Risk Control of Complex Systems: Can safety performance indicators be more informative?

Hans J. Pasman[1], William J. Rogers, M. Sam Mannan

TEES Mary Kay O'Connor Process Safety Center

Texas A&M University, College Station, Texas 77843-3122, USA

Life in general, but operational process life in particular, poses many task requirements and uncertainties. In process life it concerns observation of the extent and direction of change, responding to it by following rules or applying methods and knowledge, all directed towards optimum economic performance. At all levels of the organization one is bound by all sorts of constraints. This holds in particular for avoiding risk of injury, plant damage, and other losses. As the organizational and technical complexity obscures transparency, and often direct observation of one's actions results cannot be seen, while also most companies are under perpetual competition pressure, risk of adverse outcome increases. To counter this tableau an ensemble of monitoring safety indicators can be created, which can enable a predictive analysis of the state of risk control. But what to do if various indicators produce opposing trends, erratic fluctuations, or inconclusive changes?

Keywords: Process safety performance indicators, safety metrics, aggregation, Bayesian networks

Introduction

Maintaining a high level of process safety means tight risk control, but then one has to know very precisely where risks are to be found. Plant and process operations given a design, embedded in the hierarchy of a socio-technical system with all its technology, maintenance issues, human and organizational factors and regulatory constraints, forms for management a rather complex and not quite transparent kind of 'living organism'. In a recent perspective paper on trends and challenges in process safety, Mannan et al., 2015 analyze with a holistic view various characteristics of the interactions and dynamics of a 'process safety system'. However, in a practical sense given a state of affairs, for management the question is which way to steer and for that one needs observables for feedback whether changes of this complex 'organism' are in the right or wrong direction and for revealing clues to causality.

Indeed, in many sectors management created indicators as observables, because these are crucially needed to follow trends, to make predictions about developments, to prepare decision making, and to take action. It is about health of the activity, the economy, financial embroilment, business success, but also whether safety is on an adequate level. In the process industry personal safety performance indicators such as Lost Time Injury Frequency or Rate (LTIF or LTIR) and others have been in use a long time. In Europe after the accident frequency peak during the expansion in the 1960s, we became used to a continuous and steady decline of the number of lost days by injuries or total recorded injury rate (TRIR) and fatal accident rate (FAR), so the belief spread in the late 1990s that a zero accident level would be within reach. Also, the annual industry HSE reports showed optimism. Yet, as we all know, major accidents did not stay away.

After the introduction of safety management systems in the 1990s, it was a logical step to start measuring management performance with indicators. Following Deming's PlanDoCheckAct (or Analyze) cycle, management decision making requires indicators to correct and adjust where necessary. In 1999 in the OECD organization in Paris, an expert group under the auspices of the Working Group on Chemical Accidents began development of an extensive guidance document on safety performance indicators. This was published in 2003 and revised in 2005 (OECD, 2008), and followed by UK's Health and Safety Executive document, "Developing process safety indicators" (HSE, 2006). Later, guidance documents were released from amongst others the American Petroleum Institute (ANSI/API, 2010), the Int'l Association of Oil & Gas Producers (OGP, 2008), and AIChE's Center for Chemical Process Safety (CCPS, 2010). In 2012, many aspects of indicators were discussed at a global industry-wide, well-attended conference on Process Safety Performance Indicators organized by the European process industry association, CEFIC, and the European Process Safety Centre in Brussels.

Already years before, investigations of the Esso Longford gas plant explosion accident in Australia in 1998 and of the 2005 isomerization unit vapor cloud explosion at the BP Refinery in Texas City, Texas, made it very clear that management cannot trust information on their plants' safety level derived only from LTIF records. Major accidents occur despite high occupational safety. Ironically, the Macondo drilling blow-out disaster with the Deepwater Horizon rig occurred on the day a ceremony had been held on board to award seven years of no lost time incidents.

So, the main new insight was that a distinction is required between personal safety and process safety indicators. This led AIChE's Center for Chemical Process Safety to issue books as Guidelines for risk based process safety (CCPS, 2007) and Guidelines for process safety metrics (CCPS, 2010). New too was that indicators monitoring incidents such as injuries, fatalities, but also leakages and spills, the lagging or outcome indicators, shall be distinguished from indicators looking ahead and measuring effect of activities, the leading, activity or input indicators. The latter are functional in preventing or reducing the likelihood of major events. HSE, 2007 uses Reason's Swiss Cheese model to explain the difference in indicators: lagging indicators represent the holes in the slices and the leading indicators the slices.

