

## Dynamic Resilience Modelling of Process Systems

Mohammed Taleb-Berrouane, Faisal Khan\*

Centre for Risk, Integrity and Safety Engineering (C-RISE)  
Faculty of Engineering and Applied Science  
Memorial University of Newfoundland, St. John's, NL A1B 3X5, Canada  
[fikhan@mun.ca](mailto:fikhan@mun.ca)

The hazards in complex process systems evolve at an accelerated rate. It is extremely difficult if not impossible to identify and assess all potential hazards and develop strategies to manage them. This demands next generation of process system that is, intelligent to learn faults and prevent them from further propagating, adaptive to evolving conditions, and quick to recover in case failures take place in a component of part of the system. Resilience engineering is a comprehensive term that captures these three (absorptive, adaptive, and recovery) important characteristics of a system. There are limited tools to qualify or quantify the resilience of a system. There have been hardly any studies conducted on dynamic resilience assessment. This paper proposes a dynamic approach to quantify resilience under varying conditions. The approach uses Stochastic Petri-nets (SPN) coupled with Monte Carlo simulation to model and analyze resilience metrics. The proposed approach is tested on a crude oil pipeline system. The test results demonstrate a clear understanding of the resilience characteristics of the system and its evolving nature. This work puts forward a clear pathway for an integrated dynamic model for resilience engineering.

### 1. Introduction

Resilience engineering is a comprehensive term that captures the system's characteristics beyond the fundamental concept of reliability. The resilience of a process system is its capability to handle a disruptive event and avoid failure. This can be satisfied by lessening the impact of the disruption on the system performance and/or reducing the disruption duration. According to Bruneau and Reinhorn (2007), a resilient engineering system should operate with reduced failure probability, reduced potential consequences subsequent to failures and reduced restoration time. The U.S National Institute of Standards and Technology (Gilbert, 2010) defines resilience in term of economic saving by minimizing the cost of a disaster and the ability to return to a state as good as or better than the initial level of performance. Resilience has been largely studied in the field of natural disaster risk reduction by Bruneau and Reinhorn (2006) and (2007) and Ayyub (2014) and (2015).

There is limited work that has attempted to qualify or quantify the resilience of process systems. Sarwar et al. (2018) have assessed resilience as a function of reliability, vulnerability and maintainability. They applied a Bayesian network (BN) approach (Deyab, Taleb-berrouane, Khan, & Yang, 2018; Taleb-berrouane, Khan, Hawboldt, Eckert, & Skovhus, 2018) to analyze the response of a remote offshore vessel in a scenario of a hydrocarbon release during offloading operation. Attoh-okine et al. (2009) define a resilience index as follows:

$$\text{Resilience} = \frac{\int_{t_1}^{t_2} Q(t) dt}{100 (t_1 - t_2)} \quad (1)$$

Where Q is the performance or quality of a system,  $t_1$  is the disruption initiation or the time of incident that causes the decrease in the performance of the system, and  $t_2$  is the disruption termination or the time after recovery. The resilience index or resilience measurement as shown in equation (1) is not sufficient to assess the resilience capacity of an engineering system. Other metrics are developed by researchers in the field of natural disaster management. The main resilience metrics are:

- (i) The absorptive capacity or robustness which is defined by Bruneau and Reinhorn in (Bruneau & Reinhorn, 2007) as the strength, or the ability to withstand a given level of stress or demand without suffering degradation or loss of function. This concept has been further developed to cover the capability to absorb the impact of the disruptive event through inherent and/or adaptive mechanisms.
- (ii) The adaptive capacity is demonstrated in term of the effect of the mitigative and control actions that will temporarily stabilize the performance of the system and afterwards allow the restoration to the new stable level.
- (iii) The restorative or recovery capacity is demonstrated in term of corrective actions such as equipment replacement or system reset that will bring the system from a temporary stabilized stage to a fully operational stage in as good as new or other stable levels of performance.

