Analysis of COVID-19 Mitigation Measures on a Small Liberal Arts College Network

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***Abstract*—Small, liberal arts colleges are known to have close campus communities with strong relationships between professors and students. In this paper we consider the person-to-group and related person-to-person network at one of these institutions using student and faculty data from Fall 2019 courses, athletics, ensembles, housing, and student organizations. This data is used as a baseline to model the Fall 2020 semester with the college's COVID-19 mitigation strategies: cancel or virtualize some groups, split the semester into two independent sessions, and separate larger courses into hybrid meetings. Network analysis shows that students and faculty had at most 4 degrees of separation in Fall 2019, student organizations can have a large impact on campus connectedness, all semester modifications implemented in Fall 2020 can reduce connectedness, and the largest reduction was seen by splitting the semester into two sessions.**

***Index Terms*—social network analysis, COVID-19, coronavirus, epidemics, higher education**

I. Introduction

During the Spring 2020 semester, the COVID-19 pandemic caused widespread state and local shut downs. Most colleges were forced to complete their Spring semester with rushed virtual offerings, and Randolph-Macon College, which begins its spring semester much later than most schools, spent the final 7.5 weeks of the semester online. As a small, liberal arts, residential school with almost 80% of students living on campus and intimate class sizes, this change caused significant disruption for both students and faculty.

As the pandemic continued through the summer with varying levels of closures and restrictions, schools at all levels of education began to grapple with the prospect of a very different semester for Fall 2020. Many schools decided to go all-virtual for the entire fall semester or to start out that way. Randolph-Macon decided to get students and faculty back on campus as much as possible, and made several important scheduling decisions to make that happen: simplify group offerings through cancellation or virtualization, reduce the number of active courses through two 7-week semester sessions, and separate many larger courses into two meetings with hybrid instruction. In this paper, we explore the effects of these changes to the network of students, faculty, and courses.

In [9], agent-based simulation modelled the spread of the novel coronavirus through interactions between students and faculty on campus. The authors found that testing, reducing large classes, eliminating student contact outside of campus, contact-tracing, and quarantine were important factors in reducing the spread of disease. Although the methods in this paper differ from those in [9], the results provide important additional policy considerations for any college evaluating in-person meetings.

Networks have been used to describe and understand the dissemination of money, ideas, or disease between people and groups for almost a century [2]. There has been particular interest in using network analysis in the area of public health to characterize the spread of disease as well as information and innovations [15] such as vaccinations, mask wearing, and other protocols. Network analysis has been found to to provide better understanding of disease transmission than epidemic theory alone [14] and has been used to study the spread of the H1N1 virus during the 2009 pandemic [4], [17].

Recent work has shown an increased interest in modeling the networks of university students and their connections through course enrollments. In [21], the student-to-course network and resulting student-to-student network was analyzed for Fall 2019 registration data at Cornell University. The authors considered the university as a whole, the undergraduate network, and their smaller liberal arts college in an effort to understand the potential spread of the novel coronavirus through their university. They also simulated the network with class size thresholds that would require a course to be taught virtually. A similar study was done in [13], on the 2019 Learning Analytics Data Architecture data set out of the University of Michigan, with a focus on how important certain courses are in creating connectivity between students.

We extend the work in [13] and [21] by considering our small, stand-alone liberal arts college and include faculty data, athletics, ensembles, housing, and student organizations to create a person-to-group network and related person-to-person network. We also simulate virtual and hybrid courses, and the result of splitting the semester into two 7-week sessions, the latter of which has a significant impact on the network analysis results.

We have four major takeaways from our analysis. 1. The R-MC network of students and faculty is small: in Fall 2019 there were at most 4 degrees of separation between every pair of persons (see Table II and Section III-C). 2. Student

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organizations can have a significant impact on how connected people are on campus, even more than housing (see Table II and Section III-C). 3. Semester modifications such as canceled or virtual offerings, using shorter semester sessions with fewer active courses, and creating hybrid meetings for some courses reduce the connectedness of the network (see Table IV and Section IV-A). 4. Splitting the semester into two shorter sessions can provide the largest reduction in how connected students are on campus (see Table IV and Section IV-A).

For an overview of the Fall 2019 Randolph-Macon College data, see Section II. The network analysis of the data can be found in Section III. The COVID-19 mitigation options Randolph-Macon pursued for Fall 2020 are simulated and analyzed in Section IV. Concluding remarks are given in Section V.

