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SIMULATING PANDEMIC INFLUENZA PREPAREDNESS PLANS FOR A PUBLIC UNIVERSITY: A HIERARCHICAL SYSTEM DYNAMICS APPROACH

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ABSTRACT

Pandemic influenza preparedness plans strongly focus on efficient mitigation strategies including social distancing, logistics and medical response. These strategies are formed by multiple decisions-makers before pandemic outbreak and during the disaster by decision makers in local communities, states and nationwide. Depending on the community that will be affected by pandemic influenza, different strategies should be employed to decrease the severity of the disaster in multiple dimensions of social life. In this paper, a system dynamics methodology is applied to model the population behaviors and the effects of pandemic influenza on a public university community. The system is simulated for multiple non-pharmaceutical interventions with several policies that can be employed by local decision makers. System components are constructed from the pandemic influenza preparedness plan of one of the largest universities in the country. The policies and the decisions are tested by simulation runs and evaluations of the mitigation strategies are presented.

1 INTRODUCTION

The World Health Organization (WHO) (WHO 2008), has reported that avian influenza (H5N1) virus is threatening people worldwide with an upcoming influenza pandemic due to the fact that H5N1 may soon have the ability to efficiently transmit from human to human and cause a pandemic. Preparedness plans for pandemic influenza generally focus on establishing efficient mitigation strategies for inter-related communities and providing adequate medical services. Several decisions need to be made before the pandemic outbreak, during the pandemic, and even after the pandemic ends to manage the disaster successfully, minimize loss of life, and mitigate the effect on daily business operations. However, because the population that will be affected by pandemic influenza is very large and diverse, different strategies, including non-pharmaceutical and pharmaceutical interventions, will inevitably need to be employed in different communities.

In this paper, a system dynamics model is presented to test the preparedness plan of one of the largest public universities in the United States, Arizona State University. This model is designed to visualize system response to the policies implemented by different departments of the university during a pandemic. We first formulate the mathematical epidemiology model to have a better understanding of the disease spread over the university population under some general assumptions. Then, by using a hierarchical system dynamics modeling approach we model the university population based on their common daily activities and responsibilities as system elements. This modeling approach also allow us visualize consequences of University emergency response policies regarding academic continuity, student evacuation and medical surge capacity in real-time.

2 LITERATURE REVIEW

With the increasing threat of pandemic influenza, developing pandemic emergency response plans, at the local level (hospitals, airports, schools etc.), at the state level, and also nationwide is a critical element of preparedness planning.

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These preparedness plans can roughly be applied to other disasters and emergency situations like earthquakes and bioterrorism. A significant amount of the research that has been conducted in this area can be categorized as categorized as mathematical epidemiology based papers for modeling the disease dynamics and simulation based papers to evaluate the mitigation policies for developing best policies for the public.

In mathematical epidemiology, researchers investigate the biological structure of the disease and try to develop mathematical models that represent the spread of the disease. On the other hand simulation based papers typically try to simulate the pandemic flu spread over a certain population and evaluate potential effects on the other parts of the society like economy, education, business and food supply. Simulation based research can also be classified into two groups based on the modeling methodology used for the system. Agent based models are one class of these simulation models in which researchers model each individual as an agent and model their daily behaviors to simulate the disease spread and the consequences. These types of models require high computational resources since population under investigation is very large. It can be difficult to obtain the best policy that works for all parts of a large community with large populations. In addition to these models, there has been a considerable amount of work in the literature that focuses on simulating the system as a whole using the system dynamics approach. These models have the main shortcoming of modeling each individual with the same daily behavior assuming the same immunology conditions for all participants of the model, and assuming "random mixing" of the population which may not be very realistic.

Das et al. (2007) present a large scale simulation model for the uncertain spread of pandemic influenza caused by the H5N1 virus, and apply several mitigation strategies. In the paper, they model each individual as an agent and the performance measures that they use for the mitigation strategies are the total number of infected and dead people, denied hospital admissions, denied vaccine-antiviral drugs as well, financial measures such as healthcare related costs and lost wages. The simulation model is large-scale and the mitigation strategies over a huge population are generated by Markov Decision processes. However, the mathematical dynamics of the disease is not considered or explained with respect to mitigation policies. Several other papers in the literature also use agent-based modeling to analyze global geographical spread of disease and include decision support systems (Dibble, Wendel, and Carle 2007; Ferguson et al. 2006; Germann et al. 2006).