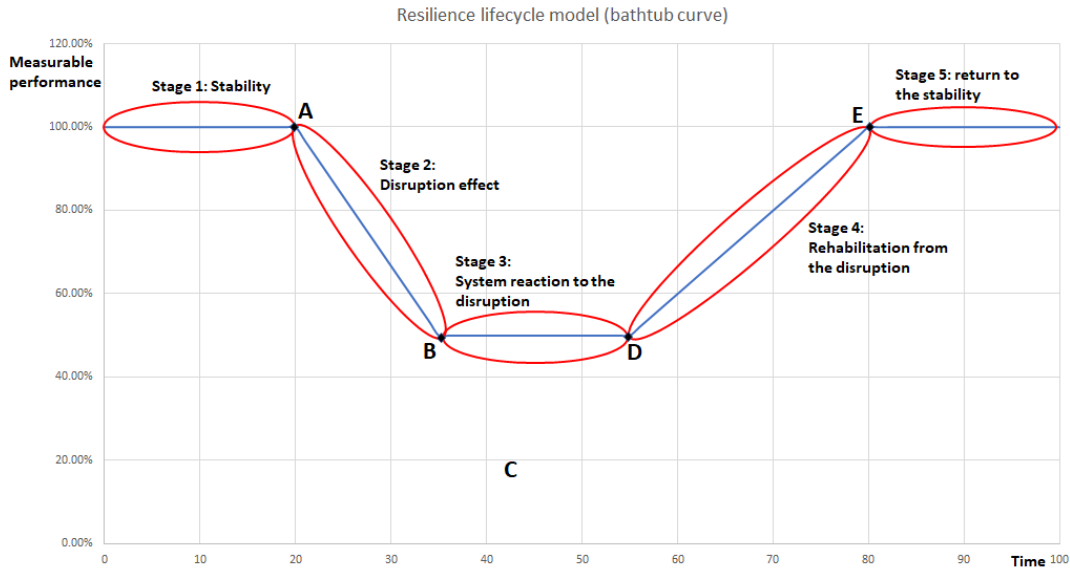


Figure 1: The proposed resilience lifecycle model (bathtub curve).

Figure 1 displays the five stages or bathtub curve of resilience. Stage 1 presents the phase where the system is monitored and stable. Point A is the incident that triggers the disruption, and it can be modeled using a Poisson process. The incident can be a failure of a critical component in the system, an external factor or any event that lowers the performance of the system. Stage 2 expresses the effect of the disruption on the measurable performance. It settles at point B where the control operations react and take effect. Stage 3 shows a temporal stability of the system at a lower performance level. Part BC presents the performance degradation of the system in case no control actions are taken or failure of the control actions. Stage 4 shows the effect of corrective actions that aim to return the performance to the initial stage or a long-term stable level. Stage 5 is the new stable level of performance that can be higher than, equal to or lower than the initial level depending on the adopted maintenance strategy.

The five stages of the bathtub curve are a function of dynamic factors and time-varying processes. This paper aims to build a dynamic resilience model able to capture those dynamic factors and time-varying processes. The present paper implements the proposed dynamic model in the field of pipeline corrosion engineering where the pipeline wall thickness is identified to be the practical measurement of system performance.

## 2. Background on the modelling technique

Petri networks (PNs) were first proposed in 1962 by Carl Adam Petri, as a new mathematical and graphical model to connect events and conditions (David & Alla, 2010). A Petri Net is a weighted bipartite graph (P,T,A,w) (Cassandras & Lafortune, 2009) with two functional parts, a static and a dynamic.

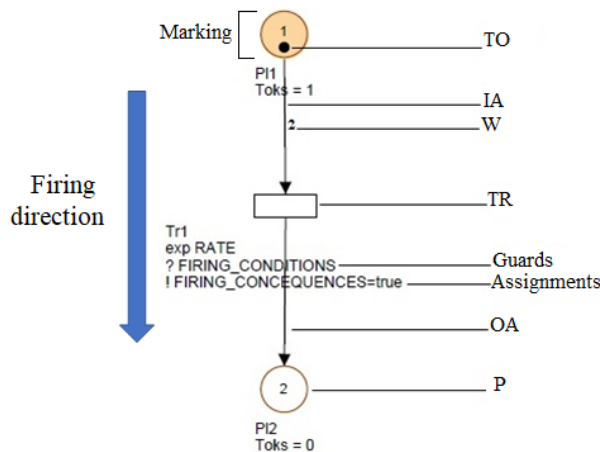


Figure 2: Glossary of Petri nets notations adapted from Talebberrouane et al. (2016).

