08-002

DYNAMIC RISK METHODOLOGY THROUGH STATISTICAL RISK CONTROL APPLIED TO THE PROJECT MANAGEMENT IN HIGH UNCERTAINTY ENVIRONMENTS.

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Unexpected events or precursors in systems with high variability, can trigger sequences that generate failures, errors, incidents and accidents, with personal, material and environmental repercussions, in projects with high uncertainty, carried out in facilities and chemical process plants or production facilities of natural gas and oil, as well as in general in projects that have a high risk component. Quantitative methods perform risk assessment by associating them with activity and process, in specific scenarios; but one disadvantage of this treatment is not to update the risk situation according to the evolution and execution of the project in order to anticipate and avoid it. Dynamic methods of risk assessment take advantage of obtaining information on events and data generated during execution, in order to update the probabilities of error, using, as tools, the Bayesian inference and Monte Carlo - Markov methods.

This work proposes a model to carry out the project management based on this methodology and through the application of Statistical Risk Control (SRC) in order to visualize its evolution associated with each process and to be able to act accordingly.

Keywords: *risk; project; bayesian; SRC; dynamic.*

METODOLOGÍA DINÁMICA DE GESTIÓN MEDIANTE CONTROL ESTADÍSTICO DE RIESGOS APLICADO A LA REALIZACIÓN DE PROYECTOS DE ELEVADA INCERTIDUMBRE.

Eventos o precursores inesperados en sistemas con elevada variabilidad, pueden desencadenar secuencias que generen fallos, errores, incidentes y accidentes, con repercusiones personales, materiales y ambientales, en proyectos con elevada incertidumbre, efectuados en instalaciones y plantas de proceso químico o en instalaciones de obtención de gas natural y petróleo, así como en general en proyectos que posean un elevado componente de riesgo. Los métodos cuantitativos efectúan la evaluación de riesgos asociándolos con la actividad y el proceso, en escenarios concretos; pero una desventaja de este tratamiento es el de no actualizar la situación del riesgo de acuerdo con la evolución y la ejecución del proyecto con el fin de anticiparse y evitarlo. Los métodos dinámicos de evaluación de riesgos aprovechan la obtención de información de los eventos y datos que se generan durante la ejecución, con el fin de actualizar las probabilidades de error, utilizando, como herramientas, la inferencia Bayesiana y métodos Monte Carlo - Markov.

Este trabajo propone un modelo para efectuar la gestión de proyectos basada en esta metodología y mediante la aplicación del control estadístico de riesgos (Statistical Risk Control, SRC) con el fin de visualizar su evolución asociada a cada proceso y poder actuar en consecuencia.

Palabras clave: *riesgo; proyecto; bayesiano; SRC; dinámica.*

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1. Introduction

Specific projects or installations related with the production of chemical, petrochemical and oil/gas extraction are critically exposed because for the handling of hazardous products the interactions between the own facility performing, the maintenance teams and the generating uncertainties allowing for the need to improve the safety reliability. The quantitative risk assessment is one of the most popular improvement methods consisting of three major steps which are hazard identification, hazard assessment and risk estimation by the use of qualitative techniques such as: Checklist analysis, What-if/Checklist procedures, HAZOP methods, Failure mode and effects analysis (FMEA). And quantitative techniques centered in: Fault-Event trees and Bow Tie analysis (Villa et al. 2016), (Rausand and Hoyland, 2004). But these models have limitations, diagrams and lists can be incomplete or bulky to work with it, the formal models can not consider all causal interactions in complexity situations and QRA is an iterative procedure applied every five years or in case of major plant changes, as stated by the Seveso III directive (European Union, 2012), (Paltrinieri and Reniers, 2017), (Paltrinieri et al., 2014).

Risk dynamic assessment is being developed emphasizing techniques for the observation of incipient faults, near miss, incidents, or accidents. The importance of near-misses in risk assessment is illustrated in the safety ratio rule of thumb which shows that, one serious incident is produced from 600 minor incidents, (Gnoni and Lettera, 2012). This method aims to estimate the expected frequency of accident by means of Bayesian inference (Paltrinieri et al. 2014) in which real time risk precursor events or incident data are used as new information to update the failure probabilities.