For simulating disease transmission, several parameters must be estimated *a priori*. Chowell et al.(2006) use the data from the 1918 influenza pandemic in Canton of Geneva, Switzerland and model the transmission dynamics of two different waves of the disease during a year. They present an estimation model for several disease spread parameters through least squares fitting of the model and provide estimation for the basic reproductive number which is critical in disease spread. Their paper present estimates for the disease parameters, but it does not include population characteristics which might affect the disease spread differently under different disease characteristics and social response. Also, their paper does not consider the policies and the strategies that can be taken by the community managers. Another mathematical epidemiology model is presented by Feng et al. (2007) to study the disease control via quarantine and isolation types of non-pharmaceutical interventions. They show that the assumptions of exponential distributions for the disease stages are not appropriate to control the disease spread. Their general integral equation model assumes more general distributions for each disease stage. They also prove that the existence and the stability of the population dynamics equation of the model depends on the magnitude of the basic reproduction ratio (R_0). In addition, they compare their model with general SEIR (Susceptible-Exposed-Infected-Recovered) models for different policy implementations through the simulation studies. Hagenaars et al. (2004) simulate the effects of possible pandemics in The Netherlands for several possible interventions such as vaccination of certain groups and antiviral prescription. Their simulation results are used for decision support for local decision makers but only on the decisions for antiviral and vaccination stockpiling. However, these two papers do not consider one of the most difficult policy implementations under emergency conditions which is developing social distancing policies to direct people in the community.

Flahault et al. (1994) study the geographical spread of influenza in France based on the population movements using railroad data and air transport related data. Their main conclusion is that, time for taking action and applying policies will be very short after detecting the influenza pandemic. Grais et al. (2003) took the 1968 Hong Kong pandemic and simulated the consequences for the year 2000. They concluded that the spread would reach global pandemic under a short time lag of 4 days. They assume uniform susceptibility for all people and point that coordinated global surveillance is very important. Most recently, Hsieh et al. (2007) study the impact of different quarantine applications on the 2003 SARS outbreak in Taiwan, such as quarantine of travelers arriving to the airports and quarantine of potentially exposed contacts of suspected SARS patients. Their results showed the benefits of mathematical epidemiology models for qualitative evaluation of the impact of traditional intervention measures for new infectious diseases when there is unknown information.

In the literature there is also considerable amount of work that simulates the system as a whole by using system dynamics methodology. Eskici et al. (2007) use system dynamics to understand the dynamics of avian influenza epidemics in a finite, closed area. The model that they developed is a network model linking the wild bird and duck populations and human population sectors in a generic way and integrating with SIR (Susceptible-Infected-Recovered) model. They perform several simulation runs to do scenario and policy analyses and concluded that growing duck and poultry populations pose great risk for a pandemic outbreak. In addition, they suggest a tentative policy for recognition of the virus and quarantining infected birds.

System dynamics methods are also applied to simulate the economic and social impacts of a pandemic flu outbreak (Ritzo et al. 2007; Ewers, Dauelsberg 2007). Ritzo et al. (2007) model the business impacts of pandemic to assist organizations by integrating the business dynamics and the disease dynamics. They simulate various mitigation strategies and demand factors related to the revenue side of businesses. In addition, resource allocation is another big problem during pandemic situations and addressed by Brandeau (2004).

3 PROBLEM IDENTIFICATION

Public universities have large student and staff populations with significant social contact within institutional boundaries. Universities have the ability and responsibility to employ policies to foster social distancing while providing medical and housing services to students. Arizona State University (ASU) Campus Health Services provides the primary healthcare services on four ASU campuses and collaborate with other external healthcare organizations and emergency personnel with other units of the university. Other campus departments are responsible for public safety, transportation of students, and providing essential services such as meal preparation and counseling. Simulation models that address these factors are useful for identification of preferred policies, improving understanding of consequences of policy decisions, and uncovering holes in emergency response plan.

