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Quantification of the Economic Resilience from the Community Level to the Individual Business Level: The Bay Area Case Study

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ABSTRACT

The paper presents a methodology to evaluate economic resilience at the community level which can be applied to any type of disruptive event rather than earthquakes. The goal is to help decision makers to understand the economic resilience problem of interdependent networks from a community level to a business level. The case study chosen in this paper is the San Francisco Bay Area, a region which is very sensitive to natural disasters as proven by the numerous projects and Institutions working on identifying performance levels to be achieved to obtain a resilient city. The two approaches which aim to compute economic resilience and identifying the effects arising from different investment allocation are compared. Some insights on how these approaches can be implemented to evaluate the life-cycle costs of structural systems and the return of investments of preparedness measures like building structures with higher performance with respect to the minimum required performance levels will be investigated.

INTRODUCTION

Modern communities are more and more evolving towards interdependent systems. While interdependencies are positively considered in normal operating conditions, because they promote a greater economic growth, they have some drawbacks in the aftermath of natural or man-made disasters. In fact, different sites which are affected by natural disasters such as earthquakes, are affected by different types of losses, downtime and restoration curves and are characterized by a large spatial and temporal variability which depends on the level of interdependency among different systems. From the economic point of view, highly interdependent systems which are affected by natural disasters generate direct economic losses which are followed by indirect economic effects on every major economic sector of the community analyzed. Recent studies addressed the issue of resiliency of a community defined, according to the current literature, as the ability of systems to rebound after severe disturbances, disasters, or other forms of extreme events (Cimellaro et al., 2010a,b). Renschler et al. (2010) in their work identify seven dimensions of the resilience problem summarized within the acronym PEOPLES. Among these dimensions, the economic one is certainly one of the most controversial. In fact, the economic aspect has been often not directly faced in the recent studies which have focused mainly in the actual applications and quantification of the other dimensions (Cimellaro et al., 2013a,b,c,d). However, the possibility to measure the economic resiliency of a community after a disaster is increasingly being seen as a crucial step towards disaster risk reduction. The authors (Cimellaro et al., 2014) have recently analyzed different approaches to evaluate economic resilience such as the Inoperability Input-Output models (IIO) and the Computable General Equilibrium (CGE) models. Furthermore, they have proposed a new method based on structural growth models (SGM) showing advantages and limitations. In the first part of the study, a comparison between IIM and SGM models is given based on a real case study, the economy of San Francisco Bay Area. These models are able to describe the behavioral response to input shortages and changing market conditions by computing the overall changes in economic variables across sectors, and compare the changes with the economy in normal operating conditions. The IIM models have been formulated by Haimes and Jiang (2001) to analyze the behavior of interconnected systems and were then expanded by Santos and Haimes (2004) to model the demand reduction due to the terrorism threat of interconnected infrastructures. Later Lian and Haimes (2006) have focused on the risk of terrorism through the dynamic IIM. More recently, Pant et al. (2011) have focused on the interdependent impacts at multimodal transportation container terminals, and offer an overview on the metrics suited to decision support. They also developed a specific approach (2013) for the evaluation of quantitative resilience metrics accounting for interdependencies among multiple infrastructures. The SGM is a new methodology for measuring economic resilience based on the Structural Dynamic Growth model described by Li (2010) adapted to evaluate the economic resilience index, using the procedure described by Cimellaro et al. (2010a,b) where the restoration curves are the activity/output curves provided by the model. The case study chosen in this paper is the San Francisco Bay Area, a region in which the issue of how to deal with natural disasters is more relevant than ever as witnessed by the numerous projects aimed at the identification of performance to be achieved to obtain a resilient city. For example, Poland et al. (2009) have established a comprehensive set of performance objectives that, if achieved, will make the city of San Francisco "back on its feet" four months after a magnitude 7.2 earthquake on the Peninsula segment of the San Andreas fault. The present paper can furthermore provide the basis for how to compute the degree of economic resiliency achieved assuming the performance objectives listed by Poland et al. are attained. Finally, the paper gives some insights on how to implement the approach to evaluate the life-cycle costs of structural systems in case of natural disasters, and the return of investments of preparedness measures like building structures with higher performance with respect to the minimum required performance levels given by IBC. This paper is linking the community economic model which is more related at the regional level, with the business economic model provided by Terzic et al. (2014) which is focusing mainly at the business interruption losses at the local level of a single individual company of a given sector in the area.

