Modeling Dynamics of Workforce Absenteeism and Effectiveness of Mitigation Actions During Pandemics

Young M. Lee, Lianjun An

IBM T.J. Watson Research Center, P.O. Box 218, Yorktown Heights, NY 10598, U.S.A.

Email: {ymlee; alianjun}@us.ibm.com

Abstract

A pandemic is likely to occur in the near future, and it could cause significant disruptions in society creating deaths, despair, fear, and monetary cost, among other losses. Firms would also be negatively affected by a pandemic through loss of revenue, profit, employees, and even through a reduction in the value of the business itself. Especially for service-intensive businesses, employee absenteeism is a key factor that impacts firms when a pandemic occurs, hampering various business operations. In this paper, we describe a system dynamics model that describes dynamics of workforce absenteeism resulting from a pandemic, and also effectiveness of corporate mitigation actions.

Keywords: Pandemic; System Dynamics, Absenteeism, Infectious Disease, Perceptions

1. Introduction

There is a high likelihood that a pandemic will occur in the not-too-distant future and that it will impact various aspects of society — creating deaths, despair, fear, and monetary cost, among other losses. Firms would also be negatively affected by a pandemic through loss of revenue, profit, employees, and even through a reduction in the value of the business itself. Employee absenteeism is a key factor that impacts firms as result of a pandemic, hampering various business operations, especially for service-intensive businesses. During and even after a pandemic, some employees would not be available for work because of various factors including sickness arising from the affliction, death, perception of risk, the need to attend to family members and non-availability of infrastructure, among other factors. Such a situation would create workforce shortfalls hampering manufacturing, the delivery of goods, and the provision of services.

To prepare firms for the possibility of pandemic, and to position firms to be able to develop response plans, it is very important to enable firms to estimate the magnitude and dynamics of workforce absenteeism prior to an occurrence of a pandemic. It is also important to enable firms to estimate the effectiveness of various mitigation actions in terms of how such actions may reduce the adverse effects of a pandemic on employee availability and productivity. The modeling work described in this paper has been used by a firm to assist business leaders in assessing the impact of a pandemic on availability of corporate workforce. An objective of the modeling was thus to quantify the impact of a potential pandemic on corporate employee absenteeism, including the effect of mitigation actions that firms may implement.

There are four categories of employee availability (and absenteeism) we model in this work. They are: number of employees available to come to work, number of employees available at home, number of employees not available for work either at work or home, and number of employees who could not survive the disease. The number of employees available at home depends on whether the nature of the work allows telecommuting, thus on what percentage of employees are allowed to work from home. Employee absenteeism, i.e. number of employees not available for work either at work or home, is estimated as a function of perceived risk and the number of infectious employees, as well as

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other factors, including the number of employees missing work to attend to family needs, the availability of infrastructure, and so forth.

The employee availability and absenteeism information estimated is used to assess the economic impact of a pandemic on the firm (Chen-Ritzo et al. 2007). The remainder of this paper is organized as follows. In section 2 we review the related literature. In section 3 we propose a model that describes the employee absenteeism resulting from a pandemic and the effectiveness of mitigation actions. In section 4 we present simulation results for several scenarios. Section 5 concludes the paper and discusses further research direction.

2. Literature Review

Influenza pandemic can cause severe social and economic disruption. Several pandemic scenarios have been recorded and analyzed in government reports. One such report (Congressional Budget Office 2005) studies pandemic outbreaks in 1918, 1957 and 1968, and provides evidences how pandemic affects human health, social behavior and business activities. Specifically, it proposes to improve preparedness for a potential pandemic related to avian influenza (H5N1) in poultry and exposes policies and options for future. Epidemiological modeling work to understand how infectious disease spreads among human population goes back to 1927 when Kermack and McKendrick (Kermack and McKendrick 1927) developed a model. In their model, three groups of population are modeled; Susceptible population (S), Infectious population (I) and Recovered population(R). Such a model is long known as the SIR model and the mathematical equation is called the Kermack-McKendrick equation. The SIR model has been used widely in epidemiology. The model describes the evolution process of a disease affecting population. Starting with some infectious population, some of the susceptible population (S) becomes infectious population (I) as a result of social contacts, and the most of the infectious population (I) gets recovered after care and becomes recovered population (R). Note that some in the infectious population might die depending the mortality rate. Also the model typically assumes that the recovered population would develop permanent immunity. For certain diseases, immunity assumption may not be valid, and the recovered person could get infected again.

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The model can be extended to include an additional group of population called Exposed population (E). In this version of the model, the susceptible population would become the exposed population first, and then it can become the infectious population (Anderson and May 1979). Such a model is called the SEIR model, and there are many varieties of the SEIR models (Trottier and Philippe, 2002 &2003). For instance, a SEIR model was extended to study the SARS outbreak from November 2002 to July 2003 (Hsu and Hsieh 2006). The authors added several other population groups such as quarantined and isolated population. They examined compound effects from intervention measures, including quarantine and public response.