II. Data Overview

We used data from Fall 2019 as a baseline of what to expect if a normal semester were to take place in Fall 2020. An overview of the data can be seen in Table I. Student registration, faculty courses, and student housing data were obtained from the registrar's office. Intramural sport data was obtained from student sign-up sheets through the Director of Recreation and Wellness. Club sport, Greek organization, and other club data was obtained from the student organization portal through the Dean of Students. All data not received from the registrar is self-reported from students. We consider registrar data first, then include other sport and club data.

There were 1,534 students with 7,505 registrations, giving an average of 4.9 courses per student. These registrations include varsity athletic teams, music ensembles, and research courses. Of these registrations, 11 courses had no meetings with professors (mostly education fieldwork) and contained 72 students, leaving a total of 7,433 registrations for courses that meet with a professor.

For faculty, there were originally 592 listed courses. After considering courses that meet individually with professors, courses that do not meet with professors, multiple sections of a course that meet together, courses that had no registrations (typically research or capstone courses that are listed every semester but more likely to have registrations in the Spring), and courses listed with more than one professor, there were 505 uniquely meeting courses. For more information on how registration data was organized, see Section II-A.

Courses were divided into the categories lecture, lecture/lab, individual, ensemble, physical, and varsity. Varsity included all varsity sports and related courses, and physical courses were all other physical education courses. Ensemble courses included all performance ensemble courses in music, theatre, and debate. Individual courses are as described in Section II-A2, lecture/lab courses are all courses listed as a lecture/lab or lab by the registrar, and lecture courses are all remaining courses.

Housing data was divided into houses, dorm rooms, and off-campus. Houses include actual houses (such as Greek and International housing), town homes, apartments, and apartment-style dorms with in-suite bathrooms. All houses were treated as a single residence with contact between all occupants of the house, regardless of the number of bedrooms and bathrooms. For dormitories with community style bathrooms, each floor was treated as a single residence. For dormitories with suite-style rooms, each suite (one or two rooms and a bathroom) was treated as a single residence. Off-campus housing data for commuter students was unavailable, however almost 80% of registered students lived on campus in Fall 2019.

Students	
Number of Students	1534
Mean Courses per Student	4.9
Faculty	
Number of Faculty	196
Mean Courses per Faculty	2.6
Courses	
Number of Courses	505
Ensemble	7
Lecture	340
Lecture/Lab	45
Independent	78
Physical	23
Varsity	12
Mean Course Size	15.7
Largest Course Size	128
Largest non-Varsity Sport Course Size	32
Smallest Course Size	2
Residences	
Number of Residences	203
Mean Students per Residence	6.0
Student Organizations	
Number of Organizations	147
Intramural Sports	86
Greek	11
Club Sports	3
Honors Societies	10
Clubs	37
Persons in Organizations	972
Mean Organizations per Person	2.3

TABLE I
OVERVIEW OF FALL 2019 STUDENT REGISTRATIONS, FACULTY COURSE LOAD, STUDENT HOUSING, AND STUDENT ORGANIZATIONS AT RANDOLPH-MACON COLLEGE. COURSE DATA INCLUDES FACULTY IN SIZE NUMBERS.

After these considerations, there were 205 total residences with 1,223 students. Two suite-style rooms had only one occupant, and that data was excluded. This left 203 unique on-campus residences with 1,221 students.

Student organizations were divided into intramural sports, Greek organizations, club sports, honor societies, and clubs. We assumed organization advisors did not participate in organizations that required an advisor. However, some professors did participate in intramural sports, and that data was included. There were 10 staff members and outside family members who participated in intramural sports, but because our analysis does not track contact with staff or family members, we did not include that data.

Student organization data was limited to student-reported membership. We accounted for 147 organizations including intramural sports, Greek organizations, club sports, honor societies, and other clubs. For organizations that required a staff or faculty member as an advisor, we assumed that the advisor would not meet with the organization. There were, however, faculty and staff members who participated in intramural sports, and the faculty were included in the data. Overall, 966 students and 6 faculty participated in the organizations. Analysis did not consider intramural sport teams interacting with each other.

A. Registration Data

To organize registration data, courses were initially divided into courses that meet as groups, courses that meet individually, and courses that do not meet. Courses that meet as groups have direct contact between all students and the professor. Courses that meet individually have contact between the professor and each student, one at a time. These courses may be listed as a single course for registration, but were treated as separate courses for each student registered in our analysis. Courses that do not meet were removed from the data.

