System Dynamics Modeling of the Earthquake-induced Interruption of a Business - SD Model details

Stocks and Flows

In this document, various stocks, flows, and the related variables that are used to model the performance and operations of a manufacturing business are discussed in detail. For convenience of the readers, the stocks and flows diagrams, which are already included in the manuscript, are reproduced here.

1. State of Residential and Commercial Infrastructures

An earthquake can damage the structural, non-structural, and contents of a building. Building contents are equipment and machinery that are not integrated with the building structure (FEMA-NIBS, 2003). They are the key assets that support the operations of a given business. Earthquake-induced damage to a commercial or industrial building can disrupt its functionality or render it unsafe for entry. This can lead to a partial or full closure of the building, which in turn disrupts the operation of the business that relies on it. It should be noted that the loss of functionality of a building can occur due to the damage sustained by its non-structural components even if structural damage is minimal (Kajitani & Tatano, 2014). In the proposed model, the effect of earthquake-induced structural, non-structural, and contents damage on business productivity is captured by the variable called *Business Functionality Level* characterized by Eq. (1) in the main manuscript.

In the proposed model, the variable called *Earthquake Magnitude* characterizes the earthquake using the moment magnitude scale. The extent of structural and non-structural damage to a business building immediately after an earthquake is characterized by the initial structural damage ratio and initial non-structural damage ratio. Damage ratio is defined as the repair cost of a damaged building divided by its replacement cost (Calvi et al., 2006). The aforementioned quantities can be estimated based on *Earthquake Magnitude* using an appropriate methodology such as the one introduced by HAZUS technical manual (FEMA-NIBS, 2003). The initial value of the stock variables characterized as the *Business Non-Structural Components* and *Business Structural Components* are set to their post-earthquake values to characterize the post-earthquake conditions.

In general, repair and recovery activities are time-consuming. In the proposed model, the recovery time is considered using the *Repair Time of Non-Structural Components* and *Repair Time of Structural Components*. The affected businesses may need to spend their *Working Capital* to repair the damaged components. The repair cost of a given damaged component is a function of its current and desired states. As the difference between the desired and current states of a given component grows, the repair costs increase. In this model, the *Structural Components Repair Cost Rate* and *Non-Structural Components Repair Cost Rate* are defined as the repair costs of components divided by their corresponding repair time. At any given time, the *Building Repair Cost Rate* is calculated as the sum of *Structural Components Repair Cost Rate* and *Non-Structural Components Repair Cost Rate*. A proportion of the building repair costs can be paid by the insurance companies. In the model, the *Business Insurance Level* determines the percentage of the repair costs covered by the insurance.

Each given business uses a set of assets to conduct its routine operations and produce goods or services purchased by its customers. These assets may sustain damage in the face of an earthquake. The earthquake-induced damage can reduce the functionality of these assets and, thus, the *Production Capacity* of the business, which is the number of units that it can produce in a month. The initial assets damage ratio characterizes the extent of damage to business assets immediately after an earthquake, which is determined based on *Earthquake Magnitude*. At a given time, the state of these assets is characterized by the variable called *Assets Value*, which is modeled as a stock with *Investment in Assets Rate* as an inflow and *Depreciation Rate* as an outflow. Immediately after the occurrence of an earthquake, damage to assets is calculated based on *Assets Value* and the initial assets damage ratio. The initial value of the stock variable characterized as *Assets Value* is set to its post-earthquake value to characterize the post-earthquake condition of the business's assets. Over their lifetimes, business assets depreciate (i.e., lose their value) due to a variety of reasons such as wear and tear or functional obsolescence. In this manuscript, *Assets Lifetime* determines the economic life of each given business asset. It is assumed that the loss of value of assets occurs at a rate, which is known as *Depreciation Rate* and is determined based on the straight-line depreciation method.

The extent of the damage to the business assets determines the *Production Capacity* of the business. During the post-earthquake recovery phase, the damaged assets will gradually be restored to the desired state and consequently, the *Production Capacity* will increase. To model this process, the initial value of the stock variable called *Production Capacity* is set to its post-earthquake value. In the proposed model, the available *Budget to Increase Capacity* as well as *Desired Supply* based on the product *Price* define *Order Capacity Rate* inflow. Also, *Investment in Assets Rate* inflow is defined based on the *Order Capacity Rate* and *Capacity Output Ratio*, which is the money needed to be invested in assets to produce one more unit of products per month. As the repair and replacement activities proceed, the difference between *Desired Supply* and

Production Capacity is adjusted. The time needed to repair or replace business assets is characterized using the variable called *Time to Adjust Capacity*.

An earthquake can also damage the residential buildings in a community. In the proposed model, the variable called *Value of Residential Buildings Stock* characterizes the state of the residential buildings of the community based on the damage that they may have sustained. The initial damage ratio of residential buildings stock characterizes the extent of earthquake-induced damage to residential buildings. Immediately after the earthquake occurrence, the initial damage ratio of residential buildings stock is estimated based on *Earthquake Magnitude* using an appropriate methodology such as the one introduced by HAZUS technical manual (FEMA-NIBS, 2003) and the initial quantity for *Value of Residential Buildings Stock* is set to its post-earthquake value to characterize the post-earthquake condition. Following an earthquake, the repair and recovery activities on residential buildings start. As the repair and recovery activities progress, *Value of Residential Buildings Stock* grows and, consequently, the difference between *Value of Residential Buildings Stock* and *Desired Value of Residential Buildings Stock* declines. In the proposed model, *Repair Rate of Residential Buildings Stock* is defined as the difference between *Desired Value of Residential Buildings Stock* and *Value of Residential Buildings Stock* divided by *Repair Time of Residential Buildings*, which is the time needed to restore the building stock to its pre-earthquake state. Fig. A. 1 shows the dynamics of the impact of an earthquake on residential buildings stock as well as the buildings and their contents that are used by the business to perform its operations.

