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On the resilience calculation of process plants in seismic regions based on Monte Carlo Simulation

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ABSTRACT
Past seismic events have demonstrated that industrial plants are highly vulnerable complex structures. Damage of any component can cause disruption of process plant functionality leading to direct and indirect economic losses due to business interruption. In order to quantify these economic losses, overall plant resilience is required. There are several frameworks described in literature, which can quantify the seismic resilience of network infrastructures, buildings and critical facilities, however there is a lack of seismic resilience estimation pertaining to industrial facilities. This paper presents a method to assess seismic resilience of process plants using probabilistic approach. Ability of plant to withstand the perturbation and recovery time, are considered as probabilistic. Monte Carlo Simulation is used in two levels, first one to define the most probable seismic damage scenarios while the second level is used to generate samples of recovery activities and equipment reconstruction cost in order to calculate the probabilistic recovery and probabilistic economic losses. Integrating business economic losses in this method, provides a complete information for decision makers, process planners and emergency managers to support their decision making process. Finally, application of methodology to a case study in Italy is illustrated.

1 INTRODUCTION

Past seismic events have shown the high vulnerability of industrial facilities and devastating consequences that can follow their failure, such as release of hazardous material, production loss, economic losses, environmental pollution etc. Kocaeli earthquake (1997), of magnitude 7.4, caused important damages to 30% of industrial plants of Izmit area, 20% of which got repaired within one month while the remaining 10% was unrepairable, leading to a production loss that was estimated around 1-1.5 bn US $ every month (Masson et al. 2001). More recent, Tohoku earthquake (2011), which was followed by tsunami and nuclear accident caused catastrophic damages in many fields including industrial facilities, where the refinery sector was the one which experienced the biggest drop in industrial production index (5 from 100) and had also the slowest recovery speed (Kajitani et al. 2013). These events have raised the interest of research community to develop frameworks not only to for risk calculations but also for resilience calculations.

There are several resilience models available in literature regarding community resilience, civil infrastructure systems, critical infrastructure and transportation system (Bruneau et al. 2003), (Cimellaro et al. 2006, 2009, 2010, 2017), (Tsionis 2014), (Shafieezadeh et al. 2014), (Ramirez-Marquez et al 2018), (Didier et al. 2017), while resilience models related to process plants are still under development.

Resilience of single unit of process plant has been studied by (Mebarki, A., 2016), but neglecting plant process flow. Some researches has been focused mainly on organizational and operational issues including human factor (Dinh et al. 2012), (Rydzak et al. 2016) or others on general modelling approach without suggesting any quantitative model (Rydzak et al. 2006).

In this paper a probabilistic resilience model based on (Caputo and Paolacci 2017) will be presented. Firstly, the resilience model will be described. Then the model will be applied to a case study that was first analysed in a deterministic way by (Kalemi et al. 2019). Recovery curve and economic losses will be calculated in probabilistic way. Finally, results, discussion and future research development will be presented.

2 METHODOLOGY

2.1 Resilience definition

Seismic resilience can be defined as ability of a system to withstand and rapidly recover from a low probability high impact event. Resilience index (R) will be defined as area under the curve of operational capacity C(t) from the time when a seismic event occurs (t_0) until a control time (t_h) usually defined from plant owner or decision makers. Plant operational capacity curve is shown in Figure 1 and characteristic times are : time when damage propagation stops (t_d), time when increase in operational capacity starts (t_i) and time when plant if fully recovered (t_r).

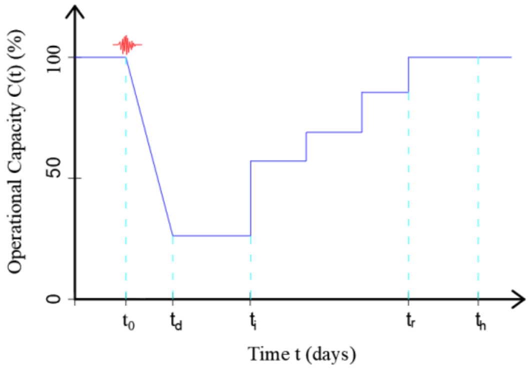


Figure 1. Plant operational capacity curve.