1.2 Objectives and scope of this work

In this study a new concept of risk monitoring based on statistical risk control charts (SRC) is introduced to update the evolution of precursor events with high uncertainty by the use of Bayesian inference and Monte Carlo Markov process under a dynamic risk approach. Events that are outside the control limits are the warning and the barometer for trigger a corrective actions, (Zio, 2013),(Puza, 2015). There is no literature on the application of control charts to risk management, Colin and Vanhoucke, (2015) apply it through the earned value method in project management, other authors in the environmental assessment (Corbett and Pan, 2002), or for cost control and project duration (Aliverdi, Naeni and Salehipour, 2013).

In section 2 the basic theoretical concepts corresponding to the statistical tools used in this work are presented in section 3 the methodology is presented, the results for an example study case and treatment for the statistical risk control is developed in section 4 and finally conclusions and further development for future research are exposed on section 5.

2. Basic theoretical concepts

Basic concepts are introduced in this section in order to understand the development of the examples.

2.1 Bayesian inference

The uncertainty of the failure probability of a safety system, θ, is modeled using a probability distribution function, $f(\theta)$, called the prior distribution. The failure probability distributions, $f(\theta / Data)$ called posterior distributions are inferred using the new data collected through the equation;

$$f(\theta / Data) = \frac{g(Data/\theta)\cdot f(\theta)}{\int g(Data/\theta)\cdot f(\theta)d\theta} = \frac{1}{c} g(Data/\theta)\cdot f(\theta) \propto g(Data/\theta)\cdot f(\theta) \quad (1)$$

Being $g(Data/\theta)$ the likelihood function, and $c = \int g(Data/\theta)\cdot f(\theta)d\theta$ a constant with respect to θ in the Bayesian equation, (Shemyakin and Kniazev, 2017).

2.2 Markov processes

It may consider a Markov process as a stochastic process that moves from state to state, with transition probabilities, (Zio, 2013), (Rausand and Hoyland, 2004). The amount of time it spends in each state, before going to the next state, is exponentially distributed. And it is possible to arrange the transition rates named a_{ij} as a matrix, called the transition rate matrix A . Then a probability distribution $P(t)$ for every state may be found from the Kolmogorov forward equations;

$$\left[\dot{P}_0(t),...,\dot{P}_r(t)\right] = \left[P_0(t),...,P_r(t)\right]\cdot A \tag{2}$$

$$\left[P_0, P_1,...,P_r\right]\cdot A = \left[0,0,...,0\right] \tag{3}$$

2.3 Control charts

The purpose of establishing a control chart or Shewhart control chart, is to systematically monitor the activity and determine if it is necessary to carry out corrective actions on it. The general model on which the Shewhart control chart is based in the measurement of a statistic Θ for which their mean is μ_Θ and the variance is σ_Θ^2 with the upper control limit (UCL), and low control (LCL) limits are defined as:

$$UCL = \mu_\Theta + C\sigma_\Theta \;; LCL = \mu_\Theta - C\sigma_\Theta \tag{4}$$

Where C is the distance of the control limits from the center line in multiples of the standard deviation. (Ross, 2009).

3. Methodology

The general proposed dynamic risk analysis mechanism is (Paltrinieri and Khan 2016): barriers are identified; event tree is used to determine the conditional relations between the events and their conditional probabilities; real data based on precursor events are monitored forming a likelihood function; a posterior distribution updating the conditional probability is obtained from the data monitored as likelihood function (Meel and Seider, 2006). A statistical chart is performed by using the events generation and the control limits obtained from the posterior statistical distribution. With the incorporation of new data modifying the prior function, there are two effects, both the evolution of the mean and the standard deviation allowing for four schemes of SRC (Statistical Risk Control) charts.

a.- Direct: The mean and sigma prior are constant and the posterior modifies in every interval with two possibilities, maintaining the mean posterior constant equal to the prior or (Direct-Mean Prior) or with modification according to the data (Direct-Mean Posterior).

b.- Recurrent: The mean and sigma prior are modified and actualized in every interval, being the new prior in the next interval. Also it is possible to maintain the mean posterior constant (Recurrent-Mean Prior), or with modification in concordance with the data (Recurrent-Mean Posterior).

4. Description of results for application of risk control charts

The Figure 1 shows a CSTR, involving an exothermic reaction system, and its seven safety systems designed to prevent the uncertainties allowing for a high-temperature state and a run-away reaction. (Meel and Seider, 2006).The event-tree is presented (Fig. 2). The number of total events for every of the 27 end states (d1–d27) collected in 20 time intervals are also presented with the calculated probabilities of success and failure for every safety barrier.

