Biological Event Modeling for Response Planning

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1.0. Introduction

People worldwide continue to fear a naturally occurring or terrorist-initiated biological event. Responsible decision makers have begun to prepare for such a biological event, but critical policy and system questions remain: What are the best courses of action to prepare for and react to such an outbreak? Where should resources be stockpiled? How many hospital resources—doctors, nurses, intensive-care beds—will be required? Will quarantine be necessary? Decision analysis tools, particularly modeling and simulation, offer ways to address and help answer these questions.

Computer models that deal with disease spread differ in scope, emphasis, details, and techniques (see References). In general they each point to the importance of early detection and early action (even if it is of limited effectiveness).

The predominant mathematical model that epidemiologists use to model disease spread is the *SIR model*, a set of differential equations that describe population flow from the state of being susceptible (S), to being infected (I), and then to being removed or recovered (R). Unfortunately, the typical epidemiological model addresses only disease spread and does not allow decision makers to examine the impacts of various policies for preparation and response. The basic parameters are contagion rate and population density. The typical SIR model does not differentiate types of people and thus cannot account for the impact of medical personnel deaths, which represent the loss of some critical resources. The typical model is also for only one location and does not consider disease spread from one city to the next.

Mitretek has built a computational model of the medical responses to a bio-event (viz., the introduction of a contagious disease) that spreads to—or even commences in—multiple cities. The model provides analytic support to aid in response planning. Our primary objective in this modeling is to reveal the relative effectiveness of different prevention and mitigation strategies. Our goal was to identify some critical leverage points – where policies or actions will make a substantial difference (in terms of lives saved). Further we wanted to determine the requirements for new response capabilities that, based upon our simulation modeling, will improve outcomes.

We extended the classic SIR model using system dynamics, an established modeling approach well suited to ensuring that all policy dimensions, alternatives, and outcomes are addressed. To help frame and answer critical policy decisions, our bio-event model goes beyond the standard SIR disease spread to address the:

- effectiveness of different therapies as a function of resource availability;
- impact of resource inventories, initial positioning, and adaptive surging;
- need to protect key health personnel who are vulnerable to infection;
- requirement to restock consumable resources such as drug-based therapies;
- potential for disease spread across independent cities, employing different preparation and response strategies; and
- limiting of two-way population movement among the cities.

2.0 Description of the Model

We have developed a system dynamics model for the spread of a biological agent (disease) covering up to four distinct interacting geographical areas (called "cities"). This model supports a variety of resource-based ways to diminish the spread and impact of the disease. The model's settings can be adjusted to correspond to essential characteristics of any communicable disease.

This bio-event model has the following major components with user settable characteristics.

- Disease (infectivity, lethality, stages and their durations);
- Treatments (effectiveness, number of medical personnel and duration required to administer);
- Cities (population, movement between cities, initial number of infectious people, contact rate within the population, available key resources including personnel and what is required by the treatments);
- Surge (timing and amount of supplied resources and personnel); and
- Policies (e.g., attempting to confine and/or reduce the contact rate with associated timings and rates of success).

2.1. Disease Stages

For greater realism in modeling disease spread we refined the Infected (I) stage of the standard SIR model. When infected, members of the Susceptible (S) population move first into a "Disease Incubation Period" stage for a user settable time duration. Next they move into an "Infectious Pre-Symptomatic" stage for another user-settable duration. In this stage they can infect people they come into contact with and, since they are pre-symptomatic, no treatment or isolation actions will be taken. Then, after entering the "Infectious Symptomatic" stage they are partitioned between "Confined Population" and "Unconfined Infectious" stages based upon a user-settable effectiveness (or likelihood of recognition) setting. Confined people will no longer spread the disease, but will continue to require treatment resources. Key Personnel follow a path similar to that of the general population in that they can become infected and thus require resources for treatment. Further, having infected key personnel reduces the capacity of the overall system to treat those who are infected.

Ultimately those infected will end up as part of the Recovered or the Deceased Population (i.e. the (R) stage for Recovered or Removed in the SIR model). The lethality of the particular simulated disease and the effectiveness of the treatment received are the key determinants of what percentage of those infected end up in the recovered stage. Of course disease lethality and treatment effectiveness are user-settable.