Resilience index will be given in percentage and will be calculated using Equation 1 as shown below:

$$R = \frac{1}{t_h - t_0} \int_{t_0}^{t_h} C(t)dt \quad (1)$$

2.2 Resilience model

The resilience model will consist on eight operational steps, using two levels of Monte Carlo Simulation (MCS), as shown in Figure 2.

Step 1, process plant mapping, consists in identification of plant critical equipment, plant configuration and physical output flows (PF).

Step 2 consists in construction of Capacity Block Diagram, where equipment of each PF are grouped in process stages (PS), strictly connected in series (Caputo and Paolacci 2017). PS can contain equipment in series, parallel or redundant, and their grouping is based on the influence they have to the production capacity of PF. When an equipment in series is damaged the entire capacity of the flow will drop to zero, while for the case of damage of any equipment in parallel the capacity will drop by the percentage that is covered by that equipment. The capacity of a PF is governed by the PS with the lowest capacity.

In step 3 the General Reconstruction Activity Network (GRAN) should be constructed, same as the one used in project management (Vanhoucke 2012). The GRAN should be constructed considering that the plant is completely damaged so the all possible reconstruction activities should be considered. All recovery activities duration $T_{i,j,}$ which corresponds to *j-th* restoration activity of *i-th* damaged equipment, will be defined as normal distribution having a mean and a standard deviation, bounded to be positive. In more details this step can be found at (Caputo and Paolacci 2017) and (Kalemi et al. 2019).

In step 4, the most probable seismic damage scenario will be defined. A binary state will be assigned to equipment (δ), zero when damaged and one when undamaged. Multiple damage states of equipment can be considered. At first, seismic hazard curve of the site should be estimated using Probabilistic Seismic Hazzard Analysis (PSHA) (Cornell 1968). Next, vulnerability of equipment should be assessed using fragility curves that can be taken from literature or can be computed using numerical models. Finally, probabilistic seismic analysis using MCS will be used in order to define most probable seismic damage scenarios, as described in (Alessandri et al. 2018).

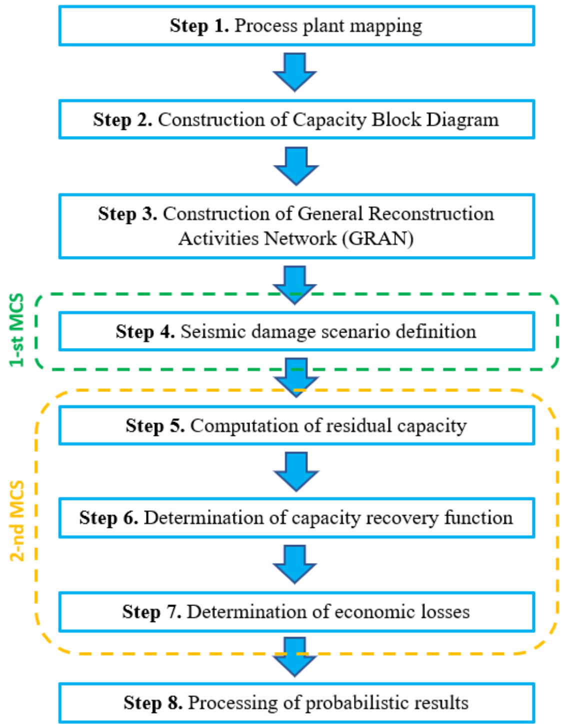


Figure 2. Operational steps for resilience calculation.

In step 5, residual capacity $C(t_d)$ should be calculated for each damaged scenario using Equation 2 as below:

$$C(t_d) = \sum_f O_f C_f(t_d) \quad (2)$$

where, O_f is the fraction of total plant capacity allocated in *f-th* PF, while $C_f(t_d)$ is the operational capacity of *f-th* PF at time when disruption has finished. Capacity of process flow can be defined using Equation 3, where $C_{s,f}$ is the capacity of *s-th* PS of *f-th* PF.

$$C_f = Min\{C^s_{s,f}, C^p_{s,f}, C^r_{s,f}\} \quad (3)$$

Capacity of PS with equipment in different working state is given in Table 1, where δ_i is the damage state variable of *i-th* equipment, while *k* is the minimum number of redundant equipment that need to be functional in order to maintain the full capacity of PS with *n* equal units.