For to model the rate of occurrence of a precursor event, it is possible to apply a Poisson - gamma model. Using a recurrent methodology with mean posterior (Table 1), until time 5 the following number N_t of precursor events are collected with y=[6 9 12 13 15] and $\overline{y} = 11$. There is any knowledge about the λ distribution a non informative prior, with $\alpha = \beta = 0.001$ is adopted. The posterior density for λ is $f(\lambda / y) \sim Gam(\alpha + N_t \overline{y}, \beta + N_t) = Gam(55,5)$ fitting a Poisson distribution with mean $\lambda_{post} = 11$ and sigma $\sigma_{post} = 1.48$. The SRC limits with $\pm 3\sigma$ are:

$$\text{LCL}=11 - 3 \cdot 1{,}48 = 6{,}5 \text{ ; MEAN } = 11 \text{ ; UCL } = 11 + 3 \cdot 1{,}48 = 15{,}4 \quad (5)$$

Collecting additional data from time 6 to time 10, are [11 16 10 11 18]. And the posterior density for λ is $f(\lambda / y) \sim Gam(\alpha + N_t \overline{y}, \beta + N_t) = Gam(55 + 66{,}5 + 5) = Gam(121{,}10)$ with mean $\lambda_{post} = 12$ and sigma = $\sigma_{post} = 1.10$. The new SRC control limits are:

$$\text{LCL}=12 - 3 \cdot 1{,}1 = 8{,}7 \text{ ; MEAN } = 12 \text{ ; UCL } = 12 + 3 \cdot 1{,}1 = 15{,}3 \quad (6)$$

Finally additional 10 data from time 11 to time 20 are [9 9 14 17 24 18 24 10 15 14] being the posterior density $f(\lambda / y) \sim Gam(121 + N_t \overline{y}, 10 + N_t) = Gam(275{,}20)$ with mean $\lambda_{post} = 14$ and sigma = $\sigma_{post} = 0.83$ and the SRC control limits are:

$$\text{LCL}=14 - 3 \cdot 0{,}8 = 11{,}5 \text{ ; MEAN } = 14 \text{ ;UCL } = 14 + 3 \cdot 0{,}8 = 16{,}5 \quad (7)$$

The SRC charts for the three time intervals are presented in the Figure 3. Examining the event tree from Fig. 2 failure and success probabilities are assigned to each of the safety systems, being $\theta_{s,j}$ the failure probability of safety system s at branch j . For modeling the safety barrier failure the Binomial - Beta model is applied and according to Meel and Seider (2006), there are two situations taking in consideration the independence or dependence of the previous safety barriers failure-success probabilities.

If the failure probabilities of a safety barrier or system are assumed to be independent of the previous safety barrier states as for example, for safety system S4, $\theta_{4,1} = \theta_{4,2} = \theta_4$, not considering the previous state for the barriers S3, S2 and S1 a only analysis is performed.

For example analyzing this safety system, S4, based on the operator action, the prior could be not known or information from reliability data bases can be obtained. Then the prior is, $\theta_4 \sim Beta(a_4, b_4) = Beta(6{,}4)$. With expected $E(\theta_j) = 0.6$, variance $V(\theta_j) = 0.022$ and standard deviation $S(\theta_j) = 0.15$. The SRC control limits with $\pm 1 \cdot \sigma_{post}$ are;

$$\text{LCL}=0{,}6 - 1 \cdot 0{,}15 = 0{,}45 \text{ ; MEAN } = 0{,}6 \text{ ;UCL}= 0{,}6 + 1 \cdot 0{,}15 = 0{,}75 \quad (8)$$

In the event-tree diagram two nodes are visualized, but according to the hypothesis of independence is $\theta_{4,1} = \theta_{4,2} = \theta_4$, applying a recurrent methodology with mean posterior the

Table 1: Evolution of the precursor events rate in the Poisson-gamma model for the recurrent method with mean posterior.

	prior		posterior					
Time interval	alfa	beta	alfa	beta	lambda	LCL	MEAN	UCL
0	0,001	0,001	-	-	0	-	0	-
1-5	0,001	0,001	55	5	11	6.5	11	15.4
6-10	55	5	121	10	12	8.7	12	15.3
11-20	121	10	275	20	14	11.5	14	16.5

