Article from:

The Actuary Magazine

February/March 2015 – Volume 12, Issue 1

QUANTIFYING PANDEMIC RISK

THE RECENT WEST AFRICA EBOLA OUTBREAK SERVES AS A REMINDER THAT IT IS IMPORTANT FOR ACTUARIES TO ACCOUNT FOR AND QUANTIFY PANDEMIC RISK. BY DOUG FULLAM AND NITA MADHAV

According to the World Health Organization (WHO), as of Nov. 21, 2014, the West Africa Ebola outbreak has resulted in over 15,300 cases and 5,400 deaths. The countries of Guinea, Liberia and Sierra Leone have borne the brunt of the outbreak, with additional cases and deaths reported in Mali, Nigeria, Senegal, Spain and the United States. This is the largest Ebola outbreak on record since the virus was first discovered in 1976, as shown in Figure 1 below.

WHY IS THE WEST AFRICA EBOLA OUTBREAK SO LARGE?

Changes in the Ebola virus itself do not appear to be the major driver behind the unprecedented size of this outbreak. Instead, socioeconomic factors, such as the lack of health care infrastructure in the worst-affected countries, are likely to blame. Guinea, Liberia and Sierra Leone rank low in response capacity, e.g., physicians and hospital beds per capita. In addition, government mistrust in the affected populations—due to decades of civil war—is high, so cooperation between government health workers and the populace, which had been critical for success in previous outbreaks, has not worked to contain the outbreak this time. This outbreak also reached densely populated urban centers, whereas previous ones remained in remote areas. Finally, initial misjudgments about the outbreak, including delays in the initial response to it, false indications that it had been contained, and a hope that it would "burn out" on its own, contributed to its large size.

Despite the initial sluggish response, the international community has contributed significantly to reducing the spread of the outbreak through donations of money, supplies, personnel and capacity building. All these measures have helped tremendously in reducing the rate of disease spread. Drug developers have also begun testing the effectiveness and safety of pharmaceutical interventions such as treatments and vaccines. By the first quarter of 2015, WHO expects that thousands of doses will be available for health care workers in the worst-affected countries, which could also help contain the spread of the disease.

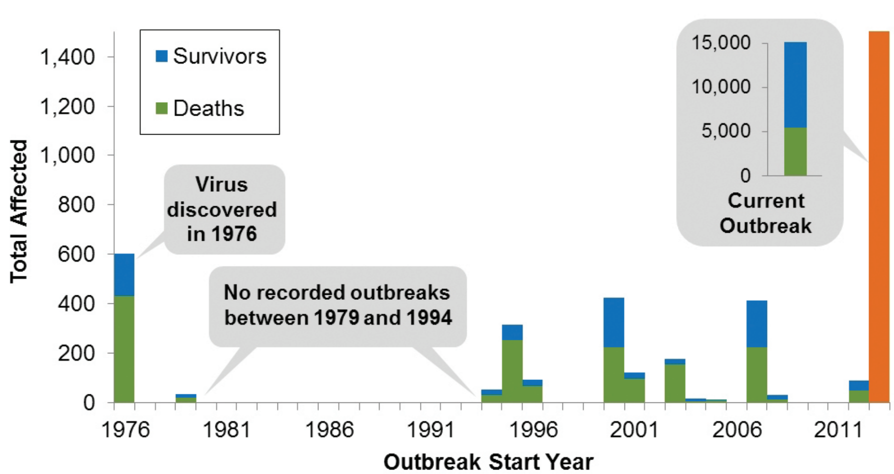
WHAT ARE THE POTENTIAL INSURANCE IMPACTS?

Although the West Africa Ebola outbreak has led to cases and deaths mainly in countries with low insurance coverage, it has far-reaching indirect insurance impacts and it is important for insurance companies and actuaries to have a clear picture of the potential risks.

Large events such as the current outbreak can affect multiple insurance industries, lines and countries simultaneously. The two industries that will likely be hit hardest by an outbreak are health and life insurance, and the severity of the impact is highly correlated to the type of disease and its characteristics. Ebola is spread through direct contact, so it is likely to affect mostly health care workers, first responders, and close family and friends of those already infected. Pandemics that are airborne, however, have the ability to transmit rapidly throughout a community.