University administration is responsible for critical decisions including cancellation of classes, closure of research facilities, and communication with university populations. Because international travel and being in such close quarters, university populations can have a large impact on the spread of the disease.

Public universities are usually required to have a pandemic influenza response plan in place that attempts to control the disease and balance the financial, operational, and public health consequences of a pandemic. The University's goal is to control the pandemic through proper actions and appropriate policies to reduce the spread of the disease while providing basic services.

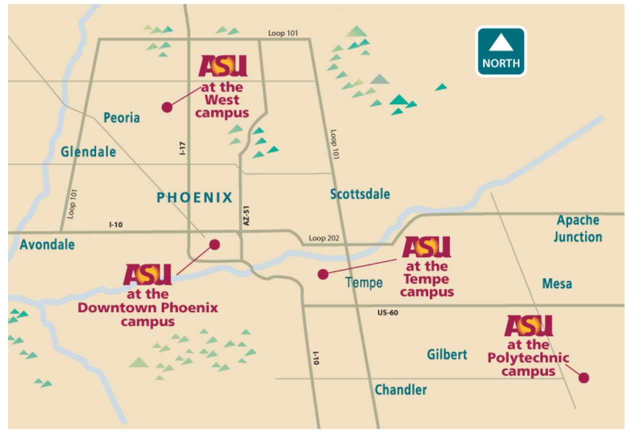

Figure 1: Map of Arizona State University Campuses

In this paper, we simulate the disease spread and population dynamics for Arizona State University, simultaneously with the policies that the university developed for the response to such an emergency. Since the University is distributed across four campuses in metropolitan Phoenix as it is seen in Figure 1, the residents, students, and employees will require different evacuation procedures and services for basic needs. The Tempe campus, the largest student body of 55,000 students, is planned as the central location for residential, food and medical services. Several student and staff sub-populations would be transported to the Tempe campus to limit external exposure to disease and evacuate students if possible. We formulated the S-E-I-R model for several subpopulations in the university and these subpopulations are affected differently based on university responses. Thus even though the biological characteristics of the disease will be same for all university subpopulations, the impact of the disease on individuals will be different depending on which population class they are belonging to, where they live, what health situation they have and what university policies are employed to them.

University faculty and staff are classified as either "essential" or "non-essential" personnel. Essential personnel provides necessary basic services on campus, while non-essential personnel is assumed to be evacuated with the evacuation plan. The students are classified into two subpopulations prior to disease onset: commuting students and students in residence halls. After disease onset students are classified according to their residential status and health situation. In the University's preparedness plan the objectives of the university response plan are listed as dispersing students out of their dorms safely and suspending all but essential operations of the university including social and community gatherings. From the strategic planning viewpoint, the most critical question appeared to be when to suspend the university operations, including human resource management, research activities, residential life and of course academic continuity. Suspending university operations will cost millions of dollars in lost revenue to the university. On the other hand, keeping the university open for gatherings and education will increase the disease transmissibility on campus in turn causing increased mortalities or severe medical conditions for the university population. Thus, the university policies are the regulators between the financial concerns and sustaining healthy conditions for the university population.

3.1 Mathematical Epidemiology Model

The simulated system is assumed to have the classical Susceptible-Exposed-Infected-Recovered (S-E-I-R) type of model for each of its subpopulations which also defines the subsystems of the university population. Thus, each subpopulation has the model variables as susceptible, *S (t)*, exposed, *E (t)*, infected, *I (t)* and recovered, *R (t)*; we also define the variable deaths *D (t)*, which could not recover. The model dynamics can be written as the following system of equations:

$$S'_i(t) = -\beta_i \alpha \frac{\left(E_i(t) + I_i(t)\right) S_i(t)}{N(t)} \quad (1)$$

$$E'_i(t) = \beta_i \alpha \frac{\left(E_i(t) + I(t)\right)}{N(t)} S_i(t) - \sigma E(t) \quad (2)$$