Note: Out of limits are remarked in blue.

determination of the events in every time interval, is obtained (Fig. 2) by applying;

$$n_{j,time} = n_{4,time} \text{ total events } 1:6 \text{ } and \text{ } 12:17 \text{ ; } K_{j,time} \text{ failure events } 2:6 \text{ } and \text{ } 13:17 \tag{9}$$

Being the failure proportion:

$$p_{j,time} = K_{j,time} / n_{j,time} \tag{10}$$

For the first interval, is; $n_{j,1} = 5$; $K_{j,1} = 1$ and $p_{j,1} = \frac{1}{5} = 0.2$ the posterior is;

$$f(\theta_j / Data_j) \propto \theta_j^{a_j+K_j-1} \cdot (1-\theta_j)^{b_j+n_j-K_j-1} = \theta_j^{6+1-1} \cdot (1-\theta_j)^{4+5-1-1} = \theta_j^{7-1} \cdot (1-\theta_j)^{8-1} \tag{11}$$

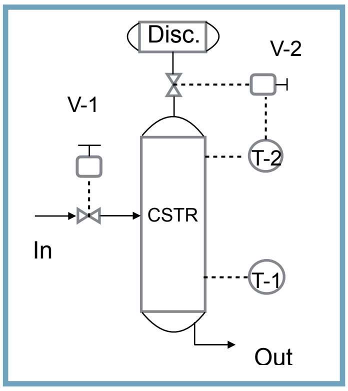
With posterior Beta distribution expected value, $E(\theta_j) = 0.47$, variance $V(\theta_j) = 0.0156$ and standard deviation $S(\theta_j) = 0.1247$. With new SRC control limits;

$$\text{LCL} = 0.47 - 1 \cdot 0.1247 = 0.34 \text{ ; MEAN } = 0.47 \text{ ; UCL } = 0.47 + 1 \cdot 0.1247 = 0.59 \tag{12}$$

The data evolution are presented in the Table 2. And the SRC charts for interval times t=8 and t=9 are presented in the Figure 4. The same analysis is performed through the binomial-beta model using a direct method with mean posterior, the SRC control chart is presented at interval t=17, (Fig. 5) alert of several out of limits are in intervals t=12, t=13 and t=16.

If the failure probabilities of a safety system are assumed not to be independent from the previous safety barrier states. As for example, for safety system S3, $\theta_{3,1} \neq \theta_{3,2}$, and it is dependent of the status failed or success from the safety barriers S2 and S1, then the analysis is performed in every case for example for the operator $\theta_{3,2}$ safety system is presented. Because there is no knowledge about the prior distribution function a non informative is adopted with values $\theta_{3,2} \sim Beta(0.001, 0.001)$ with expected $E(\theta_{3,2}) = 0.5$, variance $V(\theta_{3,2}) = 0.25$ and standard deviation $S(\theta_{3,2}) = 0.5$. Applying a recurrent method with posterior mean the control limits for $\theta_{3,2}$ with $\pm 1 \cdot \sigma_{post}$ are;

Figure 1: CSTR reactor scheme and safety systems.



ID	Safety System	Type
S1	1 Alarm - Temperature	Automatic
S2	Operator - confirmation	Human
S3	Operator - evaluation	Human
S4	Operator - action	Human
S5	2 Alarm - Temperature	Automatic
S6	2 Alarm - Shut Down	Automatic
S7	2 Alarm - Manual Shut Down	Human

$$\text{LCL}=0{,}5-1\cdot 0{,}5=0\text{ ; MEAN }=0{,}5\text{ ;UCL}=0{,}5+1\cdot 0{,}5=1{,}0 \tag{13}$$

And so on. See Table 3. Out of limits are seen from interval t=2. (Fig. 6).