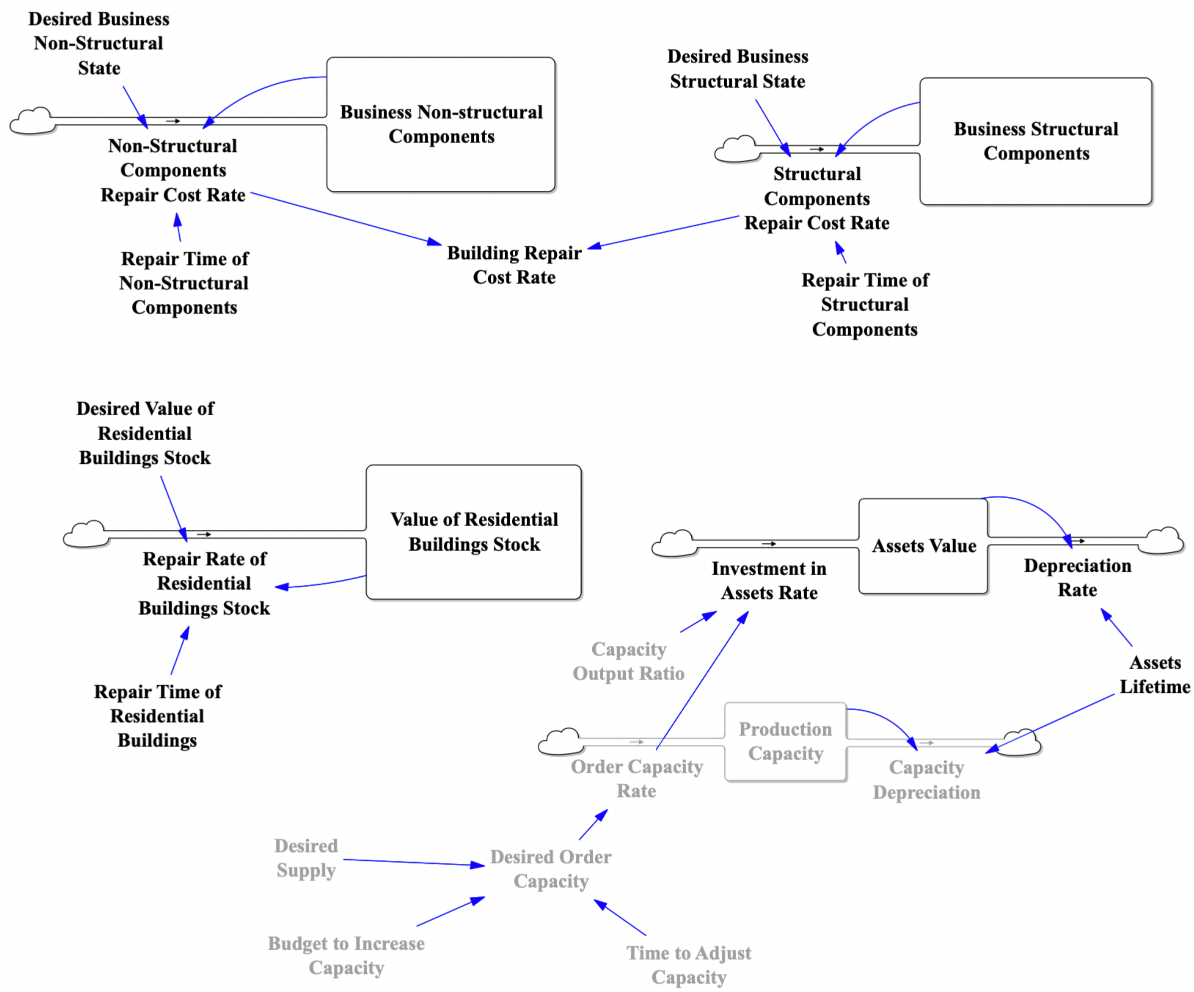

Fig. A. 1. Dynamics of residential and commercial infrastructures

2. State of Lifelines

Fig. A. 2 demonstrates the dynamics of the state of lifelines as incorporated in the model. Electricity, telecommunication, gas, water, wastewater, and transportation networks are the lifelines of a community. The interdependency among these lifelines means that the disruption in the functionality of one lifeline may lead to the loss of the functionality of others (Guidotti et al., 2016; Sharma et al., 2020). Specifically, the failure of the electricity network can disrupt the functionality of the water, wastewater, transportation, gas, and telecommunication networks. In the proposed model, the interdependency of infrastructure systems is characterized using the importance factor. The importance factor can be used to determine the percentage reduction in the output of one network caused by a 1% reduction in the performance of supporting infrastructure as shown by Eq. (A. 1).

$$\begin{aligned} &\mathit{Functionality\ of\ the\ dependent\ network} \\ &= 1 - \frac{100 - \mathit{functionality\ of\ supporting\ network}}{100} \\ &\cdot \mathit{importance\ factor} \end{aligned} \tag{A. 1}$$

Rose and Lim (2002) use the concept of importance factor to characterize the dependency of community infrastructure systems on the functionality of the electricity network. Table A. 1 shows the relationship between the functionality of the electricity network and other lifelines (Rose, 2004; Rose & Lim, 2002). Based on the damage that the electricity network has sustained, its functionality is measured from 0, which denotes the total loss of functionality, to 100, which denotes full functionality.