There have also been studies that made use of models of how the epidemiological spread of a pandemic may change human behavior (causing fear, perception of risk, flight, etc.) using causal relationship and dynamic modeling methods (Heinbokel and Potash, 2005). However, there has not been any study that made use of models of how countermeasures may have a mitigating effect, not only on the epidemiological infection of employees but also on the perception of employees as to the risk of epidemiological infection. Both the size of the infectious population and the perception of risk affect employee absenteeism. We model the effect of mitigation actions on employee absenteeism and provide visibility into how mitigation actions may offset the effect of the epidemiological spread of a pandemic.

System Dynamics (SD), introduced by Forrester (Forrester 1961), is very powerful methodology at studying dynamic and evolution processes. It allows capturing casual relationship and feedback loops within the target system, converting a mental model into practical simulation model and exposing physical laws in social behavior and physiological world. It has been widely applied in many different fields. Sterman (Sterman 2004) summaries its different applications, including the SIR model expressed through the flow-stock diagram and casual relationship. We use SD modeling and simulation tool to model people's reaction corresponding to risk perception and mitigation, and to study workforce availability as a result of physical illness, risk perception and mitigations during pandemic.

3. Model of Employee Absenteeism

We use an epidemiological model - a SEIR (Susceptible, Exposed, Infectious and Recovered) model of a pandemic - and various corporate mitigation actions to estimate employee absenteeism. We model the absenteeism as a combined effect of pandemic infectiousness and mitigation actions. The epidemiological model produces information on population affected by the pandemic, which affects employee health, perception and fear, which in turn cause employee absenteeism. The infectiousness has increasing effect on absenteeism while the mitigation actions have decreasing effect on absenteeism.

Mitigation actions to reduce the effect of a pandemic by reducing transmissibility, duration of infectivity and perception of risk may include: distributing anti-viral drugs such as Tamiflu®; distributing face masks; instituting separation policies; closing sites; restricting travel; using ancillary workers; using improved hygiene; instituting employee monitoring programs; reducing absence payments; and providing vaccination. Deployment of multiple mitigation actions may have a compounding effect on reducing absenteeism by affecting two major factors; reduction of number of infectious employees and reduction of the perception of employees as to the risk of infection.

In the model, absenteeism is estimated as a function of perceived risk and the number of infectious employees, as well as other factors, including the number of employees missing work to attend to family needs, the availability of infrastructure, and so forth, as shown in Equation 1 in a form of algebraic equation as,

$$A_t = f(P_t, I_t, F_t, S_t)$$
 (Equation 1)

where

A_t	=	Absenteeism at time t
P_t	=	Perception of risk at time t
I_t	=	Number of infectious employees at time t
F_t	=	Family needs at time t
S_t	=	Infrastructure availability at time t

The perception of risk, P_t , at time t, in the equation 1 above, is in turn expressed as,

$$P_t = \{ \int_{t_0}^t (F_i - F_d) \cdot dt \} \cdot W \cdot R_{motality} \cdot \alpha_p \cdot Eff_{mit}$$
 (Equation 2)

where

F_i	=	increasing rate of fear = $[a \cdot I_t - F_c]^+$
F_d	=	decreasing rate of fear = F_c / τ
а	=	a coefficient
I_t	=	infectious population at time t
F_c	=	cumulated fear
τ	=	duration of fear
W	=	warning factor = $f(W_{media}, W_{gov})$
W _{media}	=	media warning factor of pandemic
W_{gov}	=	government warning factor of pandemic
<i>R</i> _{mortali}	$_{ty} =$	mortality rate
α_p	=	coefficient for effectiveness of overall
		mitigation actions on perception
Eff _{mit}	=	effectiveness of overall mitigation actions

The number of infectious employees, I_t , at time t in Equation 1 above is modeled as a fraction of infectious general population reduced by the effectiveness of mitigation actions.

$$I_t = I_t^g \cdot \alpha_i \cdot Eff_{mit}$$
 (Equation 3)

where

 $I_t^g =$ number of infectious general population $\alpha_i =$ coefficient for effectiveness of overall mitigation actions on infectious employees

The effectiveness of overall mitigation actions is computed as a compounded effect of individual mitigation action as shown below.

$$Eff_{mit} = \prod_{i=1}^{N} (1 - eff_i \cdot avail_i)$$
 (Equation 4)

where

$eff_i =$	effectiveness of individual mitigation action <i>i</i>
$avail_i =$	availability of individual mitigation action <i>i</i>
N =	total number of mitigation actions

The model contains an epidemiological model of a pandemic, and determines a compounded effect of one or more mitigation actions to estimate overall workforce absenteeism based on perceived risk of a pandemic, expected number of infectious employees, expected number of employees attending family needs, and infrastructure availability.

The effect of one or more mitigation actions may be computed by multiplying effectiveness and availability of individual mitigation actions. In addition, the overall effectiveness of mitigation actions may be a factor in determining the expected perception of employees as to the risk of infection as well as the expected number of infectious employees. Furthermore, workforce absenteeism may be estimated based on expected employee perception of the risk of a pandemic, expected number of infectious employees, expected number of employees attending family needs, and expected infrastructure availability.