THE INOPERABILITY INPUT-OUTPUT MODEL

The assumptions on which the IIM is based are the same of the classical *I-O model*. Therefore it is equilibrium, time-invariant, deterministic and linear representation subjected to the same limitations of the classical Leontief's formulation (1966). The IIM formulation derive from the metrics of inoperability $\boldsymbol{q}$, a vector where each component represents the ratio of production loss with respect to the usual production level of the industry and that well applies to represent resilience metrics, and demand perturbation $\boldsymbol{d^*}$, a vector expressed in terms of normalized degraded final demand.
Combining $\boldsymbol{q}$ and $\boldsymbol{d^*}$, Santos and Haimes (2004) obtained the IIM formulation, that maintains a form similar to the Leontief I-O model, and that shows how inoperability is driven by perturbations in demand:

$$\boldsymbol{q} = \boldsymbol{A}^*\boldsymbol{q} + \boldsymbol{d}^* \rightarrow \boldsymbol{q} = [\boldsymbol{I} - \boldsymbol{A}^*]^{-1}\, \boldsymbol{d}^* \tag{1}$$

where $\boldsymbol{A^*}$ represents the normalized interdependency matrix that indicates the degree of coupling of the industry sectors. Lian and Haimes (2006) developed a dynamic extension of the IIM (DIIM) based on a first-order differential equation that incorporates a rate constant into the static IIM structure, and whose analytical equation is:

$$\boldsymbol{q}(t) = e^{-\boldsymbol{K}(\boldsymbol{I}-\boldsymbol{A}^*)\boldsymbol{t}}\boldsymbol{q}(0) + \int_{\boldsymbol{0}}^{\boldsymbol{t}} \boldsymbol{e}^{-\boldsymbol{K}(\boldsymbol{I}-\boldsymbol{A}^*)(\boldsymbol{t}-\boldsymbol{z})}\boldsymbol{K}\boldsymbol{d}^*(z)dz \tag{2}$$

where $\boldsymbol{K}$ is the rate term, a matrix with elements that represent the speed at which sectors attain particular responses to disruptions in outputs or change in demands, while *t* represent the time. Pant et al. (2013) made distinction between metrics which are able to describe the static or dynamic economic resilience, shown in Figure 1. In their definition, the static resilience corresponds to the avoided initial loss of functionality of sector *i* and can be evaluated using:

$$R_{S,i} = \frac{\sum_{j=1}^{n} x_{ij}^* d_{j,max}^* - \sum_{j=1}^{n} x_{ij}^* d_j^*}{\sum_{j=1}^{n} x_{ij}^* d_{j,max}^*} = \frac{\sum_{j=1}^{n} x_{ij}^* (d_{j,max}^* - d_j^*)}{\sum_{j=1}^{n} x_{ij}^* d_{j,max}^*} \tag{3}$$

where x_{ij}^* represents the terms of the matrix $\boldsymbol{X} = [\boldsymbol{I} - \boldsymbol{A}^*]^{\boldsymbol{-1}}$ while d_j^* and $d_{j,max}^*$ are respectively the expected and the maximum demand perturbation levels for sector j.

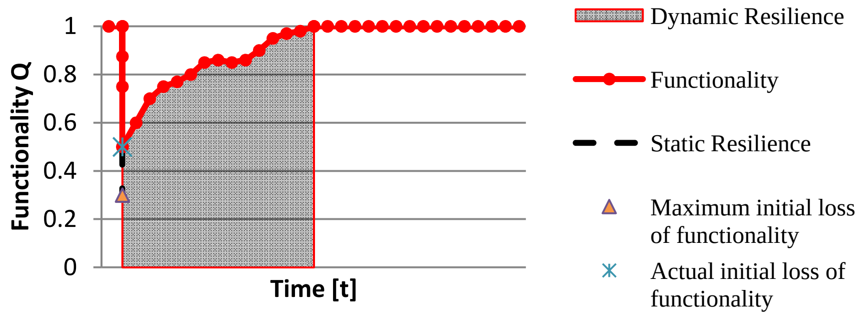

Figure 1. Economic Resilience

Assuming that the expected demand perturbation is the product of the maximum demand perturbation and a planning function $f(\beta_i) \in [0,1]$, where β_i represents the investments put into a planning strategy is possible to calculate the static resilience for sector *i* as:

$$R_{S,i} = \frac{\sum_{j=1}^{n} x_{ij}^{*} d_{j,max}^{*}(1-f(\beta_j))}{\sum_{j=1}^{n} x_{ij}^{*} d_{j,max}^{*}} = 1 - \sum_{j=1}^{n} \frac{x_{ij}^{*} d_{j,max}^{*}}{\sum_{j=1}^{n} x_{ij}^{*} d_{j,max}^{*}} f(\beta_j) \tag{4}$$

The dynamic dimension of economic resilience can be evaluated using DIIM models. A decision space can be generated by varying the values of three resilience metrics that represent the matrix K and reflect investment options. These metrics are: (i) *the time averaged level of operability* M_i which represents the overall level of functionality maintained by a system, (ii) *the maximum loss of sector functionality* q_i^m, and (iii) *the recovery time* τ_i which represents the time that the system implies to return to pre-disruption levels of functionality:

$$M_i = 1 - \frac{1}{T}\int_0^T q_i(t)dt \leftrightarrow \boldsymbol{M} = 1 - \frac{1}{T}\int_0^T \boldsymbol{q}(t)dt \tag{5}$$

$$q_i^m = \max_{t\geq 0}[q_i(t)] \leftrightarrow \boldsymbol{q}^m = \max_{t\geq 0}[\boldsymbol{q}(t)] \tag{6}$$

$$\tau_i = \{t: t > 0, |q_i(t) - q^e{}_i(t)| \leq \varepsilon \ll 1\} \tag{7}$$

where T represent the time when the system fully recovers from the initial disruption and $q^e{}_i(t)$ the equilibrium inoperability. The metrics are put in relation each other under specific assumptions (Pant et al., 2013). Considering that τ_i is function of $\alpha_i = k_{ii}\left(1 - \sum_{j=1}^{n} a^*{}_{ij}\right)$ a parameter which is a measure of interdependency (Oliva et al., 2010) and introducing another constant $\tau_i\alpha_i = L_i$, the final dynamic decision space is obtained in Eq. (8) after some mathematical manipulations:

$$M_i = 1 - \frac{1}{L_i T}[1 - e^{-L_i}]\tau_i q_i{}^m \tag{8}$$

The equations generate a decision space through contour curves that can be used to estimate the system performance for different recovery strategies.

THE STRUCTURAL DYNAMIC GROWTH MODEL

Li (2010) developed the *structural growth model* from the classical growth framework. Even if it was conceived as a growth model, it can also be used to compute the general equilibrium. The model represents the production processes in *n* economic-sectors economy through two matrices: the input and the output coefficient matrices, respectively A and B, where the i^{th} column in matrix A represents the standard input bundle of agent I, and B usually coincides with the *n*-dimensional identity matrix. While the classical economic growth framework the equilibrium price vectors and equilibrium output vectors are the left and right P-F eigenvectors of A, the Structural Dynamic Growth model tries to integrate the market mechanism into the classical growth model by embedding an exchange process in it, represented by an exchange vector, to reach equilibrium. The exchange process considers the economy as a discrete-time dynamic system and supposes economic activities such as price adjustment, exchange etc. occur in turn in each period. Giving **S** the supply matrix of the economic system, **s** the supply vector in the initial period and **z** the exchange vector that consists of purchase amounts of agents and that represents the market mechanism, is possible to derive:

$$\mathbf{u} \equiv \hat{s}^{-\mathbf{1}}\mathbf{Az} \tag{9}$$

where $\hat{\mathbf{s}}$ represents the diagonal matrix with the vector **s** as the main diagonal and **u** the *n*-dimensional sales rate vector indicating the sales rates of goods. **Az** is called the sales vector of goods. Under this assumption is possible to demonstrate that exists a unique normalized exchange vector **z** (Li, 2010). Assuming that the economic system in the period *t* is represented by the variables: **p**(t)=price vector; **S**(t) = supply matrix; **u**(t) = sales rate vector; **z**(t) = exchange vector and production intensity vector. The market mechanism is embedded considering that in period t+1 the economy runs as:

$$\begin{cases} \boldsymbol{p}(t+1) \;=\; P(\boldsymbol{p}(t), \boldsymbol{u}(t)) \\ \boldsymbol{S}(t+1) \;=\; \boldsymbol{B}\widehat{\boldsymbol{z}(t)} + Q(\widehat{\boldsymbol{e}-\boldsymbol{u}(t)}\boldsymbol{S}(t)) \\ (\boldsymbol{u}(t+1), \boldsymbol{z}(t+1)) = Z(\boldsymbol{A}, \boldsymbol{p}(t+1), \boldsymbol{S}(t+1)) \end{cases} \tag{10}$$

until the time where the system reaches the equilibrium. P represents the price adjustment process, Q is the inventory depreciation function and stands for the depreciation process of inventories and Z is the exchange function depicted above. The model is also useful because it incorporates a series of parameters that control the converging speed. This option becomes fundamental when after-disruption data are available as it allows calibrating the model on real data, increasing the reliability of the evaluation.

CASE STUDY: THE SAN FRANCISCO BAY AREA

The two approaches described above have been applied to the San Francisco Bay Area to identify the critical systems of the area after a disruptive event such an earthquake. Both approaches need as a starting point the Input-Output matrix of the economy.

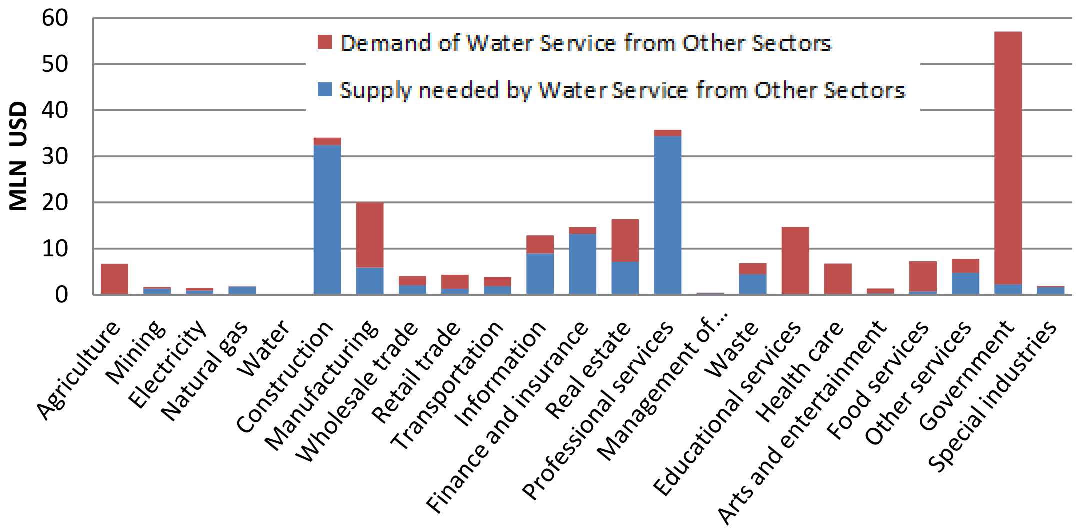

Figure 2. Interdependencies between Water Service and other economic sectors in the Bay Area

These matrices aren't public available directly, but are usually published at a national level by the BEA (Bureau of Economic Analysis) under the form of two matrices: the *Make matrix* and the *Use matrix* that can be unified under specific assumptions by the analysts. Considering that San Francisco must achieve certain performance targets to have the city fully operational in case of earthquake, our analysis starts from the projected Make and Use matrices elaborated by the Bureau of Labor Statistics (2012) for the year 2020. From these matrices, following the procedure described by Chamberlain (2011) the final Input-Output matrix at the national level has been derived. To scale the national matrix at the San Francisco Bay Area level, the RIMS II multipliers published by the BEA every year should be used. However, since the multipliers are not available for 2020 projection neither by the BEA nor by the BLS, the matrix is scaled from the national to the regional level using the ratio between the USA GDP and the San Francisco Bay Area, while keeping separated the utilities like electricity or water. Lifelines play a fundamental role in the aftermath of disruptive events, so attention is given to the Water and the Transportation Service which are also economically interdependent among other sectors in the region. Figure 2 and Figure 3 show the interdependency among different economic sectors.