For a safety system with parallel branches, their probability failures are interrelated although they are different then for example, the S5 safety system alarm has probability failure values , $\theta_{5,1}\neq\theta_{5,2}\neq\theta_{5,3}\neq\theta_{5,4}\neq\theta_{5,5}$, by analyzing this safety system collecting the events information it is possible to model by the use of bivariate or multivariate statistical correlations, (Shemyakin and Kniazev, 2017) and to perform the estimation of the dependent safety system in parallel for an interval of time in function of the evolution of one probability failure branch. To model this example, and because there is not a previous knowledge of the priors probability functions, non uninformative values are defined, (ai=0.001 bi=0.001) and collecting the 20 time intervals data in 5 times using a recurrent method with mean posterior the data are presented for $\theta_{5,2},\theta_{5,3},\theta_{5,4},\theta_{5,5}$ in the following SRC charts in Figure 7, from here it is possible to estimate future means through the following next intervals using the statistical multivariate relation correlating the variations of the failure probabilities $\theta_{5,2},\theta_{5,3},\theta_{5,4},\theta_{5,5}$ to with the probability failure $\theta_{5,1}$ by using the following covariance matrix;

$$CovS5=\begin{pmatrix} 1 & 0{,}70 & 0{,}80 & 0{,}50 & 0{,}40 \\ 0{,}70 & 1 & 0{,}50 & 0{,}70 & 0{,}40 \\ 0{,}80 & 0{,}50 & 1 & 0{,}70 & 0{,}60 \\ 0{,}50 & 0{,}70 & 0{,}70 & 1 & 0{,}60 \\ 0{,}40 & 0{,}40 & 0{,}60 & 0{,}60 & 1 \end{pmatrix} \tag{14}$$

If new data from S51 are obtained in the next interval $t=6$ as; $n_{5,1}=15$ and $K_{5,1}=5$ the point is $p_{5,1}=0.33$ and the intervals and mean are, from the posterior data obtained in to the 5th time being $beta(25+5,70+10)=beta(30,80)$; and mean $\theta_{6-5,1}=0.2700$ it is possible to deduce the safety systems mean failure probabilities $\theta_{5,2}$, $\theta_{5,3}$, $\theta_{5,4}$ and $\theta_{5,5}$ using bivariate correlation of the beta probability distributions for the failure probabilities $\theta_{j,i}$ obtaining the vector of probabilities $\left[\theta_{5,1}\ \theta_{5,2}\ \theta_{5,3}\ \theta_{5,4}\ \theta_{5,5}\right]$ with values [0.2700 0.3701 0.3742 0.1805 0.1553].

Figure 2: Event-tree for the safety systems in the CSTR example. CO: continued operation, SD shut-down, RA: run-away

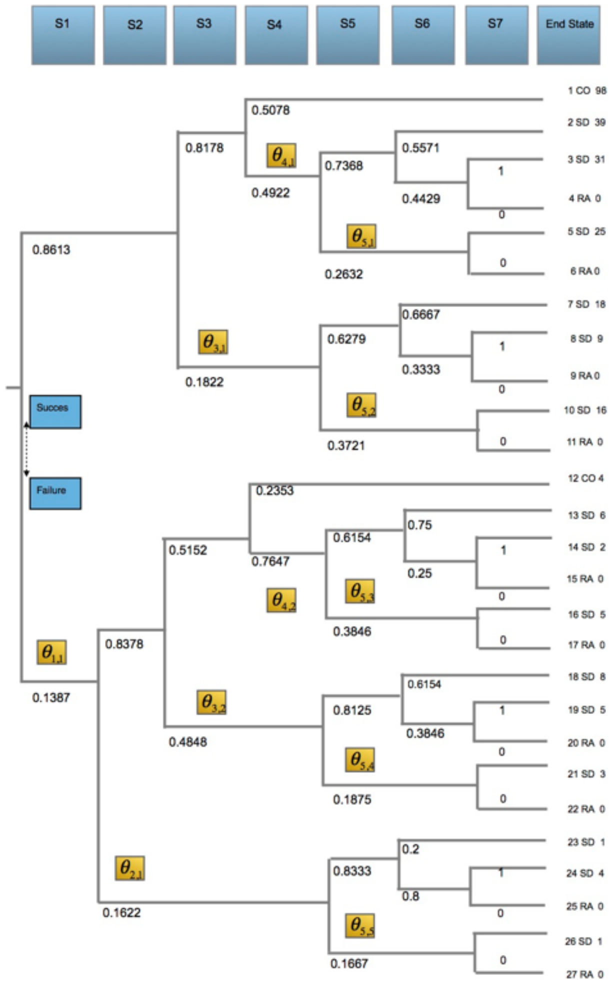


Figure 3: SRC charts in three collected interval for precursor event rate applying the Poisson-gamma model with recurrent method and mean posterior.