Figure 1 shows an overview of how workforce absenteeism is estimated in our model. First, an epidemiological model of a pandemic for an infectious population is accessed. Using the epidemiological model, a determination is made as to the degree of perceived risk and infectious population. The epidemiological spread of a pandemic has increasing effect on perceived risk and infectious population. The overall effectiveness of mitigation actions is calculated from effectiveness and availability of individual mitigation action. The overall effectiveness of mitigation actions has the decreasing effect on the perceived risk and infectious population. Therefore, the balance between pandemic spread (increasing effect) and the effectiveness of mitigation actions (decreasing effect) would determine the overall level of perceived risk and infectious employee population. When one or more of mitigation actions is deployed, the number of infectious employees would be less than the number of infectious general population.

Needs to attend infectious family members are computed using information on the degree of pandemic spread and average family size in the region of the analysis. The infrastructure availability is accessed from another model that describes the unavailability of infrastructure such as electricity, water, telecommunication etc, as a result of the pandemic.

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Figure 1. Overview of the Absenteeism Model

The workforce absenteeism is computed in four groups; number of employees available at work, number of employees available at home (telecommuting), number of employees survived but not available for work, and number of employees not survived.

Figure 2 shows a simplified overview of causal relationships modeling in the system dynamics model. Figure 3 shows more details of the causal relationships described above in Figure 2. The modeling was done with a system dynamics modeling tool called Vensim (http://www.vensim.com). The bottom portion of Figure 3 also shows individual mitigation actions. Since Figure 3 is too crowded with so much information, it is not intended to be readable. Therefore, we use Figure 2 to describe our model. Perceived risk is affected by infectious population (general), mortality rate, government warning (message), media warning (message) and corporate mitigation actions. The number of infectious corporate employees is a fraction of infected general population, and is discounted by the effectiveness of corporate mitigation actions. The needs to attend infectious family members are affected by the number of infectious population and family size factor of a geographical region of interest. The number of employees who decide to flee from job/work may depend on infectious employees, perceived risk, and attending family needs. Some employees do not survive the pandemic, and the number is affected by number of infectious employees and mortality rate. The number of employees who flee affects the number of employees available at work, the number of employees available at home (telecommuting), and the number of employees not available. Availability of infrastructure (electricity and telecommunication etc.) affects the number of employees available at work and at home. The percentage of tele-commutable employees also affects the number of employees who are available at home. The number of employees not survived is affected by number infectious employees and mortality rate.



Figure 2. Simplified Overview of Causal Relationships

4. Simulation Results

Figure 4 shows sample output from our SEIR model of a pandemic with profiles of four population for 200 days. Note that the simulation outputs shown here are only example model outputs and do not reflect the official planning assumptions of any firm. Infection of the pandemic starts around day 50 and about 25% of population becomes infectious at around day 100, a rather severe case of

pandemic. At around day 160, all the infectious population recovers. The model of absenteeism described above in Figure 3 takes the S-E-I-R information as input in computing employee availability.



Figure 3. Causal Relationship in System Dynamics Model

Figure 5 shows sample output from the absenteeism model for the case when no mitigation action is deployed. A line describes the percentage of employees available at work during 200 days of pandemic occurrence. Another line describes the percentage of employees who do not survive the pandemic. Note that the scenario we model is rather severe case of pandemic; therefore, quite a large number of employees, about 20%, do not survive the disease. The other line describes the percentage of employees available at home (for telecommuting). For this scenario, we assume that only up 30% employees can work from home due to the nature of the business we modeled. Therefore, the curve representing employees available at home (%) does not go over 30%. The other line describes the percentage of employees who survive the pandemic but not available.



Figure 4. S-E-I-R Population



Figure 5. Employee Availability Without Any Mitigation Actions

Figure 6 shows sample output from the model for the case when the firm deploys some mitigation actions. A line describes the percentage of employees available at work during 200 days of pandemic occurrence. Another line describes the percentage of employees who do not survive the pandemic. Another line describes the percentage of employees available at home (for telecommuting). The other describes the percentage of employees who survive the pandemic but not available. There are reasonable reduction on absenteeism and improvement of employee availability.

A comparison of the outputs shown in Figure 5 and Figure 6 may be used by a firm to determine which mitigation action, or combination of mitigation actions, would provide the greatest potential for reducing absenteeism in the event of a pandemic.



Figure 6. Employee Availability With Some Mitigation Actions

5. Concluding Remarks

We present a model that estimates the likelihood of employees not being available for work as a result of pandemic occurrence and effectiveness of related mitigation actions. The model allows users to assess the impact of a pandemic on availability of corporate workforce and to estimate the effectiveness of various corporate mitigation actions in terms of how such actions may reduce the adverse effects of a pandemic on employee availability by incorporating information on infection rate, perception, needs for family care and infrastructure availability into a system of algebraic and differential equations. Disasters such as pandemics, earthquakes, hurricanes and terrorist attacks do occur, and they can reduce workforce availability. Survival and success of the firms depend on how effects of such disruptions are understood. We would like to extend our model to better understand the impact of other types of disasters so that firms can better prepare for such events.

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