1) Group Courses: Courses that meet as groups fall into several distinct categories. We note that multiple sections of a course may meet at the same location and time for either lecture or lab, and those courses are considered the same course for the purpose of contact tracing. The group courses are: all courses that have a meeting date, time, and place set by the registrar (typical registrations); varsity sports; music ensembles; topics courses and seminars; independent studies; physical education courses; participation courses (debate, dramatics); and capstone courses listed or described as seminars.

2) Individual Courses: Courses that meet individually with the professor were divided into two categories: all music courses listed as private lessons (applied music); and all research courses not listed or described as a seminar (such as capstone, research, directed study, senior project).

All private lesson courses meet one-on-one with the professor, and a large majority of non-seminar research courses also meet individually with the professor. However, many of these courses allow for multiple registrations instead of providing a unique course listing for each student. For research courses in Fall 2019, there were 22 courses with a single student registered and 10 courses with two or three students registered, and likely most of the latter courses had one-to-one meetings with professors. For these reasons, we split these courses into individual sections for each student.

3) No Meeting Courses: Courses such as field studies, fieldwork, internships, and tutoring are considered to not have meetings among students and professors, and were excluded from the analysis. Some field studies or fieldwork may be led by professors, but these courses typically require work at off-campus institutions and do not create student or faculty contact, similar to internships. For tutoring courses, students register as tutors and have contact only with students who come to tutoring, however that data was unavailable, and so we excluded it from the analysis.

III. Data Network and Methods

Table II provides data from the analyzed small network of Randolph-Macon's course and group enrollments in Fall 2019. Two variations of the network were created, the 2-mode person-to-group network and the associated 1-mode person-person network. The first shows links between persons (students and faculty) and the groups they are in (courses, athletics, etc.), as seen in Figure 1, and the second network shows links between all individuals based on contact in their co-enrolled groups. Section III-A describes how these networks were created, Section III-B defines the values calculated in Table II, and Section III-C discusses the results.

A. Person-to-Group and Person-to-Person Networks

To begin looking at the data, we create a person-to-group network, or a 2-mode network [1], [3], [19] . Persons are either students or faculty and groups are courses, including athletics and ensembles for our data, and any other groups we consider: housing, intramural/club sports, Greek life, and other clubs. For the person-to-group network, persons and groups are the nodes and enrollments (from person to group and vice versa) are the edges.

This network can be represented by a matrix X with persons along the rows and groups along the columns. A 1 in a row and column pair indicates an enrollment for that person in that group, and a 0 shows no enrollment. A visualization of this network can be seen in Figure 1.

From the person-to-group network we can construct a person-to-person network, or a 1-mode network [3]. In the person-to-person network, all nodes represent persons and the edges represent co-enrollments in a group. The matrix for the person-to-person network P can be calculated by multiplying the person-to-group matrix by its transpose, $P = XX^T$. In matrix P, rows and columns represent every person in the same order, so each row and column pair provides the number of co-enrollments between two persons.

A binary person-to-person network is the person-to-person network where every value greater than 1 is converted to 1. This variation of the person-to-person network answers the question of whether two persons have contact through at least one group, whereas the original person-to-person network reveals how many groups are shared between each pair of persons. The matrix representing the binary person-to-person network, P' is the dichotomized P matrix.

Note that when calculating P and P', the matrix contains non-zero values along the diagonal, showing co-enrollments for each person with themself. These values are excluded from analysis (as described in Section III-B) and not shown in network diagrams.

Person-to-Group Network	Courses	+Housing	+Orgs
Persons in network	1730	1730	1730
Groups in network	505	708	855
Betweenness centrality	0.0014	0.0013	0.0012
Person-to-Person Network			
Mean co-enrollments	97.3	109.0	146.6
Mean unique co-enrollments	90.6	99.8	128.6
Number of unique edges	78354	86329	111275
Network density	0.052	0.058	0.074
Average clustering coefficient	0.344	0.338	0.340
Characteristic path length	2.095	2.065	1.999
Network diameter	4	4	4
k-step reach			
$k = 1$	0.0524	0.0577	0.0744
$k = 2$	0.8539	0.8786	0.9274
$k = 3$	0.9987	0.9989	0.9995
$k = 4$	1.0000	1.0000	1.0000

TABLE II
FALL 2019 NETOWRK DATA FOR COURSES (CLASSES, ATHLETICS, ENSEMBLES INCLUDING STUDENTS AND FACULTY), +HOUSING (COURSES AND HOUSING) AND +ORGS (COURSES, HOUSING, AND STUDENT ORGANIZATIONS).