$$I'_i(t) = -\mu_{I,i} I_i(t) - \gamma I(t) + \sigma E(t) \quad (3)$$

$$R'_i(t) = \gamma I(t) \quad (4)$$

$$D'_i(t) = \mu_{I,i} I_i(t) \quad (5)$$

$$N_i(t) = S_i(t) + E_i(t) + I_i(t) + R_i(t) + D_i(t) \quad (6)$$

where,
α : is the global transmission rate which depends on the structure of the virus causing the disease. It can be interpreted as the rate of infection given a contact happened between an infectious or exposed person and a susceptible person.
β_i : contact rate per day by people in subpopulation i .
$\mu_{I,i}$: Infectious mortality of subpopulation *i,* from infected class.
σ : Rate of progression from exposed to infected (σ^{-1} is latent period)
γ : Recovery rate for infected people
$N_i(t)$: Total number of people in subpopulation *i.*

In this paper we assume mixing within subpopulations, not between subpopulations grouped according to their daily behaviors, which may be influenced by policy responses to a flu outbreak. In our formulation these subpopulations are commuting students, residence hall students, faculty and staff and essential personal. The simulation model is built on the assumption that the mathematical epidemiology model is valid for all of the subpopulations defined in the model. However, in different subpopulations the local parameters of the model have different values, where the global parameters have the same values. The global parameter of the model is global infection rate and the local parameters are the latent period, infection period, infected mortality rate and the contact rate. In this model we do not consider the deaths related to pandemic flu from exposed and susceptible classes because we assume the simulation time is not large enough to consider deaths from these classes. We only consider and test the non-pharmaceutical interventions, which force people to change their states in the system and move them to other subsystems with different behavior models. Figure 2 shows the structure of disease model and its elements.

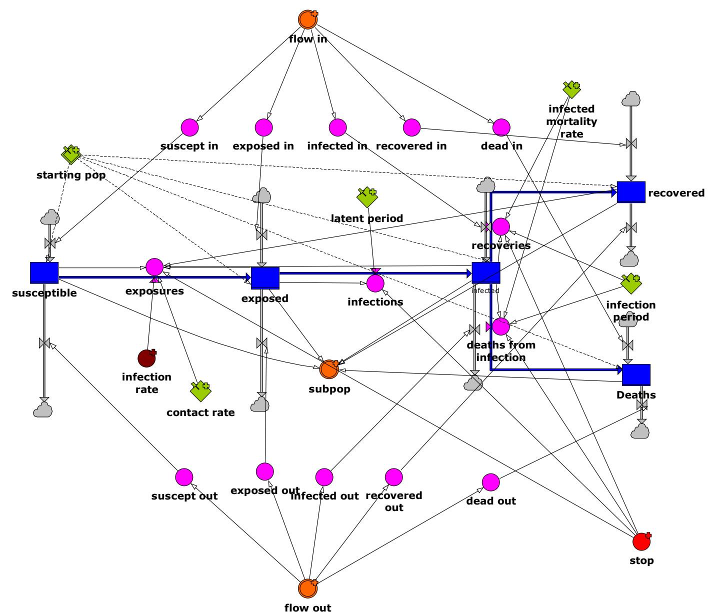

Figure 2: Basic S-E-I-R Disease Model

4 SYSTEM DYNAMICS MODEL

The S-E-I-R model of the disease for all subpopulations is constructed as a dynamic model in which people are moved from one class (S, E, I, R) to another after a certain amount of time with the given system rates. This S-E-I-R model forms the basis of our system dynamics model which is a hierarchical model, formed by this disease model running for different subpopulations. The mathematical formulation for policy implementation on subpopulations is given as: each subpopulation is formed by classes as defined earlier such as :

$$P_i(t) = \left[S_i(t), E_i(t), I_i(t), R_i(t), D_i(t)\right] \ (7).$$

Vector defined in (7) represents the state of the subpopulation i at time t in terms of number of susceptible, exposed, infected, recovered and died at time t. Applied policies generates *flow out* from one subpopulation, i.e., *flow in* to another subpopulation. This flow can be formulated as given in equation (8);

$$\frac{d}{dt}P_i(t) = f_i(P_j(t), \pi_i(t)) - g_i(P_i(t), \pi_i(t)) \qquad (8)$$

where $i=1,\ldots,n$ and π_i represents one of the possible policies that decision makers can employ; such as, evacuating dorms, canceling class, and time to evacuate etc.

