PANDEMIC BUSINESS IMPACT MODELER

Ching-Hua Chen-Ritzo, Lianjun An, Stephen Buckley,
Pawan Chowdhary, Tom Ervolina, Naveen Lamba,
Young Lee, Dharmashankar Subramanian

IBM T.J. Watson Research Center
1101 Kitchawan Road
Yorktown Heights, NY 10598, U.S.A.

ABSTRACT

The Pandemic Business Impact Modeler is a simulation tool for assisting leaders of global organizations in assessing the business impact of a potential pandemic on their organization. This tool is unique in that it integrates traditional epidemiological simulation with supply chain simulation, allowing users to quantify the impact of a potential pandemic outbreak on business operations and performance. By providing this crucial link between disease dynamics and business dynamics, this tool can aid decisions relating to pandemic preparedness. In this paper, we provide a detailed description of our simulation tool and use it to perform an experimental study of the effectiveness of various mitigation strategies for a fictitious global enterprise.

1 INTRODUCTION

The world has seen an increasing trend in the frequency and losses associated with natural disasters (Munich Re 2005). Additionally, the perceived threat of terrorism has been high since Sept. 11, 2001. In more recent years, with the occurrence of the SARS outbreaks in Asia and Canada and human incidences of the avian flu in Asia and the Middle East, there has been plenty of speculation about the probability of an avian flu pandemic. Disasters, terrorism and widespread disease threaten people as well as businesses. The ability of a company to deal with disruptions can significantly impact business performance. For this reason, companies are increasingly interested in investing in solutions that will better prepare them for business disruptions.

Pandemics are an interesting example of business disruptions due to their global reach and relatively long durations. As the trend of globalization continues and businesses become dependent on resources and markets around the world, the potential impact of a pandemic on business performance becomes increasingly relevant and complex. While epidemiological simulation models do exist, the authors are not aware of any existing models which link epidemiological phenomena to business impact. The inclusion of this link is essential if businesses are to understand the threat that a pandemic poses to their employees, customers, revenue and costs.

The Pandemic Business Impact Modeler (PBIM) addresses this need and comprises six integrated simulation modules. The **epidemiological** module simulates the spread and severity of a disease over space and time. The **behavioral** module simulates organizational, social and psychological reactions to the spreading disease. The **economic** module computes the impact of a pandemic on key economic indices, by industry sector. The **infrastructural** model computes the availability of basic infrastructure such as electricity, communication and transportation. The supply chain module models the impact of the pandemic on supply and demand, and essentially solves a **supply-demand** matching problem. Finally, the **financial** module calculates the revenue earned and mitigation costs incurred over the planning horizon.

PBIM was developed to provide companies with a tool for understanding how a pandemic might impact the company's employees and business performance. The absence of a commercially-available simulation model that could link the spread of a disease to the effects on a company motivated the development of this tool. PBIM also allows users to experiment with different mitigation strategies and disease spread scenarios. Using PBIM, we perform experiments to demonstrate how it can be used to analyze the cost-benefit trade-offs for various mitigations strategies.

This paper is organized as follows: In section 2, we provide an overview of previous work. In section 3, we describe in detail each model comprising PBIM, as well as the simulation architecture. In section 4, we present the types of mitigation strategies that the model is capable of handling. Section 5 provides an overview of our experiments. It should be noted that the content presented in this paper is not intended to be a reflection of IBM or its policies or intentions with respect to a potential pandemic.

2 PREVIOUS WORK

Several simulation models have been built to study the spread of disease among humans and communities (e.g. Barrett et al 2005, Ford et al 2006). To our knowledge, none of these models have addressed the impact of epidemic disease spread on business, although there has been some speculation on this in the popular press (e.g. Carey 2005, Ruiz 2005, Rosenthal and Bradsher 2006). Some non-simulation studies have been performed on the economic impact of a pandemic (e.g. Meltzer et al 1999, Congressional Budget Office 2006, The World Bank 2005). Much has been written about potential mitigations for pandemics (e.g. US Government 2005, Ferguson et al 2006). Many simulation models have been built to simulate the response to crises (e.g. Kaplan et al 2002, Jain and McLean 2003), but these models do not address global business impacts.