B. Data Analysis Methods

Both persons and groups have the potential to be influential components of a network. For this reason, we calculate the betweenness centrality in the person-to-group network. The betweenness centrality of a node measures the sum of the proportion of all the shortest paths that pass through the node, normalized by the total number of node pairs [1], [6]. High betweenness centrality may indicate how influential or central a node is to the network or how likely a node will share information or contact between other nodes. The betweenness centrality of the graph is the average betweenness centrality of all nodes.

For the person-to-person network, mean co-enrollments is the average number of co-enrollments a person has within all of their groups. Co-enrollments are determined by the number of groups a person shares with each other person in the network. For example, if person A is in groups with only persons B, C, D, and E, and shares two groups with person B, three groups with person C, and only one group, each, with persons D and E, then person A has 7 co-enrollments.

For the binary person-to-person network, we look at mean unique co-enrollments which is the average number of people a person is in contact with throughout their groups. For unique co-enrollments, if person A is in groups with only persons B, C, D, and E, then person A has 4 unique co-enrollments. The remaining definitions are for analysis of the binary person-to-person network.

The number of unique edges provides the number of person-to-person connections in the network, and the network density tells us how dense those connections are. The number of unique edges is the number of singular connections between two different nodes. If person A and person B are in 3 groups together, they have a single connection. The network density is the ratio of the number of edges (or links) in the network to the total possible number of edges (or links).

The clustering coefficient is related to network density, but on a local level, and the number of co-enrollments and provides insight into how clustered the data is. The clustering coeffiecient is the ratio of the number of edges that exist between all of the neighbors of a node and the number of possible edges that could exist [11], [20]. For instance, if person A is in groups with only persons B, C, D, and E (A's neighbors) then there are 6 possible connections between persons B, C, D, and E (B–C, B–D, B–E, C–D, C–E, and D–E). If 4 of those connections exist, the clustering coefficient of the node representing person A would be 2/3. The Average clustering coefficient is the average over all nodes.

The characteristic path length conveys the expected degree of separation between any two persons in the network. The characteristic path length is the average geodesic distance between any two unique nodes, where every edge has a distance of 1 [20]. In other words, if person A and person B share a group, they have a distance of 1. If they don't share a group, but they are in separate groups with person C, they have a distance of 2, etc. The characteristic path length is the average of all these shortest distances between every pair of unique nodes.

The k-step reach is the proportion of person pairs that can be linked in k-steps out of all possible pairs [21]. If two persons share a group, they can be linked in 1 step. If they do not share a group, but both share a group with another person, they can be linked in 2 steps, etc.

We used NumPy to work with the network matrices [16], [18] and NetworkX [10] for the majority of the other network analysis [8].

C. Results and Discussion

The network analysis results for Fall 2019 course registrations (including faculty), with the addition of housing data, and with the addition of student organization data can be seen in Table II. Betweenness centrality is the average centrality of