Table 1. Process Stage Capacity model.

PS with units in series	$C^s_{s,f} = \prod_{i\epsilon S[s,f]} \delta_i$
PS with *n* equal units in parallel with capacity $1/n$	$C^p_{s,f} = \sum_{i\epsilon S[s,f]} \frac{1}{n}\delta_i$
PS with redundant *k* out of *n* equal units	$C^r_{s,f} = \begin{cases} 1 \; if \sum_{i\in S[f,s]} \delta_i \geq k \\ 0 \; if \sum_{i\in S[f,s]} \delta_i < k \end{cases}$

In step 6, capacity recovery functions should be defined. A damage state coefficient ($\gamma_{i,j}$), which multiplies each $T_{i,j}$ recovery activities, is used in order to define which activities should be carried out, in case that *i-th* equipment is damaged. Recovery time of *i-th* equipment (Tr_i) will be calculated automatically from GRAN using Critical Path Method (Vanhoucke 2012). Initial value of $\gamma_{i,j}$ will be zero which mean that for undamaged state of plant all activities duration will be zero, while in case of damage of any i-th equipment all $\gamma_{i,j}$ will be switched to 1.

$$\begin{cases} \gamma_{i,j} = 1 \quad if \quad \delta_i = 0 \\ \gamma_{i,j} = 0 \quad if \quad \delta_i = 1 \end{cases} \quad (4)$$

In order to have a full information set for decision makers, plant owners or insurance companies, economic losses are integrated in step 7. Equipment reconstruction cost (ER) will be calculated using Equation 4 where the cost of *j-th* restoration task required to bring back into functionality *i-th* damaged equipment will be defined as normal distribution as the cost of each recovery activity or cost of equipment may vary due to inflation or market availability, so for every MCS a random Cr_{ij} will be generated for analysis.

Business interruption losses (BI) are also included in the model, such as the total economic losses (EL) are calculated as sum of ER and BI.

$$ER = \sum_i \sum_j \delta_i Cr_{ij} \quad (4)$$

$$BI = \sum_f \sum_z (p_f - Cvu_f)\,[C_{Nf} - C_f(t)]\Delta t_z \quad (5)$$

Business interruption losses are calculated using Equation 5, where p_f is the unit selling price of the *f-th* process flow product, Cvu_f the variable unit production cost of the *f-th* process flow product, C_{Nf} is the nominal production output of the *f-th* process flow, $C_f(t)$ is the capacity of *f-th* process flow at time t, and Δt_z is the duration of the *z-th* time interval between functional recovery of two successive units (Caputo and Paolacci 2017).

The last step, step 8, deals with processing of probabilistic results, derived in second level of MCS that includes steps 5 to 7, and it will be repeated for each seismic damage scenario of interest. Probabilistic recovery curves, probabilistic plant recovery time and probabilistic economic losses will be shown and discussed in this step.

3 CASE STUDY

3.1 *Description of case study*

A nitric acid plant as described in (Kalemi et al. 2019) is selected as case study, assumed to be located in Priolo Gargallo, south of Italy. The plant has two process flows PF, physical production lines, as shown in Figure 3. Process flow one delivers 195 ton/day of nitric acid (60% concentration) while process flow two delivers 130 ton/day of nitric acid (40% concentration). It consists of equipment of different typologies such as horizontal vessels, vertical vessels, steel storage tanks, air compressors, pumps, electric unit, bleaching columns, refrigeration units and piping systems which are given in Table 3. Each PF contain two PS with equipment in parallel and one PS with equipment in series as shown in CBD in Figure 1, which corresponds to step 2.

The GRAN will be the same as the one used in (Kalemi et al. 2019), with the only change that duration of each activity will be given as normal distribution with a mean equal to deterministic value of recovery activity of (Kalemi et al. 2019) and a standard deviation equal to 10% of mean value.