3 PANDEMIC BUSINESS IMPACT MODELER

The Pandemic Business Impact Modeler is a deterministic simulation model comprised of several interdependent modules: epidemiological, infrastructural, economic, behavioral, supply chain and financial. The relationships between the modules can be represented by an acyclic directed graph, as shown in Figure 1. A directed edge between two modules indicates the direction of information flow between them. PBIM runs each module over the entire simulation time horizon before proceeding to another module. Each module is run once in a single simulation. In the remainder of this section, we provide detailed descriptions of the individual modules.

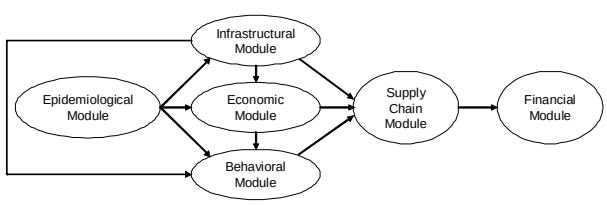

Figure 1: PBIM Simulation Flow

3.1 Epidemiological Module

As shown in Figure 1, the first module to be run in the simulation is the epidemiological module. This module models a global network of 8,000 geographical locations, 3,600 airports and the transportation links between them. Demographic information (e.g., population) is stored at the county, city and country levels. The dynamics of the pandemic is simulated using an SEIR model (Anderson 1982). The SEIR model is a well-known epidemiological model that is used to compute the proportion of a population that is in each of four states: Susceptible, Exposed, Infectious, and Recovered. Additionally, portions of the population that reach the infected state may die. The proportion of each population that exists in each of these states changes over time. The speed and intensity with which the pandemic spreads depends on the virulence of the disease, the geographical origin on the disease, population density, proximity to neighboring locations, and interactivity between locations 'connected' via transportation links.

PBIM is designed to accept different epidemiological 'engines' in a 'plug-and-play' manner. The Spatio-Temporal Epidemiological Modeler (STEM) developed at IBM Research is an example of one such engine (Ford et al 2006). The current instantiation of PBIM utilizes an engine that we developed based on systems dynamics models created using the VENSIM simulation package. The epidemiological module produces a time series of the population that is in the S, E, I and R states for every geographical location that is included in the model.

3.2 Infrastructural Module

The infrastructural module evaluates the impact of a pandemic on the infrastructure that is essential for the daily operation of most businesses. Examples of such infrastructure include electricity, air transportation, ground transportation, water, and the Internet. The infrastructural module uses a systems dynamics model to represent a network of numerical cause-and-effect relationships between the spread of the disease and the availability of infrastructure in each geographical location. The types of relationships modeled include the following:

- Utilities such as electricity and communications are constrained by workforce availability.
- Ground transportation is also influenced by government policies such as curfews, quarantines and road closures.
- Natural resources (e.g., water) could be contaminated by disease.

The infrastructural module receives input from the epidemiological module and generates a time series of the availability of various forms of infrastructure relative to a base, non-pandemic environment. Figure 2 provides an example of the type of output generated by this module.