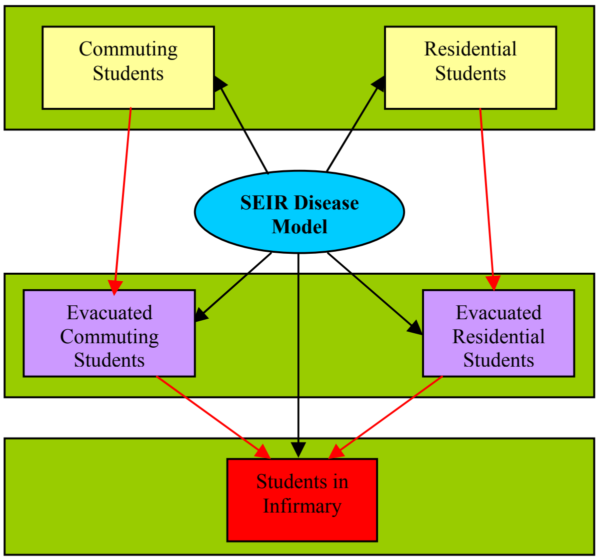

Figure 3: Hierarchical Structure of the Simulation Model

From a policy perspective, the most important and difficult decisions include how to direct people under emergency conditions, which policy should be employed to which subpopulations and which resources should be allocated to which party under what condition. Thus, the most critical characteristics of the system dynamics model presented in this paper is the robustness of moving the people from one model to another as a consequence of the decisions made by the decision and/or policy makers via their policy tool. This robustness is given to the model by allowing flows from one subpopulation to another with sub-model connectors. Figure 3 shows the structure of the hierarchical system dynamics model. With the red arrows subpopulations are directed from one state to another in the model by the policy tools used by the decision makers.

In the pandemic influenza preparedness plan, the main objectives are: 1) evacuating as many students as possible safely from the university campus, 2) providing the appropriate treatment for the students who are sick and can not leave the university campus 3) taking care of the students who are well and can not leave the campus with the help of predetermined essential personal. Therefore, we construct our simulation model based on directing the university population during the pandemic outbreak and other factors are considered as minors of the model. Thus the simulation model consists several sub-models (sectors) such as for students: commuting students who live off campus, residence hall students, evacuated students, well students left on campus, students in infirmaries of the university and for faculty and staff: non essential personal and essential personal.

In the upper level of the simulation model the population flows are modeled by allowing flows of people from one sub-model to another. These movements are done as a result of the university policy makers' decisions. For example, when the decision makers of the university decide to close the university campus except its essential operations, then all the commuting students will flow into "evacuated students" sub-model, except the ones who could not survive and can not leave the campus. This flow is illustrated with Figure 4 and 5. The influence of this decision for the residence hall students are modeled as in Figure 6 and 7.

Suspending the university operations is the most critical decision at the given phase of the pandemic and decision makers should be informed with the system environment as well because it has high relation with the system (university campuses) since there is no real physical boundaries. The events happening in the system environment are assumed as having human-to-human transmission in a country abroad, several cases in nation wide, several cases state wide and lastly one or two cases in the local community. This order also follows the order of pandemic flu/bioterrorism preparedness of the United States with respect to Homeland Security preparedness plans (Homeland Security Exercise and Evaluation Program, 2008). Thus, we can conclude that one of the critical decision elements for pandemic influenza mitigation is giving a correct answer to the question of when to close the university campus and quit the classes and social gatherings. This critical decision making process will be quantitatively analyzed in the next section with quantitative and sensitivity analyses over this decision with its consequences.

After suspending the university operations the main problem remains for the university decision makers as how to deal with the students who are living in the residence halls and could not leave the university. In addition to that, there is high possibility for non-residential students to request medical assistance from the university health services.

University health services has to mandate the students and minimize the severity of the disease. According to the preparedness plan, the well students will be housed in one location to centralize essential services.