Figure 2 displays the static part of the PN represented by places (P), transitions (TR) and oriented arcs that connect places to transitions (i.e. input arcs, IA) and transitions to places (i.e. output arcs, OA). (W) represents the weight function on the arcs. For example, an inhibitor arc weights (-1). The dynamic part is expressed by movements of tokens (TO) following firing transitions (i.e. tokens' migration from one or more input places to one or more output places). The marking represents the tokens' number in a place. In addition to the conventional PN, a stochastic Petri Net (SPN) (Dutuit, Châtelet, Signoret, & Thomas, 1997) also has non-deterministic firing delays associated with transitions. In a recent extension of SPN, the activation of a transition can be conditioned by one or more mathematical variables through the use of predicates and assertions (IEC62551, 2012). The predicates or guards, as defined by IEC 61508-6 (*IEC 61508-6 Functional Safety of Electrical/electronic/programmable Electronic Safety Related Systems*, 2010), are conditions which may be true or false, and control the transition firing. Assertions or assignments are the mathematical variables that receive predefined updates such as incrementation or state switching as consequences of the transition firing. In this paper, the SPN is coupled with Monte Carlo simulation to enhance its modelling capability. For more details, readers can refer to our previous work, Taleb-berrouane et al. (2016).

### 3. Dynamic resilience model for pipeline corrosion

As pipeline ages, the integrity faces multiple and complex threats. Corrosion is the main threat to the pipeline systems (Taleb-berrouane et al., 2018; Yang, Khan, Thodi, & Abbassi, 2017). In this paper, an SPN model is used to assess the dynamic resilience of crude oil pipeline (e.g. illustrative case). Figures 3 depicts the proposed SPN model that captures the main dynamic processes that influence the corrosion occurrence, control and mitigation.

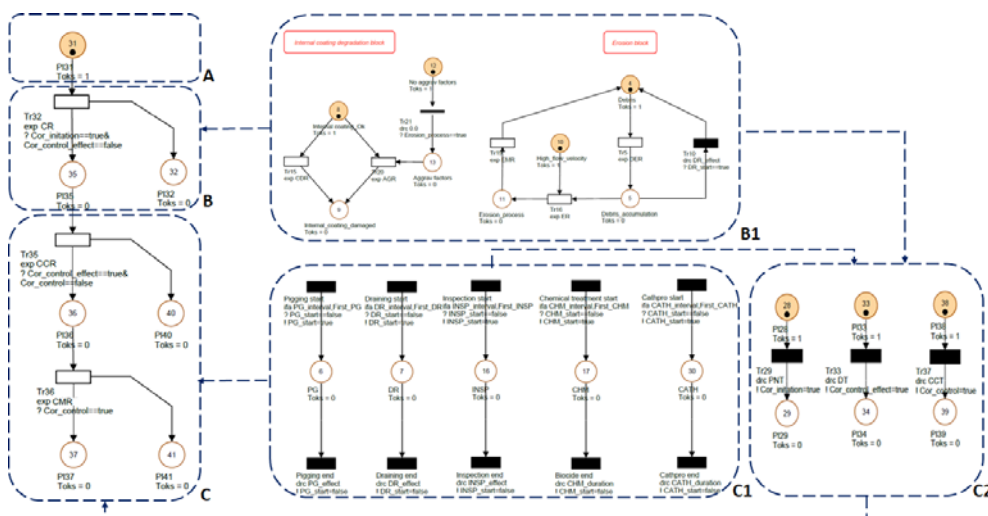


Figure 3: SPN overall network for the pipeline resilience modelling.

Figure 3 displays the overall SPN model. The model is built on the interactions between six SPN blocks or sub-networks. The first three blocks (A, B, C) are the model's interface for stage 1, stage 2 and stage 3 (according to Figure 1 definitions), respectively. Block "B1" models the erosion process and its impact on the internal coating degradation which accelerates the corrosive process. Block "C1" is assigned to the corrosion control and mitigation actions. It captures the scheduling of pipeline servicing such as pigging and draining, as well as corrosion mitigation such as the cathodic protection and chemical treatment. The variation of the interval between operations and their first-time commencements will cause changes in the model variables. Subsequently, rates such as corrosion rate (CR) and corrosion control rate (CCR) will change accordingly. These changes make the model dynamic to the variations of the coating damage level, erosion process and pipeline servicing and inspection. Table 1 summarizes the dependencies between the PN main evolutive rates.