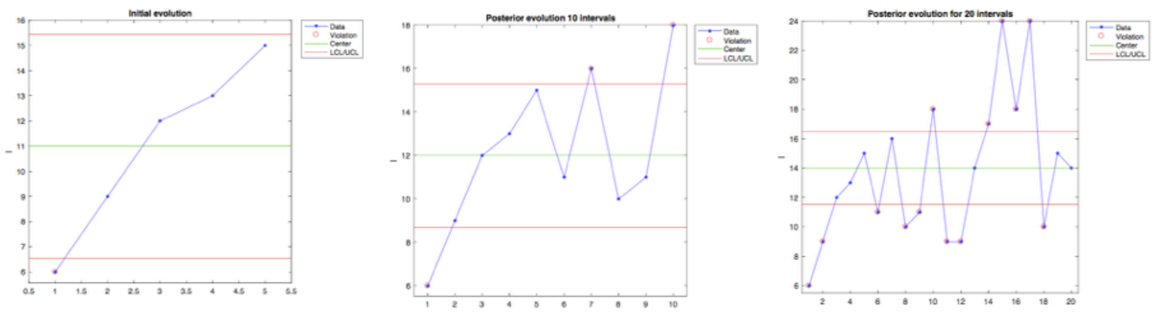


Figure 4: SRC charts in t=8, t=9 intervals for safety system S4 precursor event data applying the binomial-beta model with recurrent method and mean posterior.

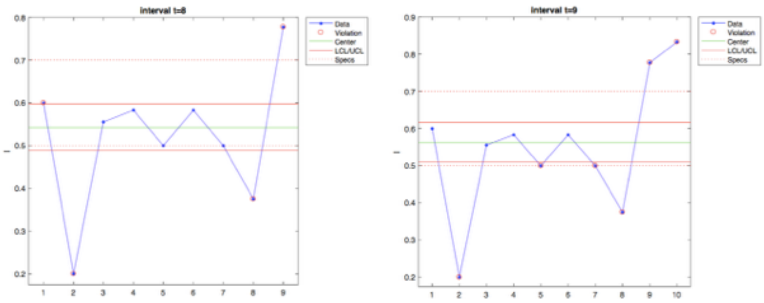
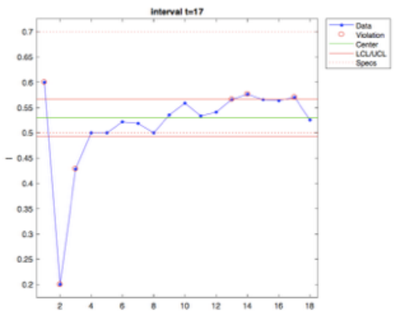


Figure 5: SRC charts in t=17 interval for safety system S4 precursor event data applying the binomial-beta model with direct method and mean posterior.



From Figure 2 the probability of shutdown situations from the total events allows for value of 0.63, that is according to the evolution in time the CSTR system has 63% in shutdown time. Considering a two state Markov process, the event tree (Fig.2) can be simplified (Fig. 8a). In this model when the system is active (state 1), precursor events arrive at rate λ (exponential time), changing to the shut-down (SD) state (state 0) then an exponential maintenance-repair action operates at rate μ, with the system returning to state 1 when is completed. The Kolmogorov equations are: (Zio, 2013), (Rausand and Hoyland, 2004).

$$\left[\dot{P}_0(t),\dot{P}_1(t)\right]=\left[P_0(t),P_1(t)\right]\begin{pmatrix} a_{00} & a_{10} \\ a_{01} & a_{11} \end{pmatrix}=\left[P_0(t),P_1(t)\right]\begin{pmatrix} -\mu & \mu \\ \lambda & -\lambda \end{pmatrix} \tag{15}$$

With $P_0(t)+P_1(t)=1$. With $P_1(0)=1$ and $P_0(0)=0$. Two stationary values are obtained;