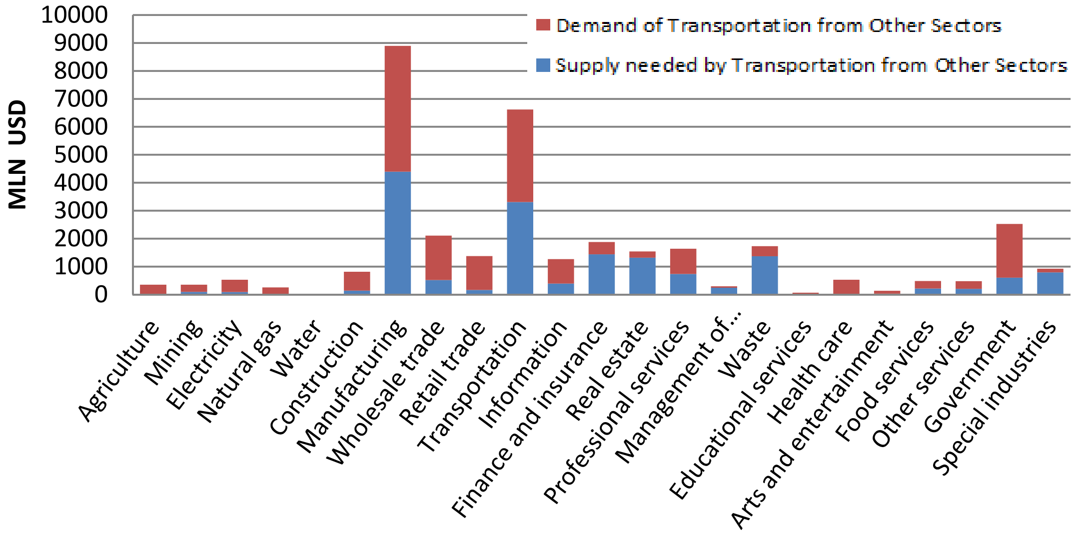

Figure 3. Interdependencies between Transportation and other economic sectors in the Bay Area

Using these data and the previous IIM set of equations, two strategies are analyzed to highlight the difference effects over static economic resilience of similar investment allocation in the economy. The outcomes of the strategies are shown in Table 2 assuming a planning function in Eq. (4) given by

$$f(\beta_i) = e^{-\beta_i} \tag{11}$$

Table 2. Outcome of two investment allocation strategies

strategy I	
βw	50.00
f(βw)	0.00
βt	2.00
f(βt)	0.14
βother	1.00
f(βother)	0.37
R̂s	65.50

strategy II	
βw	2.00
f(βw)	0.14
βt	50.00
f(βt)	0.00
βother	1.00
f(βother)	0.37
R̂s	65.70

R̂s is the average static resilience of all the economic sectors which represents a rough estimation of resilience; however, the outcomes can be computed for each sector. The results show that with the same amount of dollars of investment (β_i) using strategy II an increment of 0.2% of average resilience is obtained with respect to strategy I. Even if this seems to be a small improvement, remember that we are taking in account, for sake of simplicity, the average static resiliency that smoothes the differences among sectors.