Table 1: Summary of the main evolutive rates and their details.

Main Evolutive rates	Meaning	Estimated value	Variables affecting the rates	Relevant sources
CDR	Coating degradation rate	$1 \times 10^{-5}$	$CDR = f$ (residual stress, flow, fluid viscosity and composition, surface roughness, penetration resistance)	(Papavinasam et al. 2004)
EMR	Erosion mitigation rate	$1 \times 10^{-4}$	$EMR = f$ (fluid turbulence, shear stress)	(Ossai, 2012)
AGR	Aggravation rate	$6 \times 10^{-5}$	$AGR = f$ (residual stress, fluid turbulence, shear stress)	(Islam et al. 2013; Ossai 2012; Papavinasam et al. 2004)
DER	Debris entrance rate	$1 \times 10^{-4}$	$DER = f$ (debris source, fluid turbulence)	(Svedeman & Kuhl, 2018)
CR	Corrosion rate	$1 \times 10^{-4}$	$CR = f$ (metal conductivity, fluid chemistry, coating, temperature)	(Glass, Page, & Short, 1991)
CMR	Corrosion mitigation rate	$1 \times 10^{-3}$	$CMR = f$ (cathodic protection, chemical treatment)	(Neville & Wang, 2009)
CCR	Corrosion control rate	$1.6 \times 10^{-4}$	$CCR = f$ (corrosion rate, process anomalies, servicing, cathodic protection, chemical treatment)	(Neville & Wang, 2009)

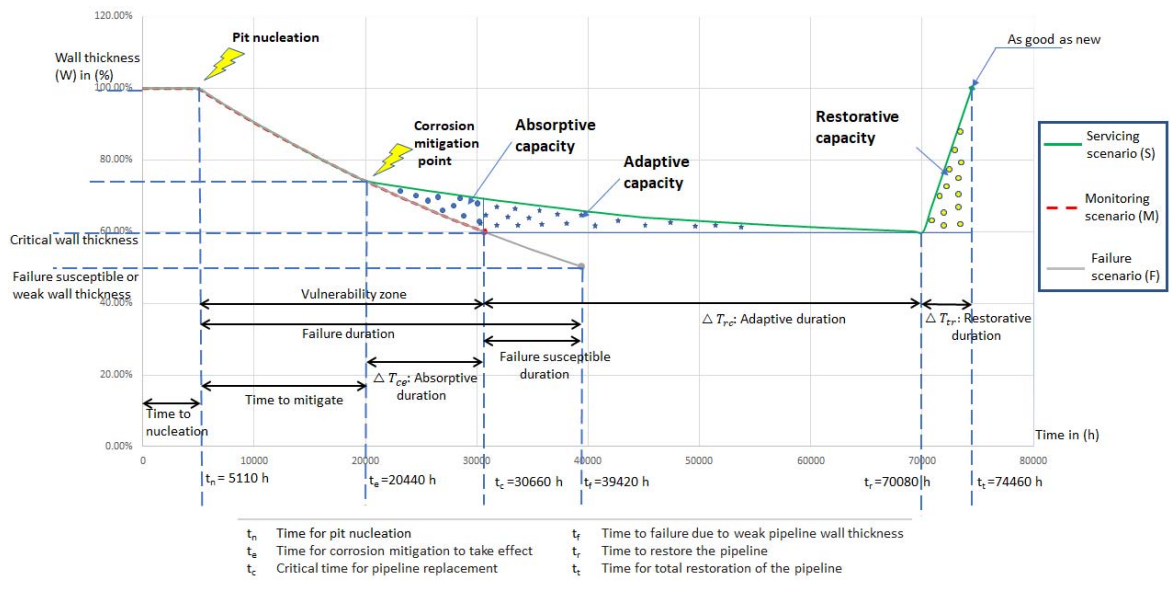


Figure 4: Resilience curve for pipeline corrosion control.