Table A. 1. Effect of electricity on various lifelines (Rose, 2004; Rose & Lim, 2002)

Lifeline	**Electricity importance factor**
Transportation	30
Water Utilities	80
Gas	80

In the proposed model, the community lifelines are modeled as stocks that characterize the functionality state of each lifeline based on the damage that they may have sustained. The extent of earthquake-induced damage to lifelines is estimated based on *Earthquake Magnitude*. Following an earthquake, the state of each lifeline that has sustained earthquake-induced damage falls below the desired level. Therefore, the initial values of the stock variables modeling the functionality level of lifelines are set to their post-earthquake value to take into account the earthquake-induced damage sustained by the lifelines. To restore the functionality of the lifelines to their pre-earthquake levels, repair and recovery activities on the damaged lifelines start. Specific to each lifeline is the duration of the repair and recovery activities, which is characterized by *Repair Time* in the model. As recovery activities on a lifeline proceed, the state of the lifeline improves and, consequently, the difference between its current and desired states decreases. At a given time, *Rate of Improvement* of a lifeline is defined as the difference between the desired and current states of a lifeline divided by the corresponding *Repair Time*.

Lifelines support the activities of businesses in the community. The earthquake-induced failure of lifelines can highly influence *Business Functionality Level*. For a given business, the condition of the buildings in which it operates and the post-earthquake functionality of lifelines affect *Business Functionality Level*. The degree to which *Business Functionality Level* is dependent upon the functionality of each lifeline varies from one business to another mainly due to the differences in production mechanisms that use critical lifeline resources in differing amounts. In the proposed model, the extent to which *Business Functionality Level* is affected by a disruption in the functionality level of lifelines is taken into account using a resilience factor. In the proposed model, this phenomenon is considered using variables that characterize the effect of disruption of the functionality of various lifelines on the performance of the business in which the variables are calculated based on Eq. (A. 2). The failure or disruption in the functionality of a lifeline reduces the business *Production Rate*.

Effect of disruption of the i-th lifeline in the manufacturing functionality= (A. 2)

$$\frac{1-RF_i}{100}.L_i + RF_i$$

Where L_i is the lifeline serviceability level, which is a dimensionless variable assumed to be between 0 and 100, RF_i is the *Resilience Factor* of the business under the disruption of the *i*-th lifeline, which represents the lifeline importance for the economic sector (Kajitani et al., 2009). RF_i is a dimensionless parameter between 0 and 1.

Most businesses heavily rely on the transportation network for their economic activities. An earthquake and the probable failure of the transportation network can disrupt the arrival of raw materials and other supplies as well as the delivery of goods and services by the business. In the model, this phenomenon is characterized using the variable called *Adjustment in Shipping based on Transportation Network State*. In addition, due to the failure of the transportation system, customers may face difficulty accessing the business. In the model, this phenomenon is characterized using a variable called *Reduction in Order Rate based on Transportation Network State*, which decreases *Product Order Rate per Customer* following an earthquake.