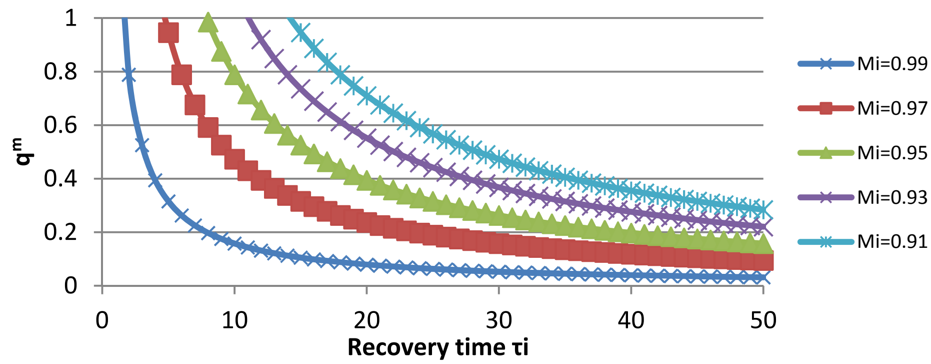

Figure 4. Contour curves of decision space for dynamic economic resilience

On the other side, the Eq. (8) generates a dynamic decision space through contour curves that can be used to estimate the system performance for different recovery strategies. Assuming the analysis addresses the time when the system recovers 95% losses and T=50 days, is possible to draw the two diagrams below. Figure 4 represents the contour curves for the dynamic resilience space, while Figure 5 the relationship between recovery time and recovery rate. The recovery time is evaluated from Figure 4 starting from the pair $(M_i, q^m{}_i)$ that indicates the desired level of overall operability during recovery. Then the recovery rate can be evaluated entering in Figure 5 with the estimated recovery time, so that the sectors that need to more investments to maintain a similar level of functionality compared to the others are identified. Table 3 shows the outcome of two strategies.

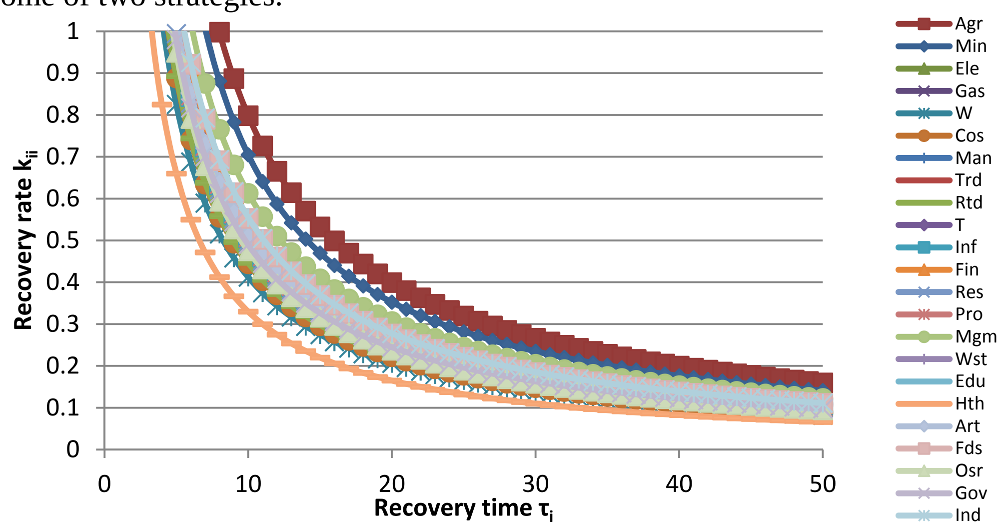

Figure 5. Recovery rate vs. recovery time for different economic sectors

As can be seen while strategy B requires quite lower recovery rates at the cost of lower resiliency, strategy A achieve a faster recovery and a higher resiliency but at the cost of a higher recovery rate for the Agriculture sector, that might be unmanageable. The estimation of the economic resilience through SGM starts again from the I-O matrices representative of the economy in normal operating condition, that are translated in terms of input and output coefficient matrices A and B. Earthquake is simulated modifying the exchange vector, which is the driver of the equilibrium process. Assuming a shock causes a 50% disruption in the water service, Figure 6 shows the restoration curve for the *Construction sector* from which the value of the economic resilience of the system can be quantified using the procedure described by Cimellaro et al. (2010, 2014). Resilience is in fact defined as "the normalized shaded area underneath the function describing the functionality of a system". Similar curves are obtained for all the other sectors. As a second case, a 50% Transportation disruption is also considered (not shown). Computing the resilience for each sector and then considering the average value of all the resiliencies founded in both cases, the effects of the two simulated shocks in Table 4 can be compared.