Figure 4 provides a schematic presentation of the system performance in term of decrease in pipeline wall thickness. The latter is a measurable performance, and it provides a clear understanding of the level of corrosion. The generated data from the SPN model, illustrated in Figure 4, allows the calculation of dynamic resilience metrics. The control mitigation point (CMP) corresponds to the moment when the corrosion control actions successfully reduce the corrosion rate, thereby decelerating the loss in wall thickness. The CMP and the following trend capture the positive effect of the corrosion control strategy in term of pipeline life extension as demonstrated in Figure 4.

The absorptive capacity (AB) depicts the ability of the system to absorb the disruption and decelerate the corrosive process. It is expressed in Figure 4 by the area limited between the “S” and “M” scenarios following equation (2). The developed formulas are inspired from the work of Ayyub (2015).

$$\text{Absorptive capacity} = \frac{\int_{t_e}^{t_c} S(t) dt - \int_{t_e}^{t_c} M(t) dt}{\int_{t_e}^{t_c} W(t) dt} \quad (2)$$

$$\text{Dynamic adaptive capacity} = \frac{\int_{t_c}^{t_r} S(t) dt - \int_{t_c}^{t_r} M(t) dt}{\int_{t_c}^{t_r} W(t) dt} \quad (3)$$

$$\text{Restorative capacity} = \frac{\int_{t_r}^{t_e} S(t) dt}{\int_{t_r}^{t_e} W(t) dt} \quad (4)$$

$$\text{Dynamic Resilience} = \frac{T_n + DAB \Delta T_{ce} + DAD \Delta T_{rc} + DRS \Delta T_{tr}}{T_n + \Delta T_{ce} + \Delta T_{rc} + \Delta T_{tr}} \quad (5)$$

The adaptive capacity (AD) is the gain in pipeline lifetime due to the adoption of proper corrosion control actions. At this stage, the pipeline survives while operating on low performance. The restorative capacity in the case of pipeline corrosion is mainly represented in terms of pipeline replacement.

Table 2: Generated results in term of Resilience metrics.

Resilience metrics	Calculated value
Absorptive capacity	13.3%
Adaptive capacity	8.7%
Restorative capacity	83.3%
Resilience	22.9%

The obtained resilience metrics, in Table 2, reveal good performances of the system. Those metrics should be analyzed and compared in terms of cost of investment and return or savings in potential direct and indirect losses such as pipeline replacement at an early age (e.g. M scenario) or pipeline failure (e.g. F scenario). This part is discussed in (Ayyub, 2015). For more details, the reader is directed to aforementioned paper.

#### 4. Conclusion and Further Work

This paper introduced the concept of dynamic resilience modelling as a dynamic approach to quantify resilience and resilience metrics under varying conditions while handling the stochastic processes that interact with the system and can impact its performances. The application of the proposed approach to the pipeline corrosion control problem demonstrated its applicability and efficiency. The approach would help prioritize action to prevent and control corrosion prior to the failure stage or the equipment replacement at an early age. Further work needs to be done to optimize this SPN based approach. It is worth noting that the uncertainty analysis and the economical aspect of resilience engineering were not discussed in this work. This will be incorporated in an upcoming paper.

#### Acknowledgement

Authors thankfully acknowledge the financial support provided by Genome Canada and supporting partners such as Suncor, Husky, Research and Development Corporation of Newfoundland (known as Innovate NL) through large-scale applied research project grant. Author Khan acknowledges the support provided by Canada Research Chair (Tier I) programme.