The discussion of which indicator is what type, has even filled Issue No. 47, Issue 4 of the journal Safety Science introduced by an editorial article of Andrew Hopkins (2009). The two indicator types shall generate dual assurance on risk controls, the lagging ones through reactive monitoring and the leading ones through active monitoring. Near misses have a hybrid nature:

[1] E-mail address: hjpasman@gmail.com

some have a lagging character others a leading one, but the fraction of investigated near misses form an important leading indicator.

Lagging indicators can be standardized and that is of course fair to keep a global level playing field. At the Brussels conference in 2012 a Loss of Primary Containment (LoPC = unintended release of substance or energy) was mentioned resulting in:

a) Lost time injury (≥ 1 day) and/or fatality, or

b) Fires or explosions producing ≥ € 20,000 of direct cost in damage, or

c) Substance release ≥ defined release threshold quantities based on toxic, flammable, or other hazardous substance properties according to the Global Harmonized System (GHS) classification.

The better the performance, the lower the values of lagging indicators though, and ideally these will be zero.

Performance indicators on the functioning of the safety management system, the leading ones, shall look ahead and forewarn for possible deficiencies rather than recording incidents. Therefore, leading indicators are important but are of a different kind. HSE, 2007 emphasized that the latter shall be put on critical risk control systems with tolerances in outcome. CCPS, 2007 or 2010, while considering the elements of a safety management system as briefly shown in Figure 1, suggests hundreds of examples. For each element of Figure 1 there may be 10 - 30 indicators proposed, sub-divided into groups under further split headings. One can make a selection based on the specific needs of plant and company. Different hierarchical levels in the organization will be interested in metrics with a different scope. One can therefore select examples from a hierarchy in which a number of indicators at a lower and more detailed level can be summarized in one at a higher level. Hence, aggregation is needed.

1. COMMIT to PROCESS SAFETY
- Process Safety Culture
- Compliance with Standards
- Process Safety Competency
- Workforce Involvement
- Stakeholder Outreach

2. UNDERSTAND HAZARDS AND RISK
- Process Knowledge Management
- Hazard Identification, Risk Analysis

3. MANAGE RISKS
- Operating Procedures
- Safe Work Practices
- Asset Integrity and Reliability
- Contractor Management
- Training and Performance Insurance
- Management of Change
- Operational Readiness
- Conduct of Operations
- Emergency Management

4. LEARN FROM EXPERIENCE
- Incident Investigation
- Measurement and Metrics
- Auditing
- Management Review and Continuous Improvement

Figure 1: The compilation of safety management elements in four main groups following the chapters of CCPS, 2010, Guidelines for Risk Based Process Safety with each chapter providing inspiration for a large number of leading metrics.

In selecting indicators one must solve questions such as what exactly makes sense to be measured, how frequently shall it be measured, and in what units it shall be expressed. For leading indicators, the unit will often be a percentage of a number of activities (e.g., inspections, reviews, audits, or trainings) deemed adequate for a safe organization or else a number of triggers of a safety critical element in a risk control system that should not have been activated.

The difference in numbers of indicators of the distinct types has been presented in pyramids with the lagging ones in the top, precursors and near-misses in the middle, and lagging ones at the bottom. In his introductory presentation, on behalf of the International Council of Chemical Associations (ICCA) to the Brussels conference in January 2012, CEFIC's William Garcia showed an indicator triangle as depicted in Figure 2. Another, even further differentiating one is found in ANSI/API (2010).

The latest guidance is by the Australian based IChemE Safety Centre (ISC), 2015 providing practical help to companies installing leading indicators. ISC developed its proposed indicators following its line of effective process safety management requirements of a company along six functional elements: knowledge and competence, engineering and design, systems and procedures, assurance, human factors, and culture, all together equipped with 21 metrics.

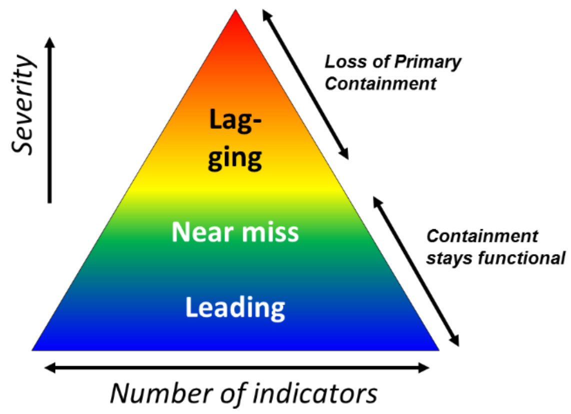


Figure 2: Indicator triangle as shown in CEFIC's William Garcia's introductory presentation, made on behalf of the International Council of Chemical Associations (ICCA) to the Brussels conference in January 2012, see also Pasman, 2015.