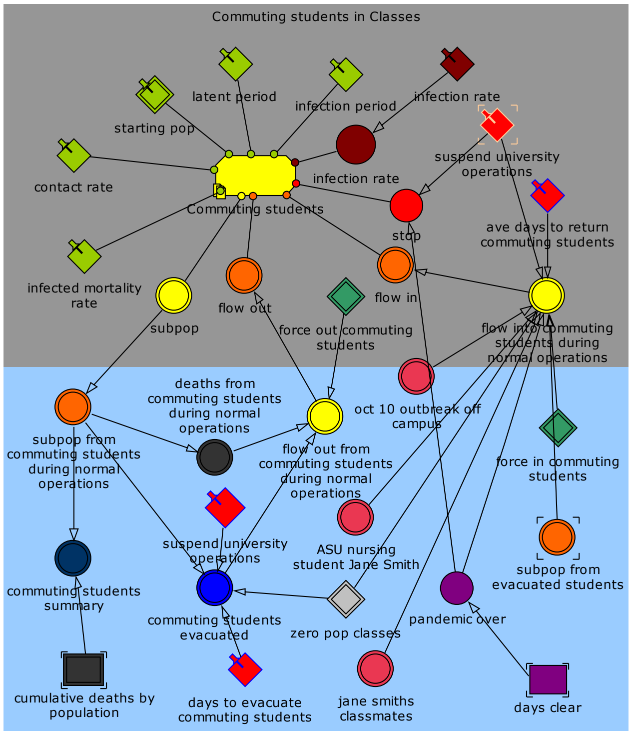

Figure 4: Commuting Students

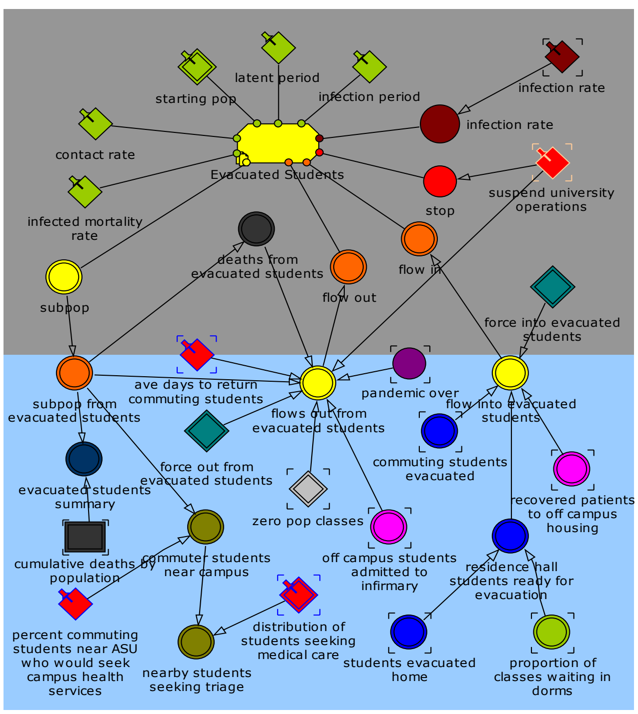

Figure 5: Evacuated commuting students

In addition to the well students on campus, the university plan includes the action plan for the infected students with respect to their severity condition. The sick students will be transferred to one main dorm and if the capacity of this dorm will not be enough, they will be transferred to alternative locations on campus. The main inspection and control locations for the students will be the triage points at certain locations on the campus.