Table 3. Comparison between two different strategies

Strategy					τ	k_{agr}	k_W
A	Mi	0.97	q^m	0.5	10	0.8	0.45
B	Mi	0.95	q^m	0.5	16	0.5	0.28

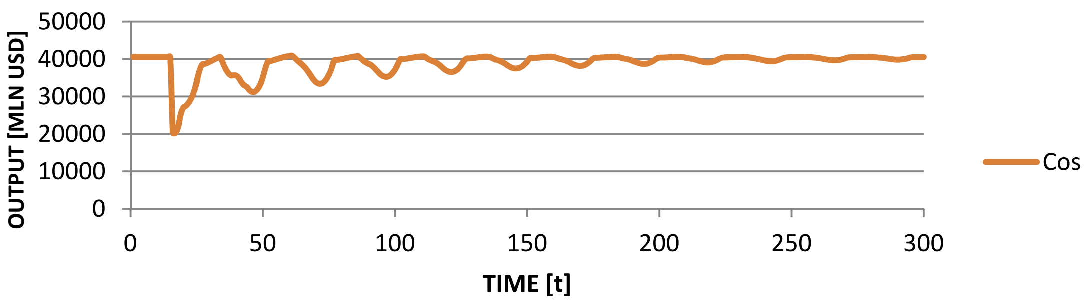

Figure 6. Restoration curve of Construction sector after Water Service disruption

A 50% disruption in the Transportation Service would lead to a lower value of average resilience, obtaining the same finding of the IIM approach. So globally, the economy is more dependent on the Transportation than the Water service, and that is why a smart investment allocation would favor the former sector respect to the latter.

Table 4. Comparison between two different disruptions

	Water Service disruption	Transportation
$\hat{R}$	96.37	89.25

FROM THE COMMUNITY LEVEL TO THE INDIVIDUAL BUSINESS LEVEL

While the economic resilience at the community level can be used as tool by Institutions which make decisions at the regional level, there is also need for a tool to evaluate economic resilience also at the local level when a single sector or a company need to be analyzed to show if it is economically resilient to disruptive events. To achieve this goal there is need to shift at the individual business level to evaluate the life-cycle costs of individual business and the return of investments for preparedness measures when building structures with higher performance with respect to the minimum required performance levels. This goal can be achieved using the framework proposed by Terzic et al. (2014), where different structural systems are compared to identify the different return of investment in case of a natural disaster strike the system. The framework they developed represents a combination of business, engineering, and seismology modeling and is divided in four steps. The first is the *Seismic Hazard Analysis* which leads to the selection of the intensity of the representative ground motion. Then, *Response Analysis* is performed through simulations and numerical modeling using OpenSees to identify the Engineering Demand Parameters for the different structures. The third step is the *Damage Analysis* which correlates EDPs with the damage state of all the components of the structures using the fragility curves which are provided in PACT. The final step is the *Loss Analysis*, which correlates damage to losses (e.g. repair cost, downtime etc.). Then the business downtime is evaluated using the downtime model developed by the authors and through a business model, the business interruption costs are evaluated and summed with the repair costs to obtain the total losses, from which the return on investments of different structural systems considering also the different intial costs are evaluated. The framework uses a business model that convert the business downtime to business interruption cost assuming the company owner is just leasing the space to businesses. However, considering the downtime business costs as a rental loss is a simplified way to approach the estimation of costs and can underestimate the return on investments. In fact interdependencies exists among different sectors and direct damage due to disruptive events will always be followed by indirect damage, which are taken in account in the framework, but in a simplified way. Nowadays, different business models have been developed to quantify the losses due to catastrophic events such earthquakes. Further research will be developed in extending the models used at the community level in a smaller scale at the local level using for example the an I-O matrix for the individual sectors or companies. This will allow to estimate the interdependencies between business and services, but at the same time between different branch offices of the same company for example.

CONCLUSION

The paper describes a methodology to evaluate economic resilience at the community level which can be applied to any type of disruptive event. The goal is to help decision makers to understand the economic resilience problem of interdependent networks from a community level to a business level. The *inoperability input-output model* and the *structural dynamic growth model* are compared starting from the same Input-Output matrix. The case study chosen in this paper is the San Francisco Bay Area. The I-O matrix has been obtained by scaling the matrix from the national to the regional level using the ratio between the USA GDP and the San Francisco Bay Area, while keeping disaggregated the utilities like electricity, water etc. Finally, the paper gives some insights on how to implement the approach to evaluate the life-cycle costs of structural systems in case of natural disasters, and the return of investments of preparedness measures like building structures with higher performance with respect to the minimum required performance levels given by IBC.

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