city public transport system, in order that the university can communicate its predicted demand to the local transport authority.

Modelling capacity: What needs to be done to model capacity under various social distancing measures? Should we simply assume that the frequency of services cannot be increased and the capacity is therefore cut by a factor equal to the average occupancy allowed by social distancing? This is the approach being taken by the transport planner we spoke to from the University of Warwick.

How much is it possible to increase service frequency beyond 2019 levels? Presumably in some places the answer is not at all, e.g. on the London Underground. We learned in an interview that bus services may be increased somewhat by moving vehicles and drivers from currently under-used leisure services. Thus universities with university-specific bus services could in principle spend more to increase their transport service capacity.

We did not explore the financial viability of providing transport services at 25% capacity; this is likely to need substantial subsidy either from local or national government or from the universities since users will not tolerate a four-fold increase in cost per journey.

Modelling and modifying demand: Can we model staff and student transport demand based only on simple data about expected total on-campus hours for different types of university members? Obviously this is insufficient information, but maybe it is sufficient for an estimate within a reasonable margin of error, say 10%.

How can transport demand be reduced and spread out by good scheduling of on-campus activities? Is it feasible to reduce each undergraduate student's attendance on campus to 1 or 2 days per week? What about staff and postgraduate students? It is very subject-dependent whether it is reasonable to expect them to do a significant proportion of their work at home. Lab-based staff cannot be expected to work at home as much as many desk-based staff who can make a lot of their meetings virtual. Many security, estates, maintenance and cleaning staff have inflexible campus attendance requirements. Cleaning staff hours may be longer than in previous years due to Covid-19 so they may use transport at different times than expected.

Waiting for public transport as a congestion point: Queueing for public transport is a potential bottleneck on campus or at halls of residence, especially when it is raining and people want to use shelters! Waiting rooms are small enclosed spaces which probably have to remain closed. Reliable real-time transport prediction is valuable here, since it enables people to wait elsewhere until shortly before a bus or train arrives.

Large crowds or queues tend to occur when the bus service is delayed or operating less well than on a typical day. Since this will inevitably happen sometimes, it is important to plan how social distancing can be maintained in this situation.

Conflict / competition: What impact does the return of university students have on public transport systems? If demand exceeds capacity what are the implications? There is potential for conflict between universities and their surrounding communities if there is insufficient total capacity.

Potential problems affecting transport demand:

- Staff/Students might not have good enough internet to give/attend lectures online. For example Edinburgh has very limited 5G and fibre in the city - it is still be rolled out fully. This could increase the need for students and staff to commute more to campus.

- Studying together in university study spaces can be important in providing motivation for studying and this may give students incentive to be on campus even when they don't need to be according to their timetables.

Modelling has to be location-specific

In follow-up work it might be valuable to model three different basic scenarios:

- Universities that are centrally based in a town/city, where the university members are heavily integrated into the local public transport network, sharing buses, trams, paths, etc. with the non-university public. Universities that are based far away from towns/cities, where most public transport useage is university-specific or university-run. Hybrids of the above two.

In a later section we consider the general transport requirements at a number of different UK universities, to illustrate the wide variation in the transport problems that they face in adapting to Covid-19.

Example: travel survey data from the University of Bristol

The University of Bristol has conducted staff and student travel surveys every two years since 1998[9]. The analyses of these surveys contain a wealth of data which will be used to help predict staff and student transport response to Covid-19 restrictions on public transport and the new mode of operation of the university.

In the latest surveys (2018), walking was by far the most popular mode of travel for students, accounting for 56% of student trips and 30% of staff trips. Cycling accounted for 8% of student trips and 16% of staff trips. These modes will not be affected much by Covid-19 restrictions. Bus and train together accounted for 21% of trips both for staff and for students. Both capacity and demand will be reduced next year for bus and train journeys, and modelling is required.

Multi-occupant car journeys accounted for 6% of staff trips and 3% of student trips, while single occupant car journeys accounted for 18% of staff trips and 3% of student trips. Car parking is a major constraint at the University of Bristol and managing the car parking equitably will need to take account of staff in vulnerable categories who can no longer use public transport. The number of university-owned spaces is very difficult to increase and on-street parking in the area around the main campus is in high demand by the surrounding residential and business community, regulated by time-limited meter parking and council-run parking permit schemes.

[9] http://www.bristol.ac.uk/transportplan/surveys/

Many students take the university-tailored public bus services U1 and U2, or other public bus services from halls of residence to campus for convenience. (27 % of student in the 2018 survey held an annual pass for these services). The bus service for students has improved significantly in recent years and this is reflected in the travel survey data. But the distance from halls to campus is in fact walkable for most of those students. Demand therefore varies with weather. The bus service also makes it reasonable for students living in halls to make more than one trip to campus during a day. 70% of students responding to the survey did not live in university allocated accommodation, but more than half of those lived in main postcode areas within reasonable walking distance of campus. These factors make demand under Covid-19 restrictions difficult to predict. In circumstances of relatively high Covid-19 prevalence where the danger of transmission on buses outweighs the convenience, the most reasonable option may be to suspend these services. Both U1 and U2 and the majority of public bus services in Bristol are provided by FirstBus and the transport planning office liaises closely with them.