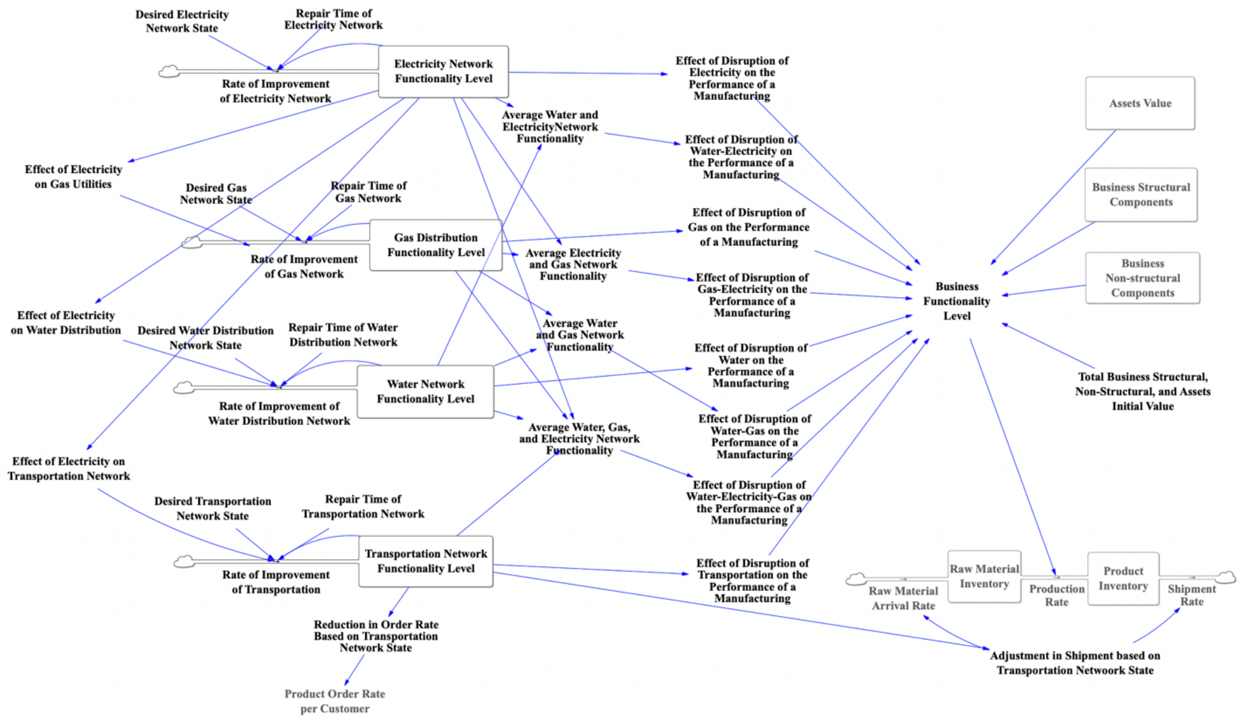

Fig. A. 2. State of lifelines

3. State of Demand

The dynamics of demand are considered in the model as illustrated in Fig. A. 3. The population of the community can be modeled using an aging chain (Sterman, 2000). To this end, the population is divided into three cohorts (i.e., those aged 0 to 17 years, those aged 18 to 64, and those aged 65 and above). Each category is modeled as a stock variable. It should be noted that domestic and international migrations that affect the population of a region are outside the boundary of this model and the community under study is assumed to be isolated. The first cohort, which comprises those aged 0 to 17 years, is referred to as the *Young Population*. It increases by *Birth Rate* and decreases by *Maturation Rate* and *Death Rate among the Young Population.* The second cohort, which comprises those aged 18 to 64 years, is referred to as *Mature Population*. It increases by *Maturation Rate* and decreases by *Aging Rate* and *Death Rate among the Mature Population.* The third cohort, which comprises those aged 65 and above, is referred to as *Elderly Population*. It increases by *Aging Rate* and decreases by *Death Rate among the Elderly Population*.

From another perspective, the population can be divided into two categories: 1) *Potential Customers*, who are not making a purchase during the current period, and 2) *Customers*, who are making a purchase during the current period. A business can use several channels to increase public awareness about its products and stimulate the demand for them. Word of mouth, which involves social exposure and imitation (Sterman, 2000), can highly influence the purchase decision of *Potential Customers*. The size of the customer population is determinant of the level impact of word of mouth effect (Sterman, 2000). In this study, the word of mouth effect is considered to be the primary source of influence that determines the adoption rate. The impact of other channels (e.g., advertising, media reports, and direct sales efforts) are not considered in the model. The customer adoption process from word of mouth is as discussed by Sterman (2000).

The stock called *Potential Customers* increases by a rate called *Rate of Increase in Potential Customers*, which is equal to the *Birth Rate*. The *Potential Customers'* stock also increases by *Loss of Customers Rate*, which decreases the customer population and moves them back to the stock of *Potential Customers* using *Loss Fraction*. The outflow from *Potential Customers* is *Potential Customers' Death Rate*, and *New Customer Rate* that converts *Potential Customers* to *Customers* as a result of customer adoption. An earthquake can lead to loss of life among the community residents and, thus, reduce *Potential Customers* and *Customers* of the business. This phenomenon is taken into account in the model by determining the loss of life caused by the earthquake, which depends on the *Earthquake Magnitude*, and setting the initial values of the stocks related to the population equal to their post-earthquake value.

Customers are assumed to order the product at a monthly rate characterized as *Product Order Rate per Customer*. *Product Order Rate per Customer* is affected by variables such as product *Price*, *Transportation Network Functionality Level*, *Delivery Delay*, which affects willingness to purchase, and *Cumulative Community Discretionary Income,* which determines their ability to purchase products or services. Other factors that can affect demand (e.g., the composition of the population, tastes and preferences, the price of related goods, changes in expectations about future prices) are not considered in the model and are out of the scope of this research.

Following an earthquake, *Product Order Rate per Customer* is expected to decline due to a variety of reasons. The failure of the transportation network can limit the customers' access to the business. This can reduce *Product Order Rate per Customer*. An earthquake can also damage the residential buildings and, thus, reduce the residents' discretionary income since residents have to spend a portion of their income on repair and recovery activities that are not covered by their insurance policies. In addition, after an earthquake people tend to save a greater portion of their income to have financial security in the face of probable future events (Aiyagari, 1994). Therefore, the earthquake can reduce the *Discretionary Income Ratio* (i.e., the fraction of income that remains after the deduction of taxes, social security charges, and basic living costs). This can reduce the demand for the product the business manufactures. In the model, this phenomenon is characterized using *Effect of Earthquake on Discretionary Income Ratio*. After an earthquake, *Discretionary Income Ratio*, which is modeled as a stock variable will be reduced. The post-earthquake recovery of the *Discretionary Income Ratio* to the pre-earthquake level takes time, which is presented as *Time to Adjust Discretionary Income Ratio*. Due to the reduction in *Cumulative Community Discretionary Income*, *Product Order Rate per Customer* is expected to reduce. To account for this effect, *Adjustment in Order Rate Based on Discretionary Income* is incorporated into the model. If *Cumulative Community Discretionary Income* is less than *Community Normal Discretionary Income*, which is the discretionary income of all community residents when *Repair Rate of Residential Buildings Stock* is zero, *Product Order Rate per Customer* will decrease, and vice versa.