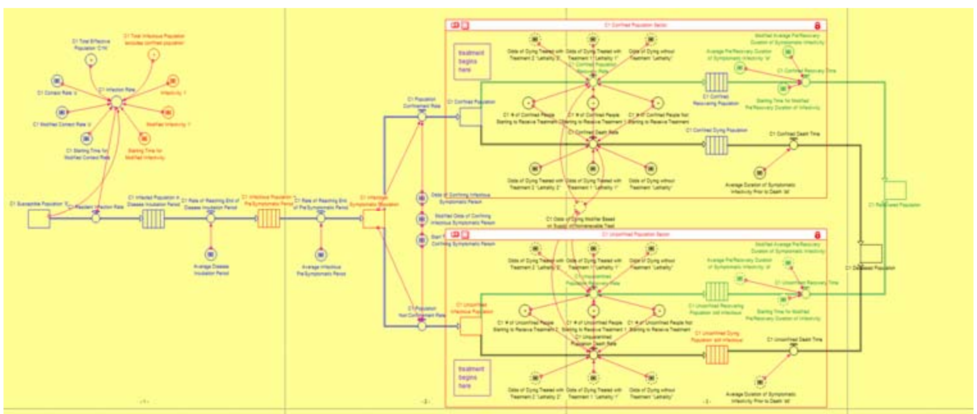

Figure 1: Disease Stages Progressing from Susceptible to Recovered or Deceased

2.2. Disease Treatment by Key Personnel

The finite resources needed (by key personnel) to treat infected patients can be reusable, such as Intensive Care Unit (ICU) beds, or one-use only resources, such as medications. When reusable resources are freed up they are returned to the pool of available resources. For example, once an ICU bed is assigned to a patient it will be “in use” until that patient either dies or recovers. This means both Key Personnel and the renewable resources have feedback loops of becoming available after a certain period of being “assigned.” (See Figure 3.)

This response model incorporates two types of resource-based treatments to reflect initial medical practice and a subsequent, more effective Treatment 2 (after more is known about the disease). If there is enough of "Treatment 2" resources available it will be administered to all who enter the treatment phase of the model. Otherwise, "Treatment 2" will be administered to as many people entering the treatment phase of the model as possible based on the current supply of resources and "Key Personnel Available to Administer Treatment 2" (i.e., who are alive, not symptomatic, and not currently busy administering treatment). Subject to available resources "Treatment 1" will be administered to as many people as possible entering the treatment phase that do not receive "Treatment 2." (Key Personnel will always receive the best treatment that has been introduced to date in the City.)