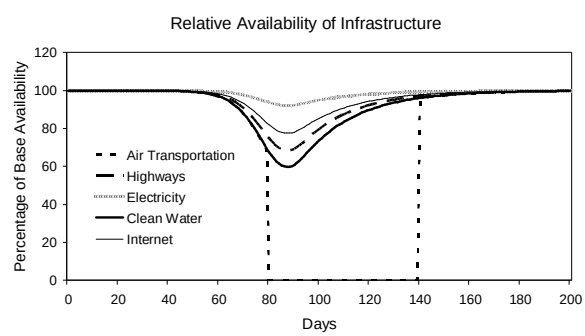

Figure 2: Exemplary Output from Infrastructural Module

3.3 Economic Module

The economic module evaluates the impact of a pandemic on the gross economic output across 20 industry sectors. Like the modules that precede it, it utilizes a systems dynamic model. In this case, it is used to represent a network of numerical cause-and-effect relationships between the spread of the disease and the economic health of each country. The calibration of this module was guided by the expected percentage change in demand for goods/services in the various industry sectors in the event of an avian flu pandemic, as published by the United States Congressional Budget Office (Congressional Budget Office 2006). The economic module receives input from the epidemiological and infrastructural modules and generates a times series of the change in gross economic output over the simulation time horizon, for each industry sector and each country.

3.4 Behavioral Module

Human behavior plays a significant role in the spread of a pandemic. The behavioral module captures the cause-and-effect relationships between the progression of the pandemic and workforce availability. In particular, it is concerned with the population of employees belonging to the company being modeled. For example, an increase in the local infectious population may worsen employees' perceptions of the threat of the disease and result in a decrease in the number of employees going in to work. An increase in media coverage and government warnings may have similar effects. While not necessarily a behavioral issue, this module also captures the fact that when electricity is not available at work, employees are not available at work.

Mitigation actions implemented by the company (e.g., vaccinations, improved hygiene) may result in increased availability of employees. The behavioral module receives input from both the epidemiological and infrastructural modules, as well as information regarding any mitigation policies that are implemented within the company. It generates a time series of the percentage of employees who are available to work from home and from the office, for each company site. Figure 3 provides an example of the type of output generated by this module.

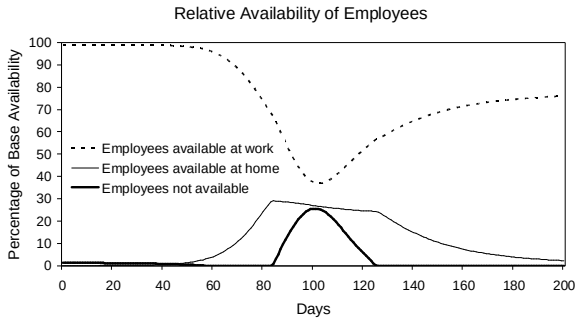

Figure 3: Exemplary Output from Behavioral Module

3.5 Supply Chain Module

The supply chain module models the company's supply chain. Its primary functions are as follows:

1. Forecast demand for products/services
2. Forecast supply of resources
3. Determine the ability of the company to deliver products and services

The demand forecast is generated using information about the economy (i.e., change in gross output in relevant industry sectors in customer locations) and the availability of employees (e.g., sales force). This information is received from the economic and behavioral modules, and is used to modify the 'baseline' forecast for products/services. The baseline forecast represents the forecast that would be used in the situation where there is no pandemic.

The types of resources for which supply is forecasted include those that are traditionally planned in materials requirements planning and capacity planning processes, such as raw materials, machine capacity and productive staffing levels. In addition to these types of resources, the supply chain module also forecasts the availability of resources such as facilities, and local and global logistics capacity. Such resources are typically assumed to be unlimited under normal conditions. However, they may become significantly constrained during a pandemic. The supply forecast is generated using information about the availability of employees and infrastructure over the simulation horizon. It receives this information from the behavioral module and infrastructural module, respectively.

The third main function of the supply chain module is to perform demand-supply matching. The supply chain module compares a time series of forecasted demand against a time series of forecasted supply via a dependency structure called a Bill-of-Resources. In PBIM, supply-demand matching is modeled using an algorithm powered by the Watson Implosion Technology (WIT) developed at IBM (IBM 2006). WIT is a patented technology currently used by IBM Systems & Technology Group to perform supply chain planning for its mainframe and server products. Ultimately, the supply chain module produces as output a time series of the volume of each product/service that can feasibly be delivered over the simulated time horizon.