Product Order Rate per Customer is also affected by product *Delivery Delay*, which is the time between the submission of an order and its fulfillment. *Delivery Delay* is characterized as the ratio of *Backlog* to *Delivery Rate*. The customers will perceive the delivery delay with a lag defined as *Time to Perceive Delivery Delay*. By comparing *Perceived Delivery Delay* with *Normal Delivery Delay*, which is the delivery delay in the ideal condition, *Adjustment in Order Rate based on Perceived Delivery Delay* will be determined. If *Perceived Delivery Delay* is more than *Normal Delivery Delay*, the *Product Order Rate per Customer* will decrease, and vice versa. Following an earthquake, *Delivery Delay* is expected to increase for a variety of reasons. The failure of the transportation network can disrupt the delivery of goods and services by the business. This can increase *Delivery Delay*. An earthquake can also induce damage to business assets and, thus, reduce *Production Capacity*. Due to the reduction in *Production Capacity*, *Production Rate* will decline. The size of the inventory decreases with the reduction of *Production Rate* and increases the *Delivery Delay*. *Delivery Delay* is also affected by the reduced post-earthquake functionality of lifelines and the condition of the business building, which will decrease *Business Functionality Level* and, thus, reduces *Production Rate*.

Another determinant of *Product Order Rate per Customer* is the product *Price*. According to the law of demand, there is an inverse relationship between price and demand of normal goods (i.e., assuming that all other variables that affect demand are held constant, a higher price leads to a lower quantity demanded and vice versa) (Ekelund et al., 1975; Gopal et al., 2007). In the model, the law of demand is incorporated by comparing the product *Price* with *Normal Price,* which is the expected price of the product in a normal condition, and computing *Expected Product Order Rate per Customer* based on this ratio.

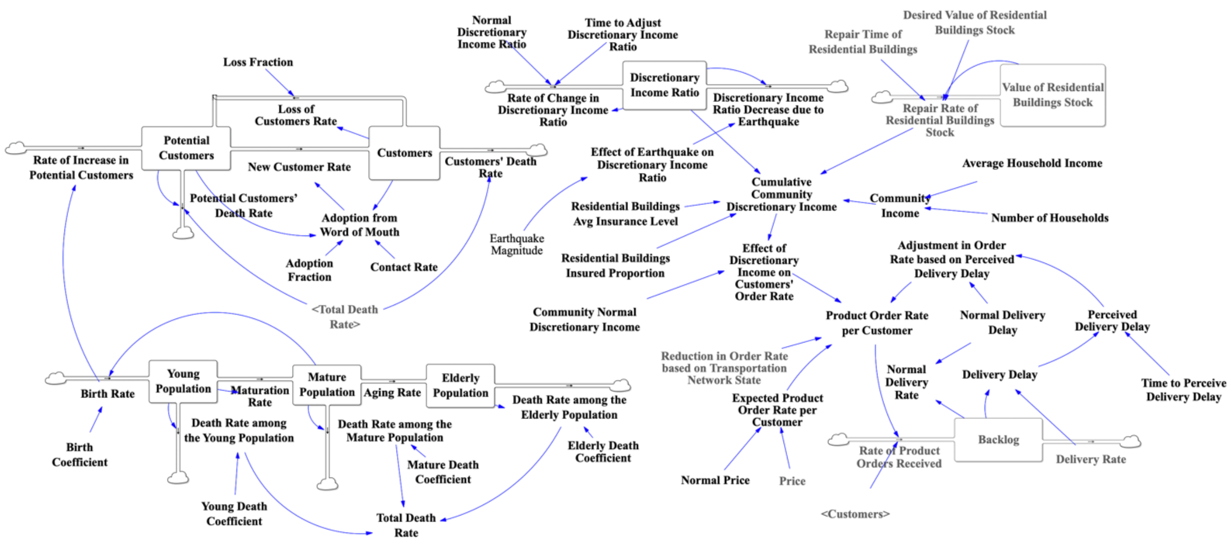

Fig. A. 3. State of demand

4. State of Inventory and Backlog

In general, manufacturing businesses use raw materials to produce products that are sold directly to consumers or other manufacturing businesses as raw material (Thankaraju, 2018). To capture the purchasing behavior of consumers as well as the delivery process of the manufactured goods, *Backlog*, *Raw Materials Inventory,* and *Product Inventory* are considered as stocks. *Backlog* represents customer orders that are not delivered yet. *Product Inventory* contains the goods that are produced but not shipped yet. *Raw Materials Inventory* contains the components used to manufacture the goods. These stocks and the related flows are shown in Fig. A. 4.

As shown in Fig. A. 4, *Backlog* increases by a rate described as *Rate of Product Orders Received*, which is calculated by multiplying the number of *Customers* and *Product Order Rate per Customer*. When the orders are shipped from *Product Inventory, Backlog* decreases by *Delivery Rate*. The business will earn *Revenue* after delivering the order. The products will be shipped from *Product Inventory*. To determine the availability of manufactured goods in *Product Inventory*, *Inventory Backlog Ratio* is calculated and compared with *Normal Inventory Backlog Ratio*, which is the desired inventory backlog ratio. If *Inventory Backlog Ratio* is equal or more than the normal ratio, there are enough products in *Product Inventory* to respond to *Backlog* and hence the entire *Backlog* will be satisfied. Otherwise, only part of *Backlog*, which is equivalent to the number of finished products available in *Product Inventory*, will be satisfied. *Product Inventory* decreases by *Shipment Rate* and increases by *Production Rate*. *Production Rate* is a rate that is governed by the policy designed by the management.

The Business will receive raw materials based on production forecast and by considering transportation network functionality. *Raw Materials Cost* is calculated based on *Raw Materials Cost per Unit* and *Raw Materials Arrival Rate*. It is assumed that *Normal Raw Materials Cost per Unit* will be adjusted following an earthquake by a specified rate presented in the model as *Raw Materials Price Increase Rate*.