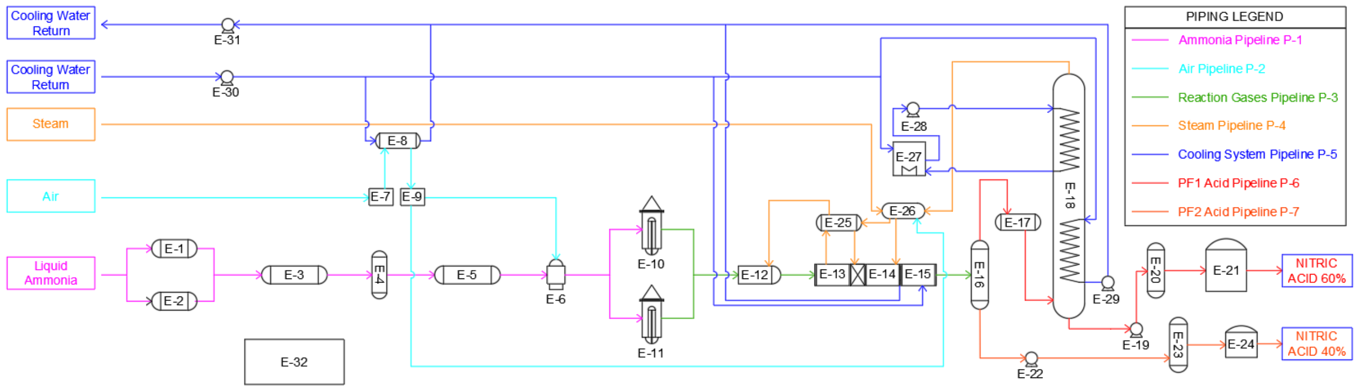


Figure 3. Process Flow Diagram of nitric acid plant.

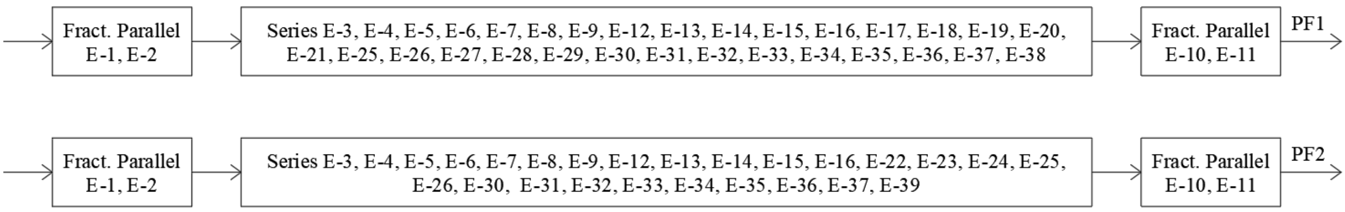


Figure 4. Capacity Block Diagram of nitric acid plant.

Only extensive damage state of equipment will be considered in this paper and damaged equipment will be assumed to replaced. Equipment reconstruction cost is assumed to be a normal distribution having a mean equal to equipment reconstruction cost given in (Kalemi et al. 2019) and a standard deviation of 10% of mean as given in Table 3.

Selling price of 60% nitric acid is 240 €/ton while the price of 40% nitric acid is 160 €/ton. Variable production cost of 60% nitric and 40% nitric are 60€ and 40€, respectively. This data will be the input of step 7 in order to define BI losses.

3.2 Seismic damage scenario definition

Probabilistic seismic analysis is conducted in order to define the most probable seismic damage scenarios using PRIAMUS (Corritore et al. 2018) software. This step, corresponds with the first MCS where earthquake magnitude (m), distance (R) and seismogenic zone are randomly sampled for each simulation. Equipment vulnerability are expressed in fragility curves considering only extensive damage state as per Table 3.

In Table 2 are shown the five most probable seismic damage scenarios (SV). The most probable seismic damage scenario is when both steel storage tanks (E-21 and E-24) fails, having an annual probability of occurrence of 1.39E-6, while the second most probable damage state is when electric unit (E-32) fails, having an annual probability of occurrence equal to 9.05E-7.

Table 2. Most probable seismic damage scenarios.

#	Seismic damage scenario (damaged units)	Annual Probability
0	None	0.999
1	E-21; E-24	1.39e-06
2	E-32	9.05e-07
3	E-24	3.22e-07
4	E-21	2.63e-07
5	E-7; E-9	1.90e-07

3.3 Probabilistic resilience and economic calculation

After defining the most probable seismic damage scenario, a second Monte Carlo simulation will be conducted for each seismic damage scenario in order to calculate probabilistic resilience and economic losses. In each simulation recovery activities and equipment reconstruction costs will be selected randomly.