Business interruption, travel insurance policies and workers' compensation are

FIGURE 1—CHRONOLOGY OF EBOLA OUTBREAKS, BASED ON DATA FROM WHO AS OF NOV. 21, 2014



lines that could also see claim payouts, although business interruption and travel insurance are unlikely to see large losses because disease is typically not considered a covered loss.

During a severe pandemic, the asset side of the balance sheet may also be adversely affected. People are likely to avoid public places, which will have an adverse effect on businesses. In addition, with people becoming sick and potentially dying, added stress will be placed on workplace labor needs and individuals are likely to take time off, which is likely to hurt their income. Both factors would contribute to an economic slowdown. In October, the World Bank provided stress-testing economic loss scenarios related to the West Africa Ebola outbreak. Their severe scenario resulted in over $30 billion in lost economic output from 2014 to 2015. They noted that this loss is driven by "fear of contagion" rather than being a direct result of the outbreak. Thankfully, in light of the international response, this estimate has been revised down to $3 billion to $4 billion. That said, a survey conducted by the World Bank in November estimates almost half (46 percent) of the working population in Liberia at the start of 2014 are now not working, with the hardest hit being the self-employed.

METHODS FOR ESTIMATING PANDEMIC RISK

Several modeling approaches can be useful for estimating pandemic risk. We will discuss the different modeling approaches and how they can be applied to better understand pandemic risk in the following sections.

Deterministic Methods

To understand the potential impact that

specific types of adverse mortality and morbidity risk—such as a pandemic—may have on a portfolio, stress-testing methodologies are often employed. Some of the most commonly used are the pandemic scenarios from the Department of Health and Human Services (HHS).[1] These scenarios provide both mortality and morbidity estimates that are useful for life and health actuaries. For firms that have exposure to both sets of risk, these scenarios help ensure consistency in modeling approaches. However, they represent only basic assumptions for life and health actuaries and need to be combined with other assumptions to incorporate into stress-testing scenarios.

In his "Potential Impact of Influenza on the U.S. Life Insurance Industry"[2] analysis, Jim Toole took these scenarios and applied them to the insurance market as a whole to estimate the industry loss. He outlines the complementary assumptions required to implement the HHS scenarios into an insurance model. Some additional assumptions applied are as follows: insured vs. population pandemic mortality rates, pandemic age and gender distribution, benefit levels by group, reinsurance credit and tax credits. These assumptions provide a framework for estimating pandemic stresses against a portfolio of risks.

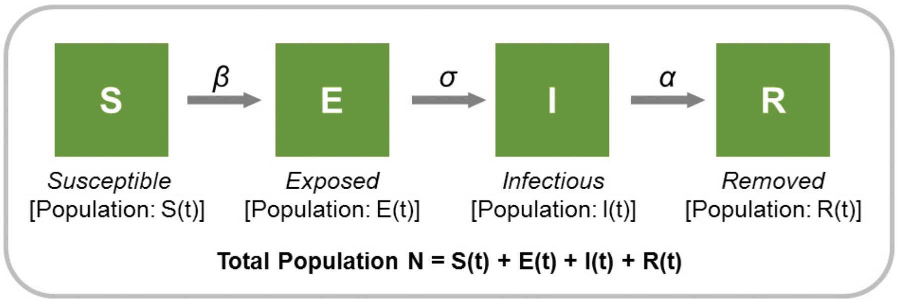
Stochastic Methods

While deterministic methods are useful, the West Africa Ebola outbreak has shown that there is a great degree of uncertainty when an outbreak is unfolding. Stochastic methods can help capture this inherent uncertainty and can provide a method for estimating the probabilities of various outcomes.

Time Series Models

One very useful approach to bringing uncertainty into the equation is through the use of time series models. Autoregressive integrated moving average (ARIMA), generalized autoregressive conditional heteroskedasticity (GARCH) and other time series models allow for fitting an equation to historical data, and for using one or more previous data points as part of the estimation for the current data point. This method is especially useful when there is

FIGURE 2—BASIC FLOW OF EPIDEMIOLOGIC MODEL



a built-in tendency in the system for the current data point to be correlated to the previous data point.