An earthquake may damage the business inventory and render a proportion of the stockpiled products or raw materials unusable. The model captures this effect and decreases *Raw Materials Inventory* and *Product Inventory* based on *Earthquake Magnitude*. In this study, it is assumed that at complete damage state a salvage of inventory (e.g., 50%) will remain (FEMA-NIBS, 2003).

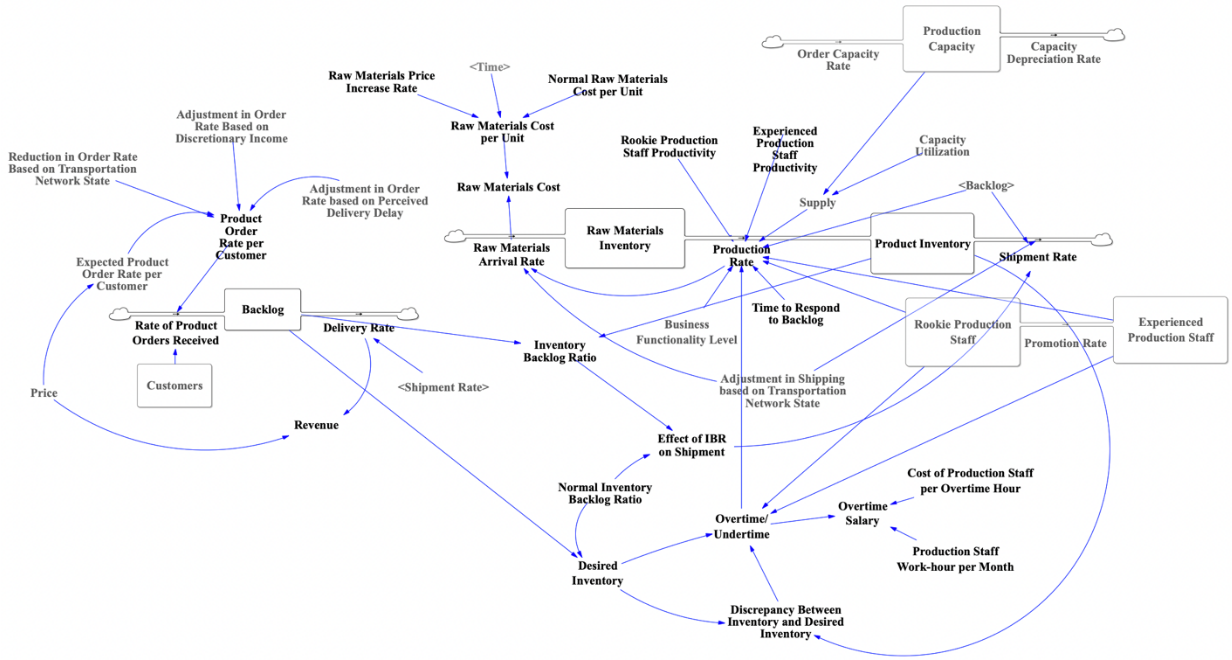

Fig. A. 4. State of inventory and backlog

5. State of Human Resources and Staffing Policy

The dynamic state of human resources of the company is considered in the model as illustrated in Fig. A. 5. In the proposed model, the production staff is presented using two stocks; *Rookie Production Staff* and *Experienced Production Staff*. *Rookie Production Staff* will be promoted to *Experienced Production Staff* after a specified time characterized by *Promotion Time* in the model. *Experienced Production Staff* will retire after a specific time that is determined by *Retirement Time*. Compared to the rookie staff members, the expert production staff members have higher productivity and monthly salary in comparison to the rookie staff members. *Rookie Production Staff* stock increases by the rate described as *Hiring Rate.* The outflows from *Rookie Production Staff* stock are *Death Rate among Rookie Staff*, *Firing Rate*, and *Promotion Rate*. It is assumed that the business only hires and fires *Rookie Production Staff.* Therefore, the number of *Experienced Production Staff* is merely affected by *Promotion Rate*, *Death Rate among*

Experienced Staff, and *Retirement Rate*. The management determines the policy for hiring and firing the production staff.

The workforce population is assumed to be a subset of *Mature Population*, which is aged 18-64 and is modeled using a stock presented in the model as *Active Workforce Population*. Following an earthquake, *Active Workforce Population* is expected to decline due to mortality or severe injury. This phenomenon is taken into account in the model by defining a stock variable characterized as *Injured Workforce Population*. *Injured Workforce Population* is presented in the model using a separate stock, which increases due to the injury of the workforce following an earthquake and decreases by a rate presented in the model as *Workforce Recovery Rate*. *Workforce Recovery Rate* decrease *Injured Workforce Population* and moves them back to *Active Workforce Population* after a period presented as *Recovery Time.* In the proposed model, the initial value of *Injured Workforce Population* is set to its post-earthquake value to characterize the post-earthquake condition. It is assumed that *Labor Population* is comprised of people aged 18 to 64 years with a high school diploma or less. When *Labor Population* becomes less than *Normal Labor Population* (i.e., the pre-earthquake population of the labor force in the community), *Rookie Production Staff Salary* and *Experienced Production Staff Salary* will increase due to a surge in demand for labor. Therefore, following an earthquake, *Rookie Production Staff Salary* and *Experienced Production Staff Salary* is expected to rise due to a decrease in *Labor Population*. In combination with the increase in production staff salary, the decrease in *Working Capital* due to the costs associated with repairing the business building will reduce *Production Staff Salary Budget* and thus, decrease *Desired Production Staff*.