In Figure 5 are shown the recovery curves of three most probable seismic damage scenarios, SV1, SV2 and SV3, where the red line corresponds to the mean recovery curve. Meanwhile, in Figure 6 are shown the distribution of maximum recovery time of those scenarios for 10000 MCS. Scenario #1 is the least resilient one with a mean resilience index (R_m=41.6%), while scenario #2 and scenario #3 have a mean resilience of (R_m=68.7%) and (R_m=77.5%), respectively. In terms of residual capacity SV#3 is the most robust one as after

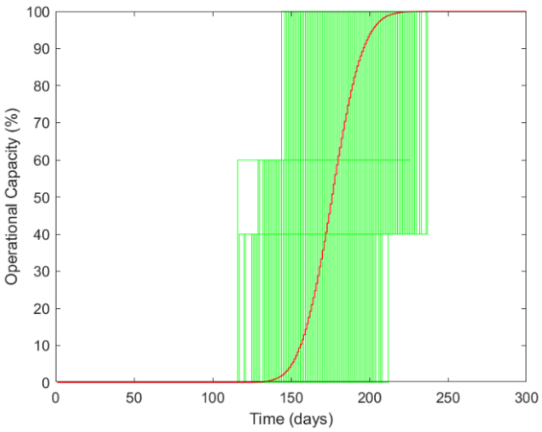
Table 3. Equipment description, replacement costs and fragility curve parameters.

Eq. Label	Process Equipment	**Replacement cost (€)**		**Fragility curve parameters**		**D.S.**	**Reference**
		Mean	**St.dev.**	**PGA_m (g)**	**β**		
E-1	Ammonia storage vessel	646,000	64,600	0.54	0.46	PL2	Horizontal Vessel [*]
E-2	Ammonia storage vessel	646,000	64,600	0.54	0.46	PL2	Horizontal Vessel [*]
E-3	Ammonia Vaporizer	70,000	7,000	0.54	0.46	PL2	Horizontal Vessel [*]
E-4	Filter	30,000	3,000	1.0	0.6	DS3	Mechanical Equipment [**]
E-5	Ammonia Super heater	34,000	3,400	0.54	0.46	PL2	Horizontal Vessel [*]
E-6	Mixer	30,000	3,000	1.0	0.6	DS3	Mechanical Equipment [**]
E-7	1-st Stage Air Compressor	1,458,000	145,800	0.77	0.65	DS4	Compressor Station [**]
E-8	Compressor intercooler	61,000	6,100	0.54	0.46	DS4	Horizontal Vessel [*]
E-9	2-nd Stage Air Compressor	2,722,000	272,200	0.77	0.65	DS4	Compressor Station [**]
E-10	Reactor	139,000	13,900	0.51	0.45	PL2	Vertical Vessel CL1 [*]
E-11	Reactor	139,000	13,900	0.51	0.45	PL2	Vertical Vessel CL1 [*]
E-12	Steam Super-Heater	74,000	7,400	0.54	0.46	PL2	Horizontal Vessel [*]
E-13	Waste Heat Boiler	86,000	8,600	0.54	0.46	PL2	Horizontal Vessel [*]
E-14	Tail Gas Pre-heater	72,000	7,200	0.54	0.46	PL2	Horizontal Vessel [*]
E-15	Cooler/Condenser	186,000	18,600	0.54	0.46	PL2	Vertical Vessel CL1 [*]
E-16	Oxidation Vessel	101,000	10,100	0.59	0.41	PL2	Vertical Vessel CL2 [*]
E-17	Secondary Cooler	250,000	25,000	0.54	0.46	PL2	Horizontal Vessel [*]
E-18	Absorption Column	2,261,000	226,100	0.67	0.37	PL2	Extrapolation [*]
E-19	Acid Pump	10,000	1,000	1.6	0.6	DS4	Horizontal Pump [**]
E-20	Bleaching Column	74,000	7,400	0.59	0.41	PL2	Vertical Vessel CL2 [*]
E-21	Nitric Acid (60%) Tank	1,160,000	116,000	0.68	0.75	DS4	Unanchored Tank [**]
E-22	Acid Pump	10,000	1,000	1.6	0.6	DS4	Horizontal Pump [**]
E-23	Bleaching Column	74,000	7,400	0.59	0.41	PL2	Vertical Vessel CL2 [*]
E-24	Nitric Acid (40%) Tank	696,000	69,600	0.68	0.75	DS4	Unanchored Tank [**]
E-25	Liquid Vapour Separator	70,000	7,000	0.54	0.46	PL2	Horizontal Vessel [*]
E-26	Tail Gas Warmer	124,000	12,400	0.54	0.46	PL2	Horizontal Vessel [*]
E-27	Refrigeration Unit	164,000	16,400	1.0	0.6	DS3	Mechanical Equipment [**]
E-28	Water pump	3,000	300	1.25	0.6	DS4	Vertical Pump [**]
E-29	Water pump	3,000	300	1.25	0.6	DS4	Vertical Pump [**]
E-30	Water pump	3,000	300	1.25	0.6	DS4	Vertical Pump [**]
E-31	Water pump	3,000	300	1.25	0.6	DS4	Vertical Pump [**]
E-32	Electric Unit	811,000	81,100	1.0	0.8	DS3	Electric Power [**]
E-33	Ammonia Pipeline	541,000	54,100	1.0	0.6	DS5	Elevated Pipes [**]
E-34	Air Pipeline	541,000	54,100	1.0	0.6	DS5	Elevated Pipes [**]
E-35	Reaction Gas Pipeline	541,000	54,100	1.0	0.6	DS5	Elevated Pipes [**]
E-36	Steam Pipeline	541,000	54,100	1.0	0.6	DS5	Elevated Pipes [**]
E-37	Cooling System Pipeline	55,000	5,500	1.0	0.6	DS5	Elevated Pipes [**]
E-38	PF1 Acid Pipeline	541,000	54,100	1.0	0.6	DS5	Elevated Pipes [**]
E-39	PF2 Acid Pipeline	541,000	54,100	1.0	0.6	DS5	Elevated Pipes [**]