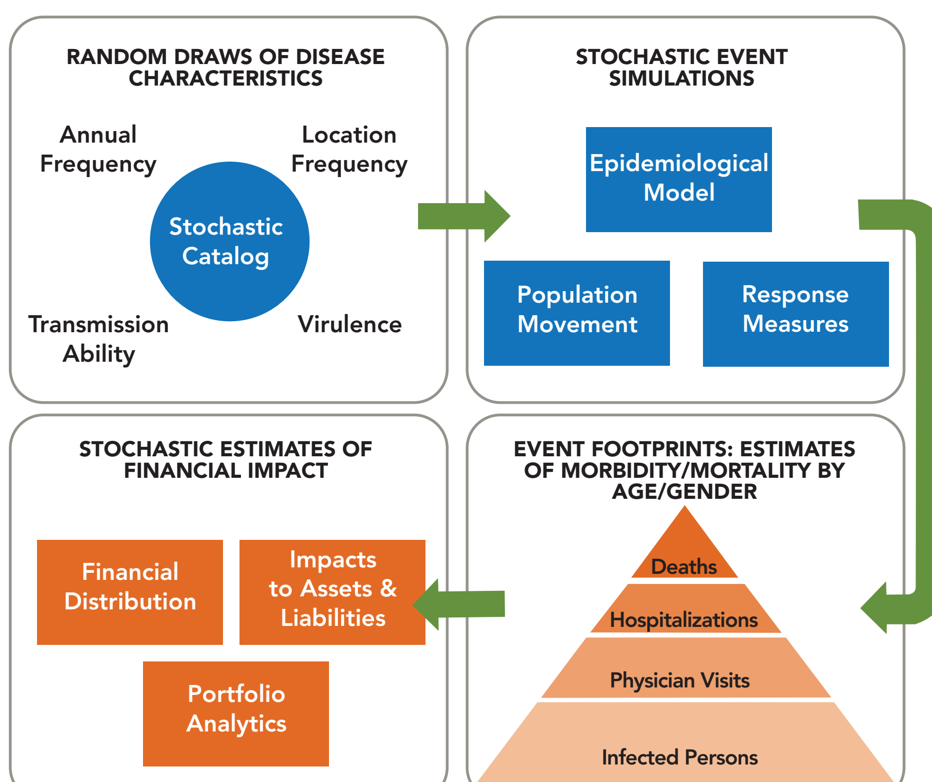
During the early phases of an outbreak, case counts grow exponentially. The rate of infection in the current week will be related to the previous week. Therefore, time series models can be used to model the early stages of outbreaks. With these models, trends, rates of change and variance can be estimated. This information can then be used to forecast future cases and deaths. However, because the outbreak eventually slows down, time series models should be used with caution during an ongoing outbreak. Time series modeling also relies heavily on the assumption that the previously reported data is an accurate representation of reality, which is often not the case during an outbreak.

Epidemiologic Models

Another type of stochastic model is the epidemiologic model, which can be especially useful for simulating the progression of a disease outbreak—even in the early stages. The general technique employed is a compartment model, which divides the population at risk into different "compartments," or disease states. Disease states include categories such as susceptible, exposed, infectious and removed, and represent various stages in disease progression (see Figure 2 above). Once the epidemic begins, anyone who is susceptible is at risk for acquiring the disease. The model then estimates the number of people in each compartment every subsequent day. The disease spreads to more people, until an inflection point is reached, after which the rate of new cases tends to decrease.

Information about the disease, such as how long it takes for someone to develop symptoms or how long someone may be sick, is required to use this type of model. Other important variables include how many people can be infected by one sick person, the percentage of those infected who go to the hospital or die, and the effectiveness of response measures, such as vaccines, during an outbreak. Because there is a great degree of uncertainty in all these parameters, statistical distributions are used for each, and stochastic variation is incorporated during the modeling process. By using this method, the same initial conditions of an outbreak can lead to vastly different final outcomes.

FIGURE 3—EXAMPLE FLOW OF CATASTROPHE MODEL



Catastrophe Models
A third type of stochastic model that actuaries can use is a catastrophe model, which is especially useful for estimating tail risk. Catastrophe models were introduced in the late 1980s to analyze hurricane risk, and now cover a variety of other perils, including pandemics. Catastrophe models use a set of hypothetical, plausible scenarios (called a stochastic catalog) to provide a broad view of risk. Typically, this is done by running many thousands of simulations whose initial conditions are sampled from statistical distributions. These statistical distributions are informed by available data and supplemented with scientific insights. Because it takes a view of an entire range of plausible events, catastrophe modeling allows for estimation of the probability different levels of loss will occur.

Figure 3 on page 32 shows a general pandemic catastrophe modeling framework. First, it is important to simulate the properties of a given pandemic. This includes the type of disease, starting location, rate of transmission from one person to another, and rate of morbidity/mortality, as shown in the upper left quadrant. This is done extensively to build a robust and statistically valid set of simulated events.