3.6 Financial Module

The financial module receives information from the supply chain module regarding the volume of product/service delivered and from the simulation manager regarding the mitigation strategies employed by the company. It then computes the revenue generated from sales and the costs incurred from implementing mitigations. The output from this module allows the user to examine the trade-offs between mitigation investments and the impact of revenue. Even in the absence of mitigation actions, users can use

this output to understand amount of revenue that is at risk under various pandemic scenarios.

3.7 Simulation Architecture

A simulation manager facilitates the integration as well as execution of the various PBIM simulation modules and storing of data in a data warehouse. It also provides an interactive web-based dashboard for defining simulation parameters and analyzing the output of simulation runs. PBIM uses a standard Java client-server architecture and the advanced Java Management Extension framework. It also follows standard component model development practice along with standard JDBC, POJO objects to access the data in the data warehouse. The dashboard was built using SPRING framework on top of Websphere Portal Server (WPS). Figure 4 illustrates the design of the simulation architecture and indicates the sequence in which the different modules are run. In Figure 4, the supply chain module is separated into its three main functions. Simulation run time varies with the size of the company being analyzed. In our experience, run times have ranged between 20 minutes and 1 hour.

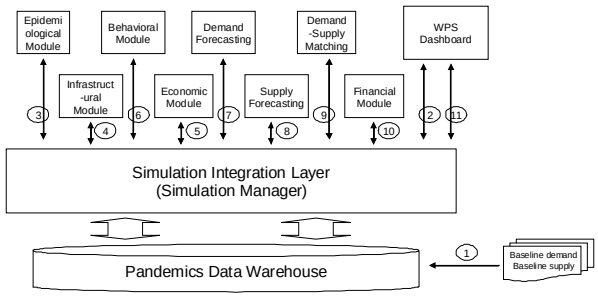

Figure 4: Simulation Architecture

4 MITIGATION ACTIONS

PBIM is capable of modeling a number of different mitigation actions. Airport closures and quarantines are examples of mitigation actions that may be taken at the government level. These mitigations are applied in the epidemiological module and could affect the spread of the disease around the world. Meanwhile, in PBIM, vaccinations and face masks are examples of employee mitigation actions that may be taken at the corporate level. They are applied in the behavioral module. These corporate mitigations may affect the disease spread within a local population, with no impact on the global disease spread. Cross-training and multi-sourcing are also examples of corporate mitigations and are inputs to the supply chain module. These mitigations do not affect disease spread at all, but may help to protect the company financially. It should be noted that the mitigations described here are not intended to be a reflection of IBM policies or intentions with respect to a potential pandemic.

5 DESIGN OF EXPERIMENT

The purpose of our experiment is to understand the impact of different mitigations on the revenue performance of a fictitious computer manufacturer, in the event of a pandemic. This manufacturer has a multi-echelon global supply chain comprising raw material suppliers who provide materials to a number of fulfillment sites, who then assemble and ship finished goods to customers around the world. The manufacturer produces 15 products spread across 3 product lines. Customers are uniformly assigned to one of 20 industry sectors. Figure 5 illustrates this global supply chain network.

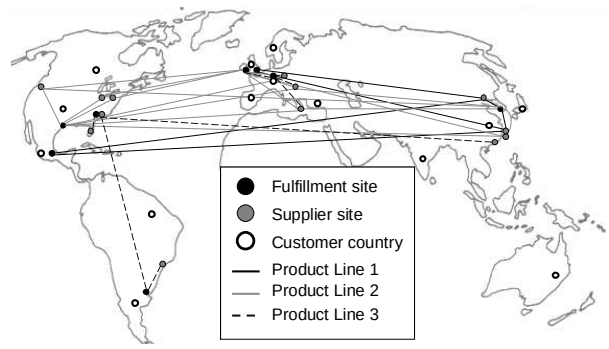

Figure 5: Supply Chain Network for Fictitious Computer Manufacturer

Our experiment comprises 6 factors. These factors and their levels are described in Table 1.