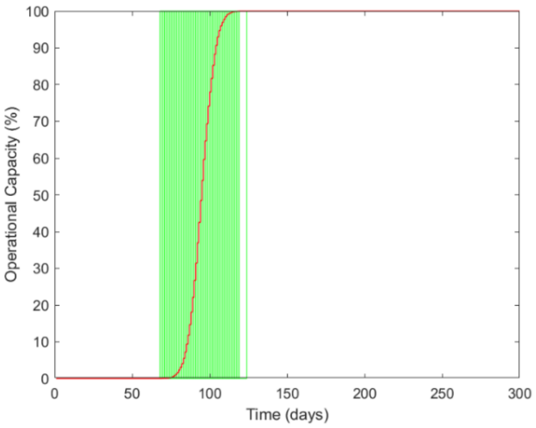
*(PEC 2017), **(Hazus)

seismic event it can maintain 60% of operational capacity while SV#1 and SV#2 are not robust at all as their residual capacity drops to zero. In terms of maximum mean recovery time, SV#1 has a mean of (t_{rm} ~184.2 days), SV#2 (t_{rm} ~94.9 days) and SV#3 (t_{rm} ~170.2days). We can observe that SV#3 even though has a bigger mean maximum recovery time than SV#2, it is a more resilient damage scenario due to its robustness.

(a)



(b)



(c)

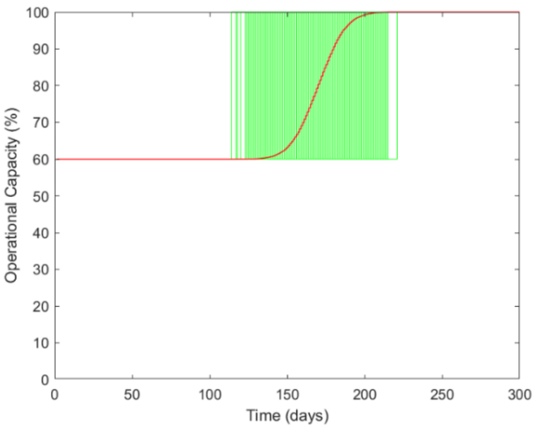


Figure 5. Probabilistic recovery curve of seismic damage scenario: (a) SV#1; (b) SV#2 and (c) SV#3.