These initial parameters are input into an epidemiological model to estimate the total number of infected people, hospitalizations, intensive care patients and deaths, as shown in the upper right quadrant. At this point, the information can be aggregated to create an event footprint. This information allows actuaries to estimate total rates of morbidity and mortality for each event. It can be broken down by region, age and gender. Finally, the appropriate policy conditions

are applied to the number of people insured in each illness outcome category to estimate the financial impact.

COMPARISONS BETWEEN DETERMINISTIC AND STOCHASTIC APPROACHES

Stress testing and stochastic modeling have their advantages and disadvantages and have a proven track record if implemented correctly. Stress testing, which can provide many useful metrics for the life or health actuary, is able to:

- Provide an estimated loss that can be measured against the base assumptions
- Highlight which policies are most at risk and/or will see the largest deviations from base assumptions
- Determine which assumption(s) are the most important
- Help assess mitigation measures.

These four key aspects of stress testing are only important, however, once framed in the context of other analyses—most notably the base analysis. Empowered with this information, the actuary can be proactive about potential issues. Mitigation methods may present themselves in product design, reinsurance programs, asset management methodologies, etc. In addition, the stresses must be reasonable. Using stresses that have little basis in reality can result in inappropriate risk management decisions. Testing assumptions are often based on past experiences to maintain reasonableness. The benefit of using historical information comes from the fact that we know the severity of these events is possible. But the problem is future pandemics will almost certainly not have the same exact characteristics of previous outbreaks. This uncertainty can limit an actuary's ability to determine if the mitigation methods implemented are appropriate for the downside risk.

Stochastic methods have their own set of advantages and disadvantages. The largest advantage comes from the ability to estimate the probability that different outcomes will occur, giving the actuary an enhanced ability to understand the probability of different loss levels and to determine how best to manage reserves.

Stochastic models also allow users to analyze events that may not be similar to historical events. Therefore, stochastic models give the actuary a much better understanding of the risks faced by their firm or client. They also allow the actuary greater flexibility when assessing the risk of an ongoing event like the Ebola outbreak in West Africa. Actuaries who use stochastic pandemic models can look at the simulations from their model and find events that are similar to the one unfolding. These simulations provide a base range of potential losses. And depending on how the model is built, users could run simulations with a fixed set of known parameters similar to the current outbreak. These can be used to create an ensemble of similar events to determine a range of output.

The major drawbacks to stochastic modeling are the time and resources it requires. Building a simulation method is an intensive process, even for the simplest of models. Pandemic modeling isn't simple and requires expertise in epidemiology, statistics, simulation programming, database management and stochastic methods. For proper modeling, it is necessary to:

1. **Analyze each disease class separately.** How disease classes impact populations varies. Some are more concentrated, others are more likely to cause severe morbidity, etc.
2. **Create a large simulation process.** Pandemics are infrequent events, which is problematic for modeling. Convergence issues are likely to arise, and the only way to avoid them is to make sure you simulate enough events. This can put added strain on systems and resources to properly analyze the losses.
3. **Validate many components with limited data.** Over the last 100 years, there have been few pandemic events. Four were caused by influenza viruses and another by HIV. Most of the data used to validate the model will likely come from epidemiology assessments of diseases.

CONCLUSION

Actuaries have already built dynamic systems to account for economic capital models. In some cases, actuaries have also built stochastic longevity and health care models to incorporate probabilistic future rates of change. Therefore, extending these methods to include stochastic mortality and morbidity modeling for pandemic events is possible. In addition, the simulated events can be tied to capital models as a feedback loop, thus creating a dynamic, more useful asset-liability management framework. Both deterministic and stochastic modeling methods are useful for quantifying pandemic risk, and collaboration between actuaries and epidemiologists could help improve modeling methodologies. We encourage the actuarial community to reach out into other fields and incorporate the best modeling methods. A

END NOTES

[1] In their "HHS Pandemic Influenza Plan," November 2005 release, the HHS provides two pandemic scenarios: moderate and severe. These scenarios have similar characteristics to the 1957 and 1968 flu pandemics, and the 1918 Spanish Flu pandemic, respectively.

[2] Jim Toole, "Potential Impact of Influenza on the U.S. Life Insurance Industry," Society of Actuaries research project, May 2007.

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