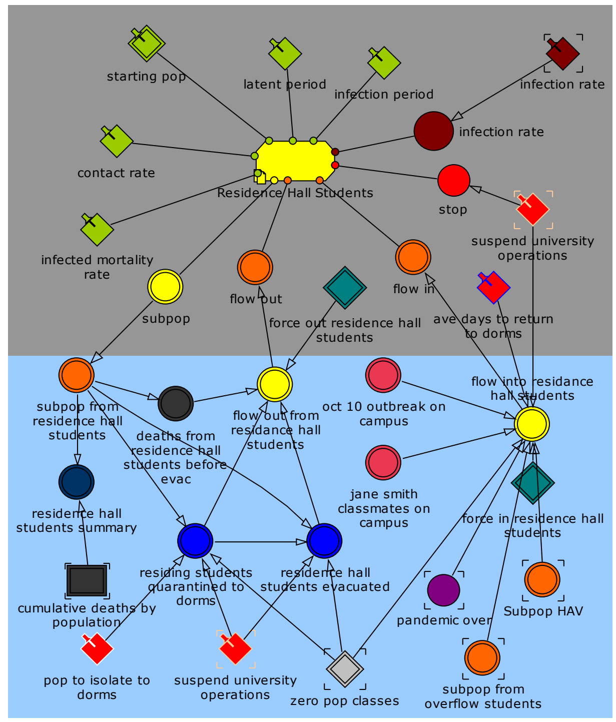

Figure 6: Residence hall students

5 SIMULATION RESULTS AND POLICY ANALYSIS

We have run several scenarios to find the best answer to one of the critical questions for the public university which is “when to suspend university operations?”. The simulation is set to run for 12 weeks with one time step corresponding to one day of a year. System performance and the applied policy effectiveness are measured by the number of people who could not survive the disease in the university compared with the normalized number of dead people of the global community (number of dead people in the state). Also another comparison is done on the numbers of total deaths and infected people without any non-pharmaceutical intervention applied to the community and the total number of people who get infected and died with the quarantining and isolation policies given in the pandemic flu preparedness plan. The simulation parameters are set to a fixed value at the beginning of the simulation and these values are obtained from the literature and World Health Organization (WHO, 2008).

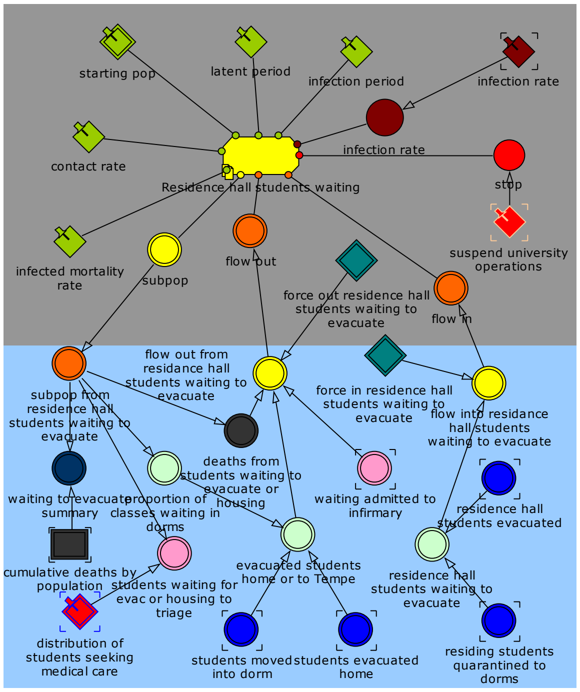

Figure 7: Residence hall students after plan activated

In our simulation model, for the university community we take the mortality rate as 0.1, the latent period as 2 days with 3 days of the infection period. The contact rate which is difficult to estimate, is assumed to be 50 ppl/da for the commuting students and it is expected to be higher for residence hall students, thus we fixed it as 75 ppl/da for the residence hall students. The global infection rate of the model is fixed to 0.015.

After determining the system parameters, we first run the simulation model for the local community (public university) without applying any intervention and policy applied. The results in Figure 8 shows that without any interventions 31,994 people will get exposed and infected and totally 575 deaths will occur off campus from the university population and 138 deaths will occur in the residence halls, with given parameters. In addition to these numbers an increment in the absentee rate of the university employers should be expected. Figure 9 shows the change in the absentee rate of the university workers. These two results show the university decision makers that, they should definitely activate their preparedness plan to better manage the disease on the university population. However, the question of when to activate this plan gets importance, at this point.