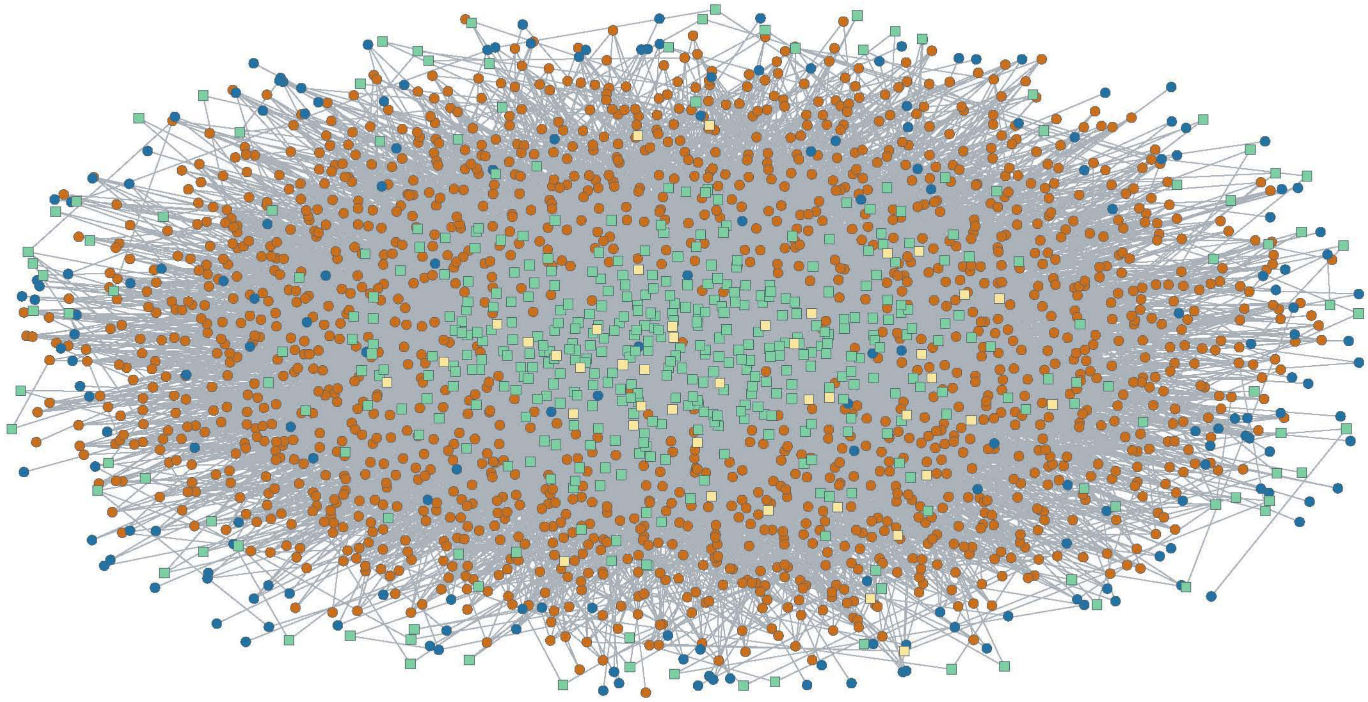

Fig. 1. Person-to-group network of faculty, students, courses, athletics, and ensembles for Fall 2019 data. Faculty are blue round nodes; students are orange round nodes; lectures, lectures with labs, and individual courses are green square nodes; varsity sports, ensembles, and physical education courses are yellow square nodes. Nodes positioned by the Fruchterman-Reingold algorithm [7] using NetworkX [10] and Matplotlib [12].

nodes along the shortest paths in the graph and can convey the influence of each node in the graph. Mean (unique) co-enrollments is the average number of (unique) co-enrollments for all persons. Number of unique edges is the total number of unique connections in the network, and network density is how dense those connections are. Average clustering coefficient is how clustered the data is. Characteristic path length is the average number of links or degrees of separation between two persons in the network, and network diameter is the largest path or degree of separation. The k-step reach is the proportion of person pairs that can be linked in k steps or degrees of separation. For further explanation of these terms see Section III-B.

As expected, Table II shows that as more groups are considered, co-enrollments, edges (links), density, and k-step reach values increase. The largest increase is seen with the addition of student organizations, showing that student organizations can have a significant impact on student connections on our campus, even more than housing. Similarly, the betweenness centrality and characteristic path length decrease, with the most significant decrease seen in the characteristic path length when student organizations are considered. This, again, shows that the network is more closely connected when student organizations are active. The small values of the betweenness centrality show that with any group consideration, no one person or group has a large influence in the network.

Table II also shows that the network has a relatively small diameter of 4, indicating that all persons in the network are closely linked. The clustering coefficient stays relatively constant when considering different groups on campus. This shows that the network is not highly clustered and no set of groups has a clustering effect on campus.

IV. Simulation of Mitigation Scenarios

In Fall 2020, Randolph-Macon changed the structure of the semester and created other policies to lower the connectedness of students and faculty on campus. We simulated the following changes using Fall 2019 registration data.

1) **Simplify group offerings**: Postpone, cancel, or require virtual meetings for athletics, ensembles, physical education courses, and student organizations.
2) **Reduce the number of active courses**: Change the semester from a single 14-week semester to two 7-week sessions and evenly divide courses between the two sessions.
3) **Separate larger courses through hybrid instruction**: Limit the number of students present in a classroom by creating hybrid courses that meet with only half the students at a time.