$$P_0=\frac{\lambda}{\lambda+\mu};\,P_1=\frac{\mu}{\lambda+\mu} \tag{16}$$

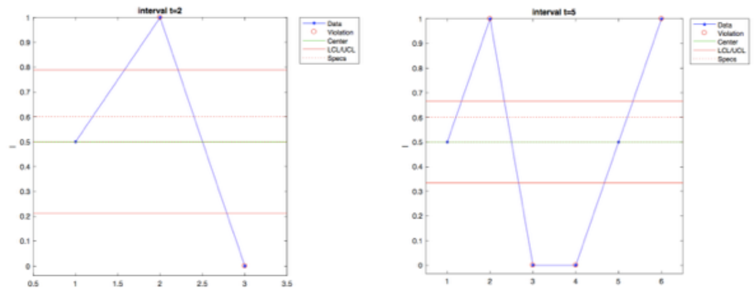
For the event-tree system arriving 275 precursor events in 20 units of time, represents $\lambda={}^{275}\!/_{20}=13.75$; a fast estimation for shutdown probability can be obtained from the number of fails 173 with a mean in 20 time intervals of 8.65 that is $\lambda=8.65$ and the number of successes 102 allowing for a $\mu=5.1$ in the same 20 time intervals with an unavailability

Table 2: Evolution of the precursor events in system safety S4 in the Binomial-Beta model for the recurrent method with mean posterior.

	Prior					Posterior					
Time interv.	a_j	b_j	n_j	K_j	p_j	a_j (aj+Kj)	b_j (bj+nj-Kj)	Desv Std	LCL	MEAN	UCL
0	6	4	0	0	0,600	-	-	0,147	0,45	0,60	0,75
1	6	4	5	1	0,200	7	8	0,124	0,34	0,47	0,59
8	37	35	9	7	0,777	44	37	0,0550	0,48	0,54	0,59
9	44	37	6	5	0,833	49	38	0,052	0,51	0,56	0,61
11	54	46	8	5	0,625	59	49	0,047	0,49	0,54	0,59
12	59	49	8	7	0,875	66	50	0,045	0,52	0,56	0,61
13	66	50	5	4	0,800	70	51	0,044	0,53	0,57	0,62
16	86	66	14	9	0,642	95	71	0,038	0,53	0,57	0,61

Note: Only out of limits marked in blue are presented.

Figure 6: SRC charts in t=2 and t=5 intervals for safety system $S_{3,2}$ precursor event data applying the binomial-beta model with recurrent method and mean posterior.



percentage of ;

$$\frac{\lambda}{\lambda+\mu}=\frac{8.65}{8.65+5.1}=0.63 \tag{17}$$

And from the probability of state 0 inactive it is possible to deduce μ as;

$$P_0=\frac{\lambda}{\lambda+\mu}=\frac{13.75}{13.75+\mu}=0.63 \rightarrow \mu=8.07 \tag{18}$$

Thus the event tree system from Figure 2 can be substituted by a system consisting of a Markov process with arrival rate events λ and a recovery rate μ. For $\lambda=13.75$ and $\mu=8.07$ the unavailability of the system is 0.63 the same as obtained from the resolution of

Table 3: Evolution of the precursor events in system safety $S_{3,2}$ in the Binomial-Beta model for the recurrent method with mean posterior.

	Prior					Posterior					
Time interv.	$a_{3,2}$	$b_{3,2}$	$n_{3,2}$	$K_{3,2}$	$p_{3,2}$	$a_{3,2}$ (aj,i+Kj,i)	$b_{3,2}$ (bj,i+nj,i-Kj,i)	Desv Std	LCL	MEAN	UCL
0	0,001	0,001	0	0	0,5	-	-	0,5	0	0,50	1,00
1	0,001	0,001	1	1	1,0	1	0,001	0,022	0,98	0,99	1,00
2	1	0,001	1	0	0	1	1	0,288	0,211	0,50	0,78
5	3	2	1	1	1	4	4	0,166	0,333	0,50	0,66
7	4	4	2	2	1	6	4	0,147	0,452	0,60	0,74
10	9	7	1	1	1	10	7	0,116	0,472	0,58	0,70
14	10	9	3	3	1	13	9	0,102	0,488	0,59	0,69
18	14	16	1	1	1	15	16	0,088	0,395	0,48	0,57

Note: Only out of limits marked in blue are presented.

the differential equation, $\frac{dP_0(t)}{dt} = \lambda - P_0(t)(\lambda+\mu)$. Two Poisson's distributions with $\lambda = 13.75$ and $\mu = 8.07$, can be correlated with a bivariate model (Fig. 8b). if additional 5 new precursor events are collected from time 20 to time 21 with a total value of 38 the posterior density for λ is from, the Poisson-gamma model;

$$f(\lambda / y) \sim Gam(\alpha + N_t \bar{y}, \beta + N_t) = Gam(275+38, 20+5) = Gam(313,25) \quad (19)$$