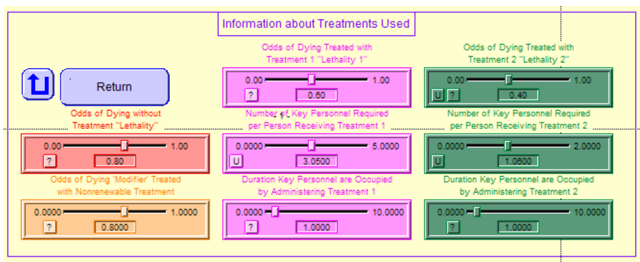

Figure 2: User Interface for Disease Lethality and Effectiveness of Treatments

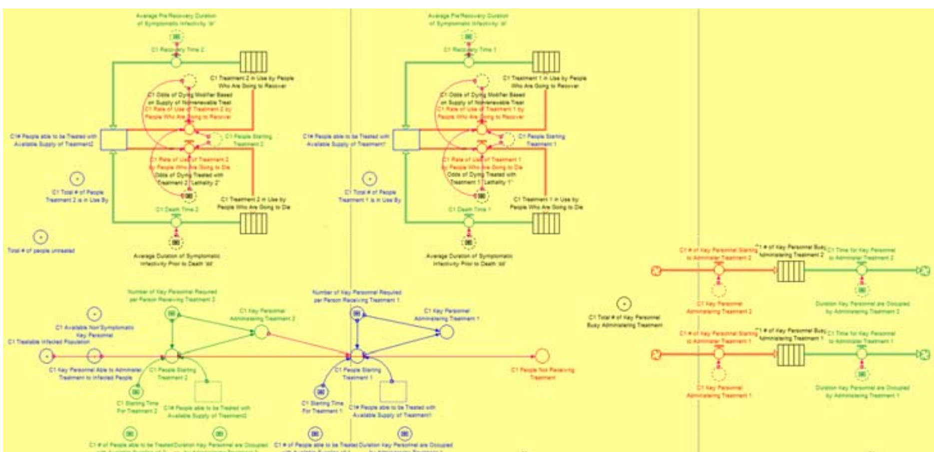

Figure 3: Feedback Loop of Reusable Resources

2.3. Surge Response: Timing and Amount

It is not feasible for cities to maintain a supply of the best possible treatment for each known disease in sufficient quantity to treat all members of their population. As a result, to deal with a major disease outbreak the nation needs the capability to rapidly supply (i.e., to surge in) additional key personnel and treatment resources to where they are needed. The elements of *surge capacity* are evident in its definition: the "ability to manage a sudden, unexpected increase in patient volume that would otherwise severely challenge or exceed the current capacity of the health-care system." Clearly, surge must deal with major unknowns, including a high volume of patients, some way to identify the bioagents used, treatment for the bioagents, and the attack locations.

The model allows the user to surge key personnel and treatment resources (both renewable and non-renewable) to each city in whatever quantity the user wants at whatever time the user wants. The user is also able to set the starting times for Treatment 1 and Treatment 2 for each city individually in order to represent those treatments arriving in the cities at different times.

Thus the user can experiment with scenarios that vary the timing and the amount of the surge response.

2.4. Multiple "Cities" and Population Movement

The model provides for two-way movement between cities which is specified as the percentage of the population in city C_i that moves to city C_k each day (as i and k range from 1 to 4). The four cities with population movement allow users to investigate disease spread as well as different pre-positioning and surge strategies for different cities.

With the four cities and population movement, with disease characteristics, treatments involving key personnel, renewable (e.g., ICU's) and non-renewable (e.g., medicine) resources -- some pre-positioning and some surged at user-specified times – our Extended Bio-Event model has 118 different, user-settable parameters.

2.5. Results

The model provides a variety of ways to try to limit the spread and impact of a disease. These ways include to:

- Use initial and improved medical treatments (with specified effectiveness);
- Confine symptomatic people (by isolating a percentage of the population immediately after they become symptomatic),
- Modify the contact rate and/or the disease infectivity at a specific time (e.g., reflecting a policy to advocate staying at home and using surgical masks),
- Modify the odds of confining symptomatic people at a specific time, and
- Surge extra supplies of key personnel and/or the various types of treatment resources into the affected areas.

Sensitivity analysis of the model's results can help identify "leverage points" where earlier and/or more effective action has a major impact on, say, lives saved. We built an Excel interface to *iThink* in order to run sensitivity analyses and to produce three-dimensional graphs of the results (e.g., comparing the number of fatalities as parameters X and Y each vary over 20 values).

For example the surface in Figure 4 shows how the number of deaths can vary with respect to changes in two key parameters. One axis varies the likelihood (from 5% to 100%) of confining a symptomatic person. The other axis varies when the contact rate is modified (from day 1 to day 20). These results reveal that the early reduction of the contact rate (e.g., through voluntary measures and surgical masks) is more important than near perfection in confining those who are infectious.