The simplify, reduce, and separate policies described above were not exact or rigid for Fall 2020. For instance, some ensembles, sports, and physical education classes may have met in a limited fashion, and other courses such as lectures and independent courses were completely virtual as decided by individual faculty members. A few courses still utilized the entire 14-weeks, but most were distributed into the 7-week sessions. Whether a course needed to meet separately

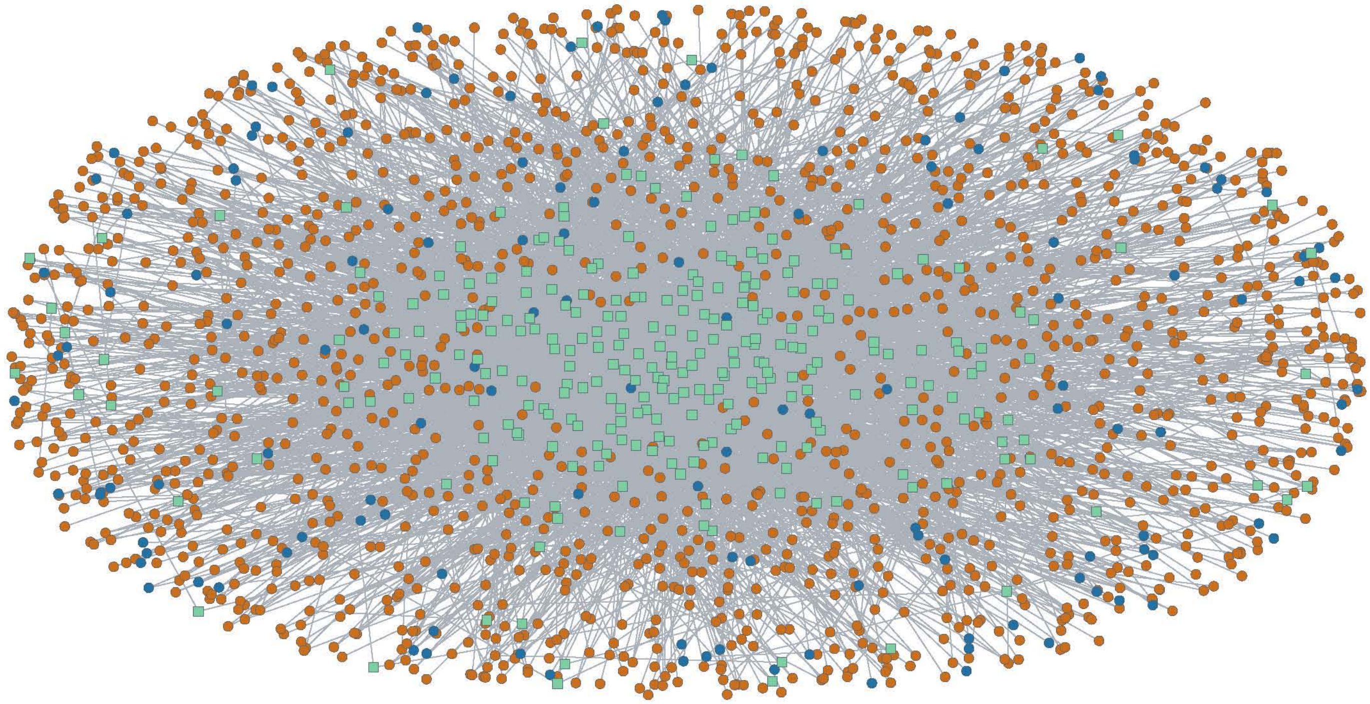

Fig. 2. Person-to-group network (largest component) of faculty, students, courses, athletics, and ensembles from simulated data from Fall 2020 session 1 using the simplify, reduce, and separate policies. Faculty are blue round nodes; students are orange round nodes; courses are green square nodes. Nodes positioned by the Fruchterman-Reingold algorithm [7] using NetworkX [10] and Matplotlib [12].

was dependent not only on the size of the class, but also on the size of available classrooms, and for the simulated data, we estimated whether a hybrid courses was required. Overall, the choices in the single set of simulated data are comparable to those made in Fall 2020, and the results provide a close estimate to the changes implemented.