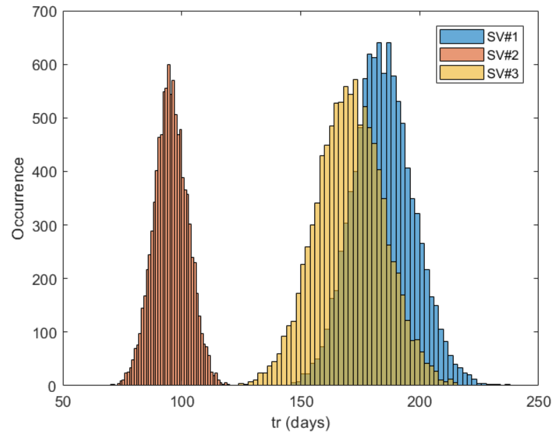


Figure 6. Distribution of maximum recovery time of seismic damage scenario SV1, SV2 and SV3.

Distribution of economic losses for all 5 most probable seismic damage scenarios are shown in Figure 7. Scenario #1 has the biggest EL with a mean of approximately 10.8 million euros, while scenario #3 has the smallest EL with a mean approximately 3.3 million euros. In terms of ER costs scenario 5 has the biggest one being around 4.2 million euros. It is easily noticeable from the Figure 7 that the BI has the biggest influence in EL being around 78%.

Analysing both mean annual frequency of occurrence of damage scenarios from Table 2 and economic losses from Figure 7, it can be concluded that seismic damage scenario #1 is the most critical one due to the highest mean annual frequency of occurrence and highest economic losses. The other seismic damage scenarios are comparable to each

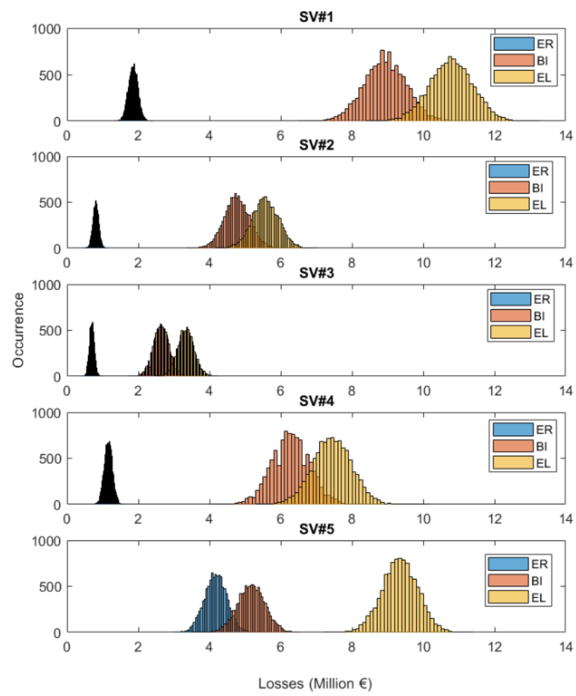


Figure 7. Distribution of economic losses.

other and their ranking has to be made by decision makers, plant owners based on their priority, mean annual frequency of occurrence or economic losses or as a combination of both.

4 CONCLUSIONS

This paper briefly describes operational steps for the calculation of probabilistic seismic resilience of process plants including economic losses using Monte Carlo simulations.

Actual plant layout, process flow diagram and capacity block diagram are used to calculate plant operational capacity. Probabilistic recovery functions based on General Reconstruction Activity Network are used to calculate the plant recovery. Nitric Acid plant is used as a case study in order to show the potentiality and applicability of the method.

Steel storage tanks are the most critical component of Nitric Acid plant due to high annual probability of being seismically damaged and long restoration time which leads to low resilience and high economic losses, so much attention should be paid to this equipment.

Business interruption losses are the one that influence more, around 77% of total economic losses, so in order to reduce them, redundant equipment should be added in plant especially to most vulnerable equipment which work as equipment in series for both process flows.

Results provided from this methodology can help insurance companies, facility planners and plant owners in decision making process for the case of earthquakes.

Further studies will be focused on including more damage states of equipment and also accounting for damage propagation.

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