In the proposed model, the salary dynamics are characterized based on (A. 3) (Hallegatte, 2008). This relationship assumes that the salary is responding linearly to the labor population as follows:

$$S(t) = S_0 \cdot (1 + \gamma_p \cdot \frac{NL - L(t)}{L(t)}) \tag{A. 3}$$

Where *S(t)* is the staff salary at time *t*, S_0 is the normal staff salary, which is the pre-earthquake staff salary, γ_p is the price elasticity parameter, *NL* is the normal labor population, which is the pre-earthquake staff population, and *L(t)* is the labor population at time *t*.

In the aftermath of an earthquake, the members of managerial staff may not be available due to death or injury. To replace the unavailable managerial staff members the business starts hiring. The hiring process continues until the number of managerial staff reaches *Desired Number of Management Staff*, which is determined based on the number of production staff. *Desired Number of Management Staff* defines *Hiring-Firing Rate of Management Staff*. In the proposed model, *Hiring-Firing Rate of Management Staff* is defined as the difference between *Desired Number of Management Staff* and *Management Staff* divided by *Time to Adjust Management Staff*, which is the time needed to restore *Management Staff* to the desired state. As a consequence of the reduction in *Management Staff*, there will be a *Budget Waste*, which decreases *Working Capital*.

In the proposed model, *Working Capital* is modeled as a stock, which increases by a rate presented as *Cash In* and decreases by a rate characterized as *Cash Out*. *Cash In* is assumed to be equal to *Revenue* generated by delivering products to the customers. *Cash Out* is equal to the sum of the proportion of the *Building Repair Cost Rate* that is not paid by the insurance company, *Total Rookie Production Staff Salary, Total Experienced Production Staff Salary*, *Total Management*

Staff Salary, *Overtime Salary*, *Budget Waste*, *Raw Materials Cost*, *Overhead Cost*, *Capacity Increase Cost*, and *Tax*.

Following an earthquake, a fraction of production staff is expected to be unavailable due to death or severe injuries. In addition, a portion of the production staff may be unavailable due to the difficulty in reaching the business due to the failure of the transportation system, which is not determined in this model and is out of the scope of this research.