Similar travel surveys at other universities

- The analysis of the University of Edinburgh's 2017 survey has lots of detail, at a similar level to the Bristol survey discussed above. The overall mode share for the Central area is strikingly similar to the 2018 Bristol mode share, but Edinburgh has the complication of having both city centre and suburban campuses [10]
- University of Southampton. Some survey data about overall travel mode share is presented on page 7 of the full transport plan [11]

Data on capacity of public transport prior to Covid-19

- StationPassengerLinkFlows.csv shows the number of people on the London Underground every 15 minutes per line [12]
- Percentage capacity of the London Underground per line. The data is at the bottom of the page [13]

The National Public Transport Data Repository (NPTDR)[14] is a snapshot of route and timetable data for all public transport services in the UK for a particular October week

10 https://www.ed.ac.uk/files/atoms/files/2017_staff_and_student_travel_survey.pdf

11 https://www.southampton.ac.uk/transport/our-travel-plan.page

12 http://crowding.data.tfl.gov.uk/

13 https://www.london.gov.uk/questions/2019/19838

14 http://data.gov.uk/dataset/nptdr

from 2004 to 2011. To achieve consistency, this week is chosen in order to ensure that the database avoids school holidays or seasonal variations.

The database classifies divides the country in 11 traveline regions such as East Anglia, Yorkshire, Scotland and London, to name a few. National coach and train information is also available, although this information could be less relevant for the current analysis. Note that files can be large (in the order of Gigabytes). Opening and processing them might impose limits on computer power and memory.

A detailed exploratory analysis would be required in order to determine whether we extract relevant data for university-related transport.

Data on capacity of public transport under social distancing

- Public Transport Operations After Lockdown: How to Make It Happen? [15]
- Reduction of public transport capacity to 10 % owing to social distancing (Grant Shapps)[16]
- Scottish transport transition plan indicates 10 %-25 % capacity[17]

Open data

Some cities have open data agreements, e.g. Bristol has a transport API which is used by a variety of users, include apps that provide real-time bus predictions.

Examples of transport needs at UK universities

Transport varies greatly from one university to another. Examples familiar to members of the study group:

- London Universities: staff and most students in years 2,3,4 live far from campus and use public transport, mixing with the general public. Can scheduling help most of them to avoid peak times and to travel on fewer days?
- Newcastle - a city centre university; students and staff are responsible for their own transport, no parking. Does this mean that transport is not the university's problem? Probably not - see "conflict/competition" above.

15 https://link.springer.com/article/10.1007/s41403-020-00121-x (Table 1 has capacities according to social distancing requirement.) (This paper is a case study of routes in Delhi, using.)

16 https://www.bbc.co.uk/news/av/uk-52602227/coronavirus-social-distancing-cuts-public-transport-passenger-capacity-by-90

17 https://www.transport.gov.scot/coronavirus-covid-19/transport-transition-plan/

- University of the West of England has two widely separated campuses in Bristol. Students and staff mostly use the public metrobus service that links them through the city centre. Not much staff parking; lots of staff cycle. 50% face to face teaching in 1st year is planned for 2020/21 but most 1st year students live on campus. Later years will have most teaching online so student transport demand will be much reduced compared with normal operation. Some privately owned and managed accommodation blocks are occupied by students from both UWE and the University of Bristol.

- University of Edinburgh - two campuses. City centre and King's buildings a few miles away. Some students and staff have to move between the two campuses; the university provides a dedicated shuttle bus (only for students and staff) in addition to the public buses. Some locations shared with Heriot-Watt. University of Edinburgh has one dedicated bus between the central campus and the King's buildings - this runs roughly every 30 minutes. Outside of this most students use standard Lothian buses or cycle. Heriot-Watt is supplied by Lothian Buses also - the lectures there are scheduled compatibly with the bus timetable.

- Lancaster University: a campus where many students live, not too far from the town centre but with ample parking for staff. They may have one of the easiest transport adaptations to Covid-19. University of Essex main campus (Colchester) is similar.

- Warwick - via interviews

- University of Bath is on a campus where first year students live. It is separated from the city where most other students live by a formidable hill, so it will be difficult to encourage more cycling or walking. But there is plenty of space for installing extra bicycle storage facilities. Most students and many staff rely on the frequent bus service from the city centre.

- University of Bristol - see case study above.

- University of Southampton - similar situation to University of Bristol. The university bus service (Unilink) is open to the general public. It connects the university with halls, train stations, airport, hospital and other parts of the city. Usage is dominated by students on certain routes at certain times in term time, but is more mixed at other times. Staff also use buses, including as last leg of a train journey. Southampton has two main train stations and various other smaller ones, and has a regional airport. Buses are needed to connect different campuses within Southampton (Oceanography, Winchester School of Art, Hospital) but also halls, which are fairly widely spread across the city.

- Collegiate universities: Cambridge, Oxford, Durham. Most students live in halls, most walk or cycle. Most traffic is barred from the city centres. Relatively low use by students of public transport. These cities have other issues - in normal circumstances they are very busy with tourists, mainly international. Anglia Ruskin in Cambridge and Oxford Brookes are located outside of the city centres and rely more on privately rented accommodation and public transport.
- University of Nottingham. Many students live on or near to campus but many use public transport including buses that specifically service the University. There is also a tram service with the city's largest hospital at the adjacent stop.
- Aberystwyth University students use Mid Wales Travel buses bu

5 List of Acronyms

BAME Black, Asian, and Minority Ethnic

HE Higher Education

HESA Higher Education Statistics Agency

NPTDR National Public Transport Data Repository

ODE Ordinary Differential Equation

ONS Office for National Statistics

PDE Partial Differential Equation

RAMP Rapid Assistance in Modelling the Pandemic

SEIHRD Susceptible, Exposed, Infected, Hospitalised, Recovered, Dead

SEIR Susceptible, Exposed, Infected, Recovered

SIR Susceptible, Infected, Recovered

TTT Test, Track & Trace

V-KEMS Virtual Forum for Knowledge Exchange in the Mathematical Sciences

VSG Virtual Study Group

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