Factor	Level 0 (low)	Level 1 (high)
AIR	All airports open	All airports closed
EMP	Low availability (10%) of employee mitigations*	High availability (90%) of employee mitigations*
SUP	No alternative raw material suppliers available	Alternative raw material suppliers available**
FUL	No alternative fulfillment sites available	Alternative fulfillment sites available**
SFS	Low sensitivity (10%) of demand to sales force availability	High sensitivity (50%) of demand to sales force availability
ECN	Low sensitivity (1%) of demand to economic indicators	High sensitivity (5%) of demand to economic indicators

* We assume that 50% of employees who would have become infectious without the employee mitigation (e.g., face masks) will not become infectious if the mitigation is made available to them.

** We assume that alternative suppliers and fulfillment sites are 100% reliable in the event of a pandemic.

Table 1: Six Experimental Factors and Their Levels

We designed a full factorial experiment comprising 64 simulation runs. We seeded the disease in Vietnam and used a simulation horizon of 52 weeks. The spread of the disease in select countries is illustrated in Figure 6.

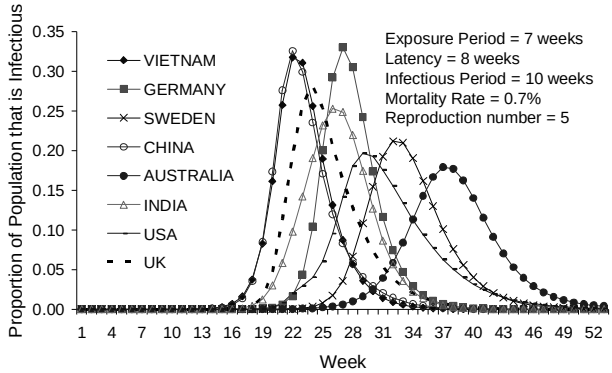

Figure 6: Spread of Disease Over 52-Week Horizon

6 RESULTS

Figure 7 plots the revenue earned for each of the 64 runs. According to this figure, annual revenue does not fall below 30% of the annual revenue earned under normal conditions. In run 1, all factors are set to level 0. Maximum revenue is achieved in run 57, when AIR, EMP, SUP and FUL are at level 1 and all other factors at level 0. However, run 42 achieves comparable revenue with just three mitigations, AIR, FUL and SUP in place (i.e., at level 1). Therefore, there is little value in investing in employee mitigations if airports are closed and alternative fulfillment and supplier sites are already in place.

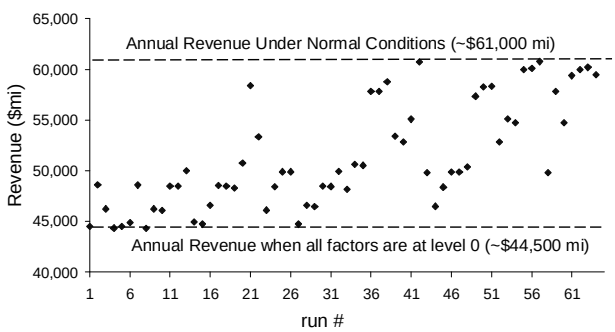

Figure 7: Revenue Associated with Simulation Runs

Figure 8 plots the main and *n*-way interaction effects, relative to run 1. Balakrishnan et. al (2002) use a similar method for displaying their simulation results. Treating all effects with absolute value greater than $1 billion as significant, Figure 8 shows that the factors AIR, EMP and SUP, corresponding to runs 2, 3 and 7, respectively, have significantly positive main effects. It appears that airport closures and alternative suppliers are equally effective as isolated mitigation strategies, each resulting in roughly $4 billion of additional revenue relative to run 1, but still shy of the baseline revenue by roughly $13 billion.