In Fall 2020, all students had registered for courses before the semester was divided into a two-session semester. Courses were distributed into sessions by department and faculty member so that no faculty member taught more than 2 courses a session. Students were also moved between sections of the same course, and sometimes, required to register for other courses so that they had not more than 2 or 3 courses a session. Because these changes created a hard scheduling problem, we used randomization to distribute courses for the simulation and did not make changes if particular students or faculty had heavy loads in one session.

To construct the simplify, reduce, and separate simulation data for Fall 2020, athletics, ensembles, physical educations classes, and student organizations were removed from the original Fall 2019 data. The remaining courses were randomly distributed into two sessions by type: lecture, lab, and independent. In each session, all lab courses containing over 9 students were split into two hybrid meetings with the faculty member teaching both meetings and students randomly distributed between the two meetings. Also for each session, half of all lecture courses containing over 20 students were split into two hybrid meetings in a similar fashion. We note that historical housing data was kept the same and included with the simulated data. Figure 2 shows the the network created by the simplify, reduce, and separate plan for the simulated Fall 2020 session 1.

Each step in the simplify, reduce, and separate process was analyzed as an additional measure to lower connectedness on campus. Table III provides an overview of the simulated Fall 2020 student, faculty, and course registration data based on applying this process to the Fall 2019 data. The table provides the data from the original semester (also seen in Table I, 'Orig.'), the data for simiplified group offerings over a 14-week semester ('Limit'), data for two sessions that reduced the number of active courses ('Sess. 1' and 'Sess. 2'), and the data after larger courses were separated into hybrid courses ('Hyb.1' and 'Hyb. 2').

After the data was split into two sessions, the number of active students and faculty in each session was lower than for a full 14-week semester, as seen in Table III. This is a result of not guaranteeing that every faculty and student has a balanced number of courses across the two sessions. Since each meeting of a hybrid course was considered an individual group, the total number of courses increased when some courses were divided into hybrid courses.

A. Simulation Results and Discussion

The networks created by splitting the semester into two sessions were not completely connected, meaning a few persons and groups were only connected with each other and no one else in the network. The largest component in the

Students	Orig.	Limit	Sess. 1	Sess. 2	Hyb. 1	Hyb. 2
Number of Students	1534	1534	1456	1472	1456	1472
Mean courses per Student	4.9	4.4	2.3	2.3	2.3	2.3
Faculty						
Number of Faculty	196	179	136	136	136	136
Mean courses per Faculty	2.6	2.6	1.7	1.7	2.1	2.1
Courses						
Number of Courses	505	463	231	232	282	280
Lecture	340	340	170	170	201	197
Lecture/Lab	45	45	22	23	42	44
Independent	78	78	39	39	39	39
Mean Course Size	15.7	15.6	15.4	15.8	12.8	13.3
Largest Course Size	128	34	33	34	31	32
Smallest Course Size	2	2	2	2	2	2

TABLE III

OVERVIEW OF SIMULATED FALL 2020 STUDENT REGISTRATIONS AND FACULTY COURSE LOAD SIMULATED BASED ON THE SIMPLIFY, REDUCE, AND SEPARATE PLAN. COURSE DATA INCLUDES FACULTY IN SIZE NUMBERS.

network is the largest set of persons and groups who are connected through enrollments and further contact. When a network is not completely connected, we must use the largest component to thoroughly analyze the network, as some values cannot be calculated on an unconnected network. Although the proportion of persons and groups in the network is relatively close to 1, this small change in the value shows that splitting the semester into two sessions reduces the connectedness on campus.

Lowered connectedness on campus can be seen in Figure 2 (density is 0.027), as the edges are not as dense as those in Figure 1 (density is 0.074). Figure 2 shows the network of students, faculty, and courses from the simulated data for Fall 2020 session 1 with hybrid courses.

The network analysis results for simulated Fall 2020 course registrations (including faculty), with simplified group offerings ('Limit'), with the addition of reducing active courses through two semester sessions ('Sess. 1' and 'Sess. 2'), and the addition of separating larger courses through the use of hybrid teaching ('Hyb.1' and 'Hyb. 2') can be seen in Table IV. The results are also compared with the original Fall 2019 semester data ('Orig.'). For definitions of the following analysis terms see Section III-C, and for more detailed description of these terms see Section III-B.