With mean $\lambda_{post} = 12.5$ and sigma $\sigma = 0.70$. From the previous bivariate correlation with $\lambda = 12.5$ a estimated mean value for $\hat{\mu} = 7.8$ is obtained allowing to a new unavailability steady probability of $P_0 = \frac{\lambda}{\lambda+\mu} = \frac{12.5}{12.5+7.8} = 0.616$

5. Conclusions

In this work a previous analysis for the application of Bayesian methods and inference tools have been exposed for to apply in the control of precursor failure events by the use of control charts as a statistical risk control concept. The example has been developed for a CSTR installation with uncertainty and high events risk. The procedure is valid and presents the out of controls according to the incidences evolution in time intervals enough for allowing for corrective actions. The application of Bayesian control charts for statistical risk control has begun to test in two execution projects with high uncertainty environment considering the events that affect incidences in time, cost, human teams execution, installation performance, maintenance work and the risk for environmental emissions.

Figure 7: SRC charts in 5 times for safety system S5 precursor event data applying the binomial-beta model with recurrent method and mean posterior.

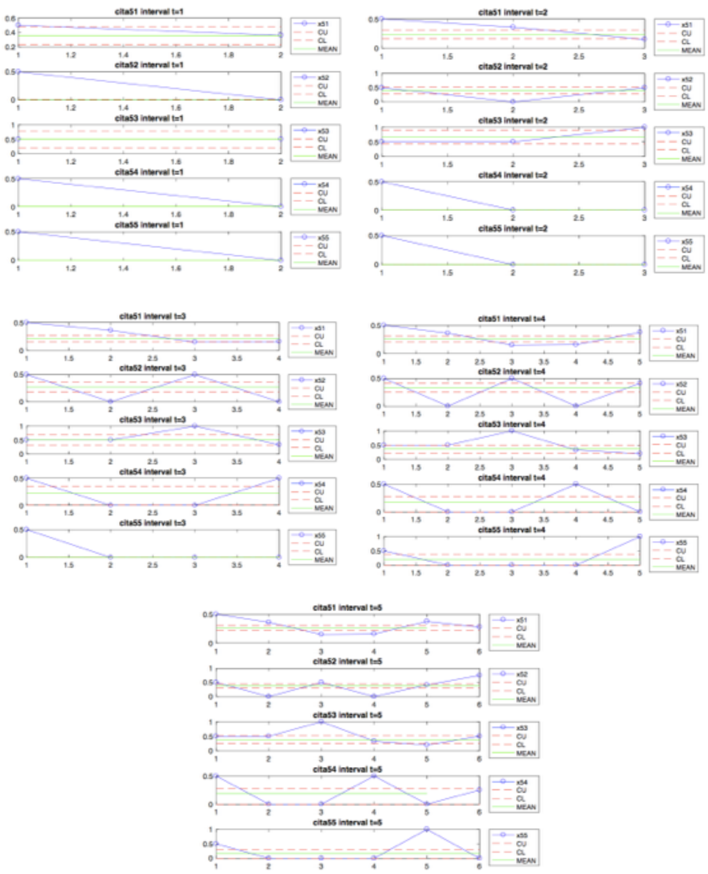
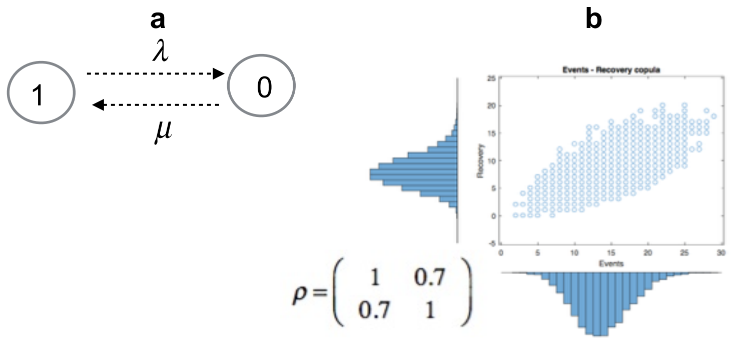


Figure 8: a: Two sates 0-1 Markov process; b:Bivariate Poisson correlation ρ for the λ ratio of arrival precursor events and μ as recovery ratio.



$$\rho = \begin{pmatrix} 1 & 0.7 \\ 0.7 & 1 \end{pmatrix}$$

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