## References

- Attoh-okine, N. O., Member, S., Cooper, A. T., & Mensah, S. A. (2009). Formulation of Resilience Index of Urban Infrastructure Using Belief Functions, *3*(2), 147–153.
- Ayyub, B. M. (2014). Systems resilience for multihazard environments: Definition, metrics, and valuation for decision making. *Risk Analysis*, *34*(2), 340–355. <https://doi.org/10.1111/risa.12093>
- Ayyub, B. M. (2015). Practical Resilience Metrics for Planning , Design , and Decision Making, *1*(3), 1–11. <https://doi.org/10.1061/AJRUA6.0000826>.
- Bruneau, M., & Reinhorn, A. (2006). Overview of the Resilience Concept, (2040).
- Bruneau, M., & Reinhorn, A. (2007). Exploring the Concept of Seismic Resilience for Acute Care Facilities. *Earthquake Spectra*, *23*(1), 41–62. <https://doi.org/10.1193/1.2431396>
- Cassandras, C. G., & Lafortune, S. (2009). *Introduction to discrete event systems*. Springer Science & Business Media.
- David, R., & Alla, H. (2010). *Discrete, continuous, and hybrid Petri nets*. Springer Science & Business Media.
- Deyab, S. M., Taleb-berrouane, M., Khan, F., & Yang, M. (2018). Failure analysis of the offshore process component considering causation dependence. *Process Safety and Environmental Protection*, *1*(8), 220–232. <https://doi.org/10.1016/j.psep.2017.10.010>
- Dutuit, Y., Châtelet, E., Signoret, J. P., & Thomas, P. (1997). Dependability modelling and evaluation by using stochastic Petri nets: application to two test cases. *Reliability Engineering & System Safety*, *55*(2), 117–124. [https://doi.org/http://dx.doi.org/10.1016/S0951-8320\(96\)00108-1](https://doi.org/http://dx.doi.org/10.1016/S0951-8320(96)00108-1)
- Gilbert, S. W. (2010). *Disaster Resilience: A Guide to the Literature*. NIST Special Publication 1117. Gaithersburg, Maryland.
- Glass, G. K., Page, C. L., & Short, N. R. (1991). Factors affecting the corrosion rate of steel in carbonated mortars. *Corrosion Science*, *32*(12), 1283–1294.
- IEC 61508-6 *Functional Safety of Electrical/electronic/programmable Electronic Safety Related Systems*. (2010). International Electrotechnical Commission.
- IEC62551. (2012). *Analysis techniques for dependability – Petri net techniques*. International Electrotechnical Commission.
- Islam, A., Farhat, Z. N., Ahmed, E. M., & Alfantazi, A. M. (2013). Erosion enhanced corrosion and corrosion enhanced erosion of API X- 70 pipeline steel. *Wear*, *302*(1–2), 1592–1601. <https://doi.org/10.1016/j.wear.2013.01.041>
- Neville, A., & Wang, C. (2009). Erosion – corrosion mitigation by corrosion inhibitors — An assessment of mechanisms, *267*, 195–203. <https://doi.org/10.1016/j.wear.2009.01.038>
- Ossai, C. I. (2012). Advances in Asset Management Techniques: An Overview of Corrosion Mechanisms and Mitigation Strategies for Oil and Gas Pipelines. *ISRN Corrosion*, *2012*, 1–10.
- Papavinasam, S., & R.Winston Revie. (2004). COATINGS FOR PIPELINES, 1–25.
- Sarwar, A., Khan, F., Abimbola, M., & James, L. (2018). Resilience Analysis of a Remote Offshore Oil and Gas Facility for a Potential Hydrocarbon Release. *Risk Analysis*, *38*(8), 1601–1617.
- Svedeman, S. J., & Kuhl, C. A. (2018). Pipeline Purging Principles and Practice.
- Taleb-berrouane, M., Khan, F., Hawboldt, K., Eckert, R., & Skovhus, T. L. (2018). Model for microbiologically influenced corrosion potential assessment for the oil and gas industry and gas industry. *Corrosion Engineering, Science and Technology*, *0*(0), 1–15. <https://doi.org/10.1080/1478422X.2018.1483221>
- Talebberrouane, M., Khan, F., & Lounis., Z. (2016). Availability Analysis of Safety Critical Systems Using Advanced Fault Tree and Stochastic Petri Net Formalisms. *Journal of Loss Prevention in the Process Industries*, *44*, 193–203.
- Talebberrouane, M., Khan, F., & Lounis, Z. (2016). Availability analysis of safety critical systems using advanced fault tree and stochastic Petri net formalisms. *Journal of Loss Prevention in the Process Industries*, *44*, 193–203. <https://doi.org/10.1016/j.jlp.2016.09.007>
- Yang, Y., Khan, F., Thodi, P., & Abbassi, R. (2017). Corrosion induced failure analysis of subsea pipelines. *Reliability Engineering and System Safety*, *159*, 214–222. <https://doi.org/10.1016/j.ress.2016.11.014>