There are significant positive 2-way interaction effects for AIR*SUP and FUL*SUP, corresponding to runs 21 and 22, respectively. These interactions reveal a non-linear relationship between revenue and the AIR and SUP mitigations and the FUL and SUP mitigations. It is interesting to note that while the main effect of FUL is small, its 2-way interaction with SUP is quite large. This is because the value of alternative fulfillment sites is enhanced by the concurrent availability of suppliers. When airports are closed and alternative suppliers are available, the revenue earned is just $3 billion (or 5%) shy of the baseline revenue under normal conditions.

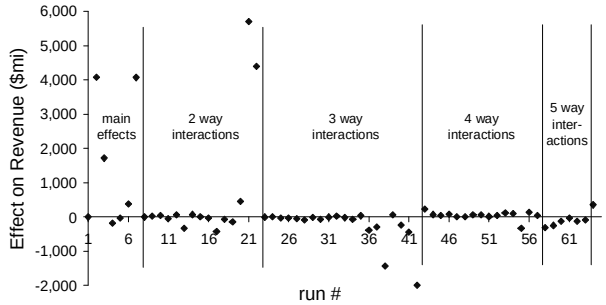

Figure 8: Effect on Revenue by Run

While a couple of 3-way interactions display absolute effects exceeding $1 billion, they are small relative to their lower level effects. The demand-related factors, SFS and ECN, do not appear to have a significant effect on revenue relative to the mitigation-related factors. This is because the disease scenario used in our experiment reflects a mild pandemic, for which the United States Congressional Budget Office (Congressional Budget Office 2006) predicts relatively small changes in demand (~4% decline, on average). Meanwhile, our models predict a relatively stronger impact on resource availability. Therefore, supply, as opposed to demand, is the bottleneck for our fictitious manufacturer.

Our results suggest that the closing of airports and setting up of alternative suppliers and fulfillment sites may be the most effective combination for mitigating the impact of a pandemic on the revenue of this fictitious computer manufacturer. Closing airports and establishing alternative suppliers is also an effective combination of mitigations if the number of mitigations that can be employed is constrained. Since these results are dependent on the structure of the supply chain network, they cannot be generalized to all manufacturing supply chains.

SUMMARY

We have described a framework and model for combining epidemiological and business models. We designed and implemented an experiment for studying the effect of various mitigation and demand-related factors on the revenue of a fictitious computer manufacturer. This approach can be used to experiment with alternative business models and mitigation policies.

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AUTHOR BIOGRAPHIES

CHING-HUA CHEN-RITZO is a member of the Mathematical Sciences department at the IBM T.J. Watson Research Center in Yorktown Heights, NY. Her e-mail address is <chenritzo@us.ibm.com>.

LIANJUN AN is a member of the Mathematical Sciences department at the IBM T.J. Watson Research Center in Yorktown Heights, NY. His e-mail address is <alianjun@us.ibm.com>.

STEPHEN BUCKLEY is a manager in the Mathematical Sciences department at the IBM T.J. Watson Research Center in Yorktown Heights, NY. His e-mail address is <sbuckley@us.ibm.com>.

PAWAN CHOWDHARY is a member of the Mathematical Sciences department at the IBM T.J. Watson Research Center in Yorktown Heights, NY. His e-mail address is <chowdhar@us.ibm.com>.

TOM ERVOLINA is a member of the Mathematical Sciences department at the IBM T.J. Watson Research Center in Yorktown Heights, NY. His e-mail address is <ervolina@us.ibm.com>.

NAVEEN LAMBA is managing consultant in operations analytics with IBM Global Business Services in Fairfax, VA. His e-mail address is <naveen.lamba@us.ibm.com>.

YOUNG LEE is a member of the Mathematical Sciences department at the IBM T.J. Watson Research Center in Yorktown Heights, NY. His e-mail address is <ymlee@us.ibm.com>.

DHARMASHANKAR SUBRAMANIAN is a member of the Mathematical Sciences department at the IBM T.J. Watson Research Center in Yorktown Heights, NY. His e-mail address is <dharmash@us.ibm.com>.