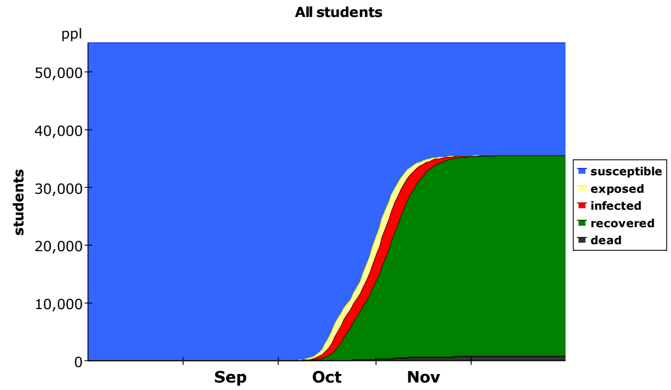

Figure 8: Number of people in each class without any intervention

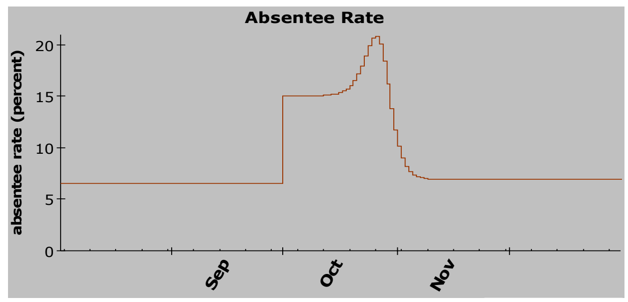

Figure 9: Absentee rate change of the university workers during the pandemic

If university decision makers decide to suspend university operations based on the events occurring in the world, country and state the simulation results show that the severity of the disease can be reduced significantly. However, the date of canceling the classes will generate different consequences on the numbers of infection and mortality from the students that will be living on campus. These students will be forced to live in pre-determined dorms to be easily taken care off. However, due to increased contact rate in dorms, the attack rate (total number of students who are exposed and infected) for on campus students will still remain high. The results for suspending the university operations and starting the evacuation of students on different dates are presented in Table 1.

In addition, our simulation experiments show that due to the increased contact rate in dorms, time for evacuation is a key factor. In Table 2, we can see that when the time for evacuation increases, mortality in dorms also increases. The results are given first with the default setting scenario of our model and with a scenario in which 5 exposed students are modeled as active in the dorms.

Table 1: Results on number of attacked students and deaths

Decision for evacuation	Date of Evacuation	Pandemic Over Date	WHO Level	Severity Index	Deaths off Campus	Deaths on Campus	Total Number of Attacked Students	Attacked Students on Campus
Yes	**1-Oct**	**20-Nov**	6	5	5	51	1853	1338
Yes	**2-Oct**	**18-Dec**	6	5	5	64	2208	1690
Yes	**5-Oct**	**1-Dec**	6	5	6	68	2320	1768
Yes	**6-Oct**	**29-Nov**	6	5	14	78	2950	1945
Yes	**13-Oct**	**11-Dec**	6	5	34	84	4063	1928
Yes	**15-Oct**	**17-Dec**	6	5	60	97	5666	2035
No		**31-Dec**	6	5	575	138	31994	6169

Table.2: Resulting mortality on time to evacuate the dorms in two different scenarios

Time to Evacuate Dorms (Days)	Default Setting (Mortality)	5 Exposed Cases In Dorms (Mortality)
1	98	146
2	110	147
3	124	147
4	131	147
5	135	147
6	139	147
7	141	148

6 CONCLUSIONS AND FUTURE WORK

In this paper we simulate the pandemic preparedness plan of a public university to help university decision makers to visualize and understand the consequences of their policies. The performance of the system and the plan is measured in terms of the number of infected students and the mortality occurred on and off campus for the university students, faculty and staff. The simulation results show that even during a mild pandemic, the decision for suspending the university operations is critical. The main conclusion that needs to be stated from this study is that public universities should act as early as possible to protect their people and secure their operations, wherever the disease outbreak occurs in the world. The appropriate decisions can significantly reduce the severity of the pandemic influenza for local communities.

In this paper we focused on the non-pharmaceutical interventions. Since the vaccination strategies might not be effective in the early stage of the pandemic and because of poor vaccine matching, lack of delivery and low public awareness we did not consider the vaccination policies in our simulation model. However this assumption can be relaxed for the future research investigations.

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