Table IV shows that as the number of groups are lowered through simplifying group offerings and splitting the semester, and as course meetings are made smaller through hybridization, we see co-enrollments, edges (connections), density, and k-step reach values decrease. The largest decrease is shown with the use of two semester sessions, showing that this semester modification has an important effect on the connections between students and faculty on campus. Similarly, the betweenness centrality, characteristic path length, and network diameter increase with these semester modifications, showing that the network is less connected with these changes. The largest effect on these values was also shown with the use of two semester sessions.

Interestingly, in Table IV, we see a significant increase in the clustering coefficient when the semester is split into two sessions. This clustering effect shows that students and faculty have smaller spheres of influence when the number of active courses is substantially reduced. Overall, all semester modifications had the effect of reducing the connectedness on campus with the two semester sessions having the largest effect. It may be possible that with the inclusion of more virtual and hybrid classes, we could see larger effects in those choices.

V. CONCLUSION

Analysis of the student and faculty network indicates that Randolph-Macon is a closely connected campus, with all students and faculty connected within 4 steps (or degrees). Analysis also indicates that student organizations increase the connectedness on campus even more than housing. For Randolph-Macon and other similar schools considering in-person meetings during a pandemic, canceling or requiring virtual meetings for student organizations may be an important choice to reduce potential spread of disease.

We simulated the altered Fall 2020 schedule using the Fall 2019 data as a baseline. We focused on three choices to reduce contact on campus: simplifying group offerings by postponing, canceling, or requiring virtual meetings for particular groups; reducing the number of active courses by splitting the semester into two shorter and compact sessions; and separating larger courses into different meetings through hybrid instruction. Each of these choices showed a reduction in connectedness among students and faculty on campus, with the biggest reduction seen through splitting the semester into two sessions. This drastic approach had a large impact on the structure of the network indicating that it should be considered for future semesters. Increasing the number of virtual and hybrid courses could potentially provide similar large impacts.

Another series of decisions Randolph-Macon made that were not considered in our network analysis, but are important

Person-to-Group Network	Orig.	Limit	Sess. 1	Sess. 2	Hyb. 1	Hyb. 2
Persons in network	1730	1713	1644	1657	1644	1657
Groups in network	855	666	434	435	485	483
Prop. persons in largest comp.	1.0000	1.0000	0.9988	0.9994	0.9988	0.9994
Prop. groups in largest comp.	1.0000	1.0000	0.9977	0.9977	0.99794	0.99793
Betweenness centrality	0.0012	0.0014	0.0019	0.0019	0.0019	0.0019
Person-to-Person Network						
Mean co-enrollments	146.6	94.0	54.1	55.8	46.5	47.0
Mean unique co-enrollments	128.6	86.9	51.8	53.1	44.8	46.0
Number of unique edges	111275	74442	42498	43992	36762	38094
Network density	0.074	0.051	0.032	0.032	0.027	0.028
Average clustering coefficient	0.340	0.329	0.525	0.518	0.513	0.506
Characteristic path length	1.999	2.106	2.451	2.438	2.541	2.522
Network diameter	4	5	5	6	6	6
k-step reach						
$k=1$	0.0744	0.0508	0.0315	0.0321	0.0273	0.0278
$k=2$	0.9274	0.8452	0.5389	0.5460	0.4626	0.4735
$k=3$	0.9995	0.9982	0.9789	0.9839	0.9701	0.9772
$k=4$	1.0000	1.0000	0.9996	0.9996	0.9994	0.9995

TABLE IV
SIMULATED FALL 2020 DATA BASED ON THE SIMPLIFY, REDUCE, AND SEPARATE PLAN.

to discuss, were to start a week early, cancel fall break, immediately begin the second fall session after the first session, and hold courses completely online after Thanksgiving (one reading day and two final exam days). These decisions reduce, but do not eliminate, the chance that students have off-campus contact while living on-campus. The only point in the semester when students and faculty will have much greater contact with each other is in the days surrounding the change in the sessions: students and faculty will be meeting with one set of groups and then, after only a weekend separation, meet with an entirely different set of groups. Although other mitigation policies such as those described in [9] and health protocols given by the CDC [5] are essential at any time, they will be particularly important during the session change.

We recognize that not every school is able to make as many distinct choices as Randolph-Macon made for Fall 2020. In particular, completely reorganizing a semester by splitting it in half may be difficult to scale, and focusing on virtual and hybrid courses could be the only option for larger schools. However, for schools that are able to consider restructuring their semester schedule, our analysis indicates that this is a valuable option to explore in an effort to reduce contact and associated disease spread among students and faculty.

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