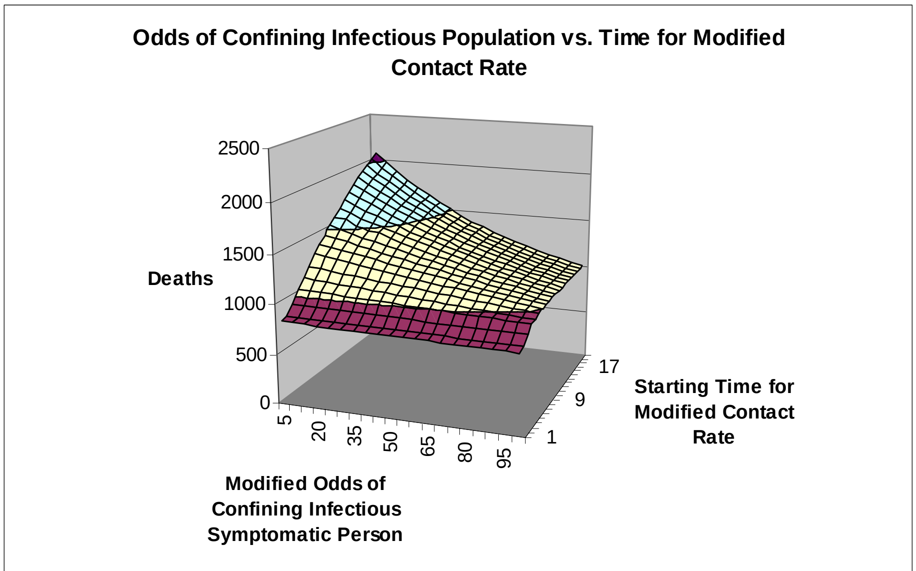

Figure 4: Reducing the Contact Rate vs. Confining the Symptomatic

The results represented in Figure 5 provide a striking comparison of timing versus the effectiveness of treatment in responding to a major bio-event. The scenario depicted here is for Plague with a severe Lethality (i.e., Odds of Dying without Treatment if Infected) of 80%. Treatment 2 is significantly more effective than Treatment 1. (In this case the Odds of Dying when Treatment 1 is applied are still 50%, whereas the Odds of Dying when Treatment 2 is applied are much lower at 20 %.) The surface reflects deaths as the timing of the availability of (an adequate amount of) the two treatments vary from 1 to 20 days.

Clearly timing is of the essence. In this scenario early use (e.g., Day 2) of the less effective Treatment 1 can save about the same number of lives as providing the much more effective Treatment 2 at the end of only the first week (viz., Day 7).

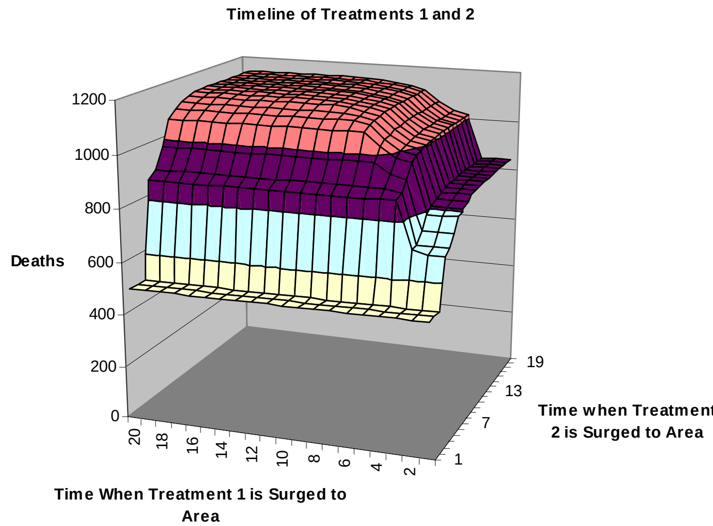

Figure 5: Treatment effectiveness and when available

3.0 Policy Inferences

Systems engineering, as a discipline and approach to large complex problems, grew out of the perceived threat that the former Soviet Union posed to the US. The perceived threat today is no longer bombers and missiles but terrorists attacking with biological, chemical, radiological, or explosive means. And as it did previously, the US will have to make major investments in planning, equipment, and personnel to address the bioterrorism threat—system investments that are a natural consequence of agreeing upon an overriding national defense requirement to act effectively to prevent and respond to an attack. And if such a requirement is in place, surge-capacity planning necessarily follows.

As a "system" the nation's biomedical surge capacity could be viewed as a specialized supply chain. And instead of pre-positioning extensive resources (using forecasting) modern supply chains are generally organized for rapid replenishment. How long will it take to replenish resources as they are used in response to a bio-event? The replenishment supply-chain strategy ideally holds enough medical resources in a city to handle the initial demand surge until the resources can be reliably replenished. So the greater the system's ability to resupply, the less there is a need for pre-positioned resources.

Adopting a replenishment supply chain approach to medical surge capacity would generate at least two major requirements. First, because they are now part of a supply chain, the disaster-response tiers—individual facility, local coalition, jurisdiction of an emergency operations center, region, state, and federal—would have resupply obligations. Second, rapid resupply implies a major investment in a national capability (including transport), not unlike the investment the US made in the 1950s (and beyond) to have an early-warning capability to combat a perceived threat.

4.0 Conclusions

Jay W. Forrester, the developer of system dynamics, said recently (2001) that "the most important use of system dynamics should be for the design of policies." We are using sensitivity analyses of our system dynamics, bio-event model to explore the consequences of different response policies and strategies.

To further leverage our work we have transferred this bio-event model to a systems engineering student team from George Mason University (GMU). As part of a year long project the GMU team added resource management components to the bio-model and investigated resupply strategies as part of the surge response.

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