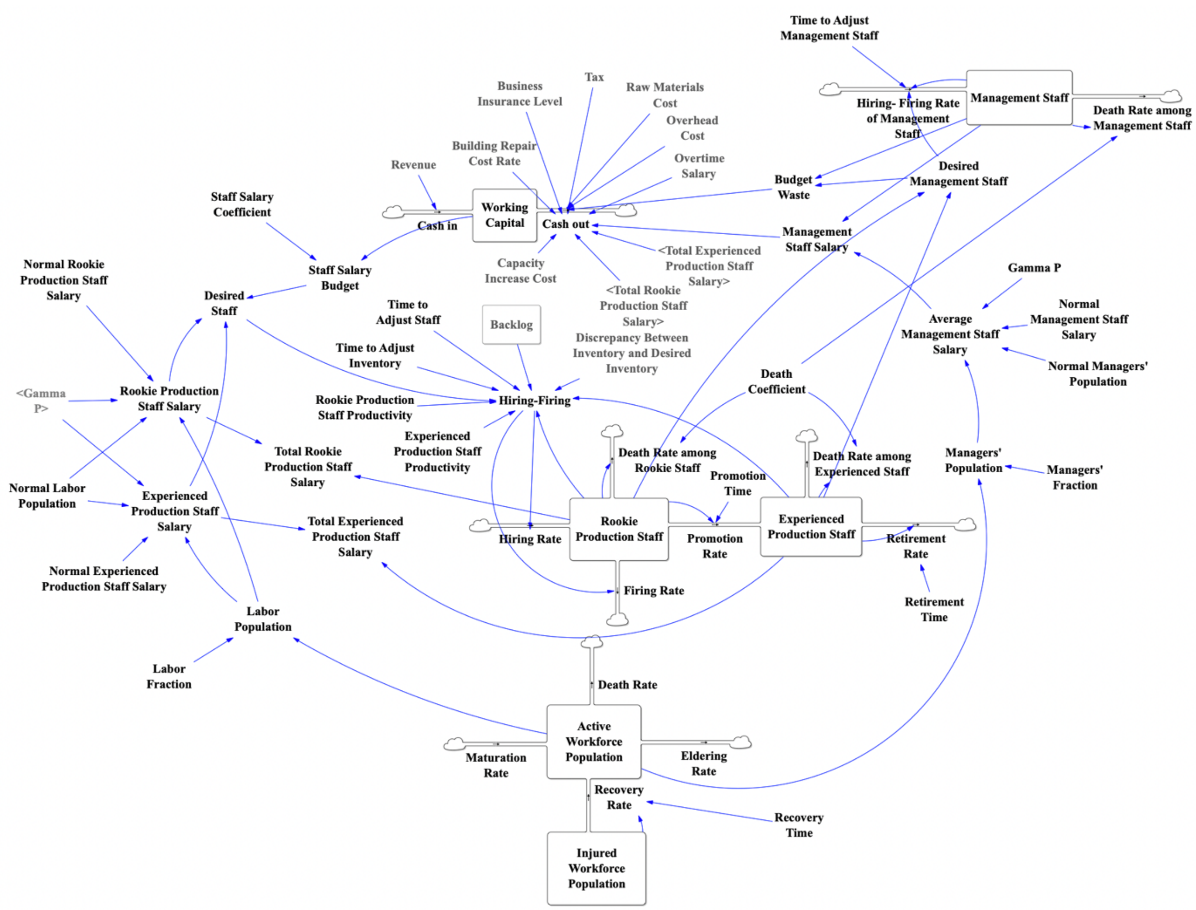

Fig. A. 5. State of human resources and staffing policy

6. Price Adjustment Based on Supply and Demand Dynamics

In the proposed model, *Price* is determined considering two distinct policies, in which the first policy is as follows. Product *Price* is a key determinant of *Desired Supply* and *Expected Product Order Rate per Customer*. In the proposed model, *Price* is determined considering two distinct policies. According to the law of supply, an increase in product *Price* causes *Desired Supply* to increase, and vice versa. The law of supply assumes that all other variables that affect demand are held constant (Gopal et al., 2007). To meet *Desired Supply*, *Production Capacity* should be adequate. Otherwise, the company increases its capacity proportional to its *Budget Allocated to Capacity Increase*. The business does not always use the entire capacity when there are enough products in *Product Inventory*. Therefore, *Capacity Utilization* will be determined based on the ratio between *Inventory Backlog Ratio* and *Normal Inventory Backlog Ratio,* which is the expected inventory backlog ratio. *Inventory Backlog Ratio* is the ratio between *Product Inventory* and *Backlog*. It should be noted that *Capacity Utilization* is assumed to range between 0 and 1. If *Inventory Backlog Ratio* is less than *Normal Inventory Backlog Ratio*, the entire capacity will be utilized. Alternatively, if *Inventory Backlog Ratio* is more than *Normal Inventory Backlog Ratio*, *Capacity Utilization* will decrease. Nevertheless, *Capacity Utilization* cannot become zero since there should always be a minimum production so that the business does not ground to halt.

According to the law of demand, a higher *Price* leads to a lower *Product Order Rate per Customer* (Gopal et al., 2007). The ratio between *Inventory Backlog Ratio* and *Normal Inventory Backlog Ratio* is a determinant of the consequent price adjustments. If the ratio mentioned above is smaller or bigger than 1, *Indicated Price* will be higher or lower than the current *Price*, respectively. *Price* will be adjusted to *Indicated Price* in a period presented in the model as *Time to Adjust Price*.

7. References

Aiyagari, S. R. (1994). Uninsured idiosyncratic risk and aggregate saving. *The Quarterly Journal of Economics*, *109*(3), 659–684. https://doi.org/10.2307/2118417

Calvi, G. M., Pinho, R., Magenes, G., Bommer, J. J., & Crowley, H. (2006). Development of seismic vulnerability assessment methodologies over the past 30 years. *ISET Journal of Earthquake Technology*, *43*(472), 75–104.

Ekelund, R. B., Jr., & Hébert, R. F. (1975). *A history of economic theory and method* (4th ed.). McGraw Hill.

FEMA-NIBS. (2003). *Multi-hazard loss estimation methodology – HAZUS technical manual*. Federal Emergency Management Agency and National Institute of Building Sciences.

Gopal, M. R., Rajasekaran, V., Neelavathy, P., Singari, M., Rajendran, S., & Kennedy, S. R. (2007). *Economic theory* (1st ed.). Government of Tamilnadu.

Guidotti, R., Chmielewski, H., Unnikrishnan, V., Gardoni, P., Mcallister, T., Lindt, J. Van De, Guidotti, R., Chmielewski, H., Unnikrishnan, V., & Gardoni, P. (2016). Modeling the resilience of critical infrastructure : the role of network dependencies. *Sustainable and Resilient Infrastructure*, *1*(3–4), 153–168. https://doi.org/10.1080/23789689.2016.1254999

Hallegatte, S. (2008). An adaptive regional input-output model and its application to the assessment of the economic cost of Katrina. *Risk Analysis*, *28*(3), 779–799. https://doi.org/10.1111/j.1539-6924.2008.01046.x

Kajitani, Y., Eeri, M., & Tatano, H. (2009). Estimation of lifeline resilience factors based on surveys of Japanese industries. *Earthquake Spectra*, *25*(4), 755–776. https://doi.org/10.1193/1.3240354

Kajitani, Y., & Tatano, H. (2014). Estimation of production capacity loss rate after the great east Japan earthquake tsunami in 2011. *Economic Systems Research*, *26*(1), 13–38. https://doi.org/10.1080/09535314.2013.872081

Rose, A. (2004). Defining and measuring economic resilience to disasters. *Disaster Prevention and Management: An International Journal*, *13*(4), 307–314. https://doi.org/10.1108/09653560410556528

Rose, A., & Lim, D. (2002). Business interruption losses from natural hazards: Conceptual and methodological issues in the case of the Northridge earthquake. *Environmental Hazards*, *4*(1), 1–14. https://doi.org/10.3763/ehaz.2002.0401

Sharma, N., Nocera, F., & Gardoni, P. (2020). Classification and mathematical modeling of infrastructure interdependencies. *Sustainable and Resilient Infrastructure*, 1–22. https://doi.org/10.1080/23789689.2020.1753401

Sterman, J. D. (2000). *Systems thinking and nodeling for a complex world*. http://dx.doi.org/10.1057/palgrave.jors. 2601336

Thankaraju, P. (2018). *Startup manufacturing business ideas 200* (A. Issac (ed.)). Nest Fame

Creations.