So far, in general, management would be content if values of monitored indicators move in a favorable direction. But suppose we are doing well and lagging indicators all approach zero; then we must rely fully on the leading ones. As leading indicators shall cover the many aspects of the safety management system, by nature these are numerous. Applying only a small subset may lead to unrealistic or false conclusions. Assuming a minimum of three hierarchical layers and following the CCPS configuration as depicted in Figure 1, the question arises how to keep an overview, certainly at higher management levels? Nobody unsupported can judge a situation using more than 5 to 10 indicators simultaneously, in fact, three would already be fine. Of course, one can suppose that selected indicator metrics can be assessed at specialist departments in the lower organizational levels. But for an assessment at higher levels, somehow a multiple of indicators should representatively be aggregated. How should this be done? Are all of the same weight? Probably not. In case the indicator metric is indicating an unfavorable result, one may assume there is a relation with associated risk, but what risk and how?

No indicator metric will be constant over time. There will be fluctuations from one recorded period to another. For leading indicators, a certain tolerance due to uncertainty will be permitted. But there may be also a trend, so the latter is important. If an organization moves in continual improvement, averaging will be sufficient. However, possible degradation of safety culture (also called drift) is a luring threat. It does not occur overnight. It is a slow process, not perceived as a threat by many involved. However, can we make such organizational drift reliably visible with indicator metrics that are subject to temporal fluctuations? And tying this question to the previous one, one can ask whether we can establish a relation between indicator values and a changing risk level of the process, which would really be an analysis under uncertainty.

In the paper we shall address the questions formulated. For aggregation, guidance will be sought from a research study by Hassan and Khan in 2012. Other questions will be answered in a rather technical sense, amongst others by applying Bayesian statistics and Bayesian networks (BNs). These have been seen lately in an exploding number of reliability engineering and risk applications (e.g., Weber et al., 2012, and the research directed by Faisal Khan and Paul Amyotte, e.g., in plant safety reported by Yuan et al., 2015 and drilling operations by Bhandari et al., 2015), in human-reliability analysis, and even in relating aspects of working conditions (e.g., García-Herrero et al., 2012 and Mkrtchyan et al., 2015). It is the most effective way to analyze dependability, while Dynamic Bayesian Network (DBN) can infer and prioritize hidden causes from changes in monitored process variable values, e.g., Naderpour et al., 2015 and earlier papers. For a brief explanation of Bayesian statistics and networks, reference is made to Pasman, 2015 (Chapter 7).

The present contribution consists of examples to show the potential to extract longer-term influences on risk level using indicator metric information. In section 2 is shown given data points how a trend and its uncertainty can be established. In section 3 it will be shown how metrics collected at the work floor can be aggregated to indicators usable at higher management levels. The last section 4 will present a simplified example how indicator metrics and their trends can be linked to risk level and its change. Once installed for a specific application use of the methods will be relatively simple, but before that further work will be needed to identify what counts and what can be neglected. To that end, partnering of university with industry over a longer time interval to collect data and validate models will be required.

Given data points, what is the trend?

We shall be particularly interested in cases in which real change is not that fast and in which data over each monitoring period show considerable fluctuation, so that a conclusion at just looking at the data is not immediately clear. Following ISC, 2015 we must distinguish between leading indicators that indicate a positive result such as number of trainings in a period, and negative leading ones such as the number of unplanned shutdowns. We shall therefore subtract the negative ones from the maximum number physically possible over the period, so that improvement shows positively. It is self-evident that lagging indicators belong to the negative group. Further, all numbers will be normalized as a percentage with 100% as the achievable maximum.

Table 1: Mock-up example of fluctuating indicator data recorded over 12 periods

Period		1	2	3	4	5	6	7	8	9	10	11	12
Number of unplanned shutdowns		1	2	4	0	3	2	0	1	5	2	1	0
Max. number/period = 10, equivalent to 0%		90	80	60	100	70	80	100	90	50	80	90	100
Moving average over six periods							80	82	83	82	78	82	85
Application Bayesian network	μ						76	78	80	79	78	80	83
	σ						17	15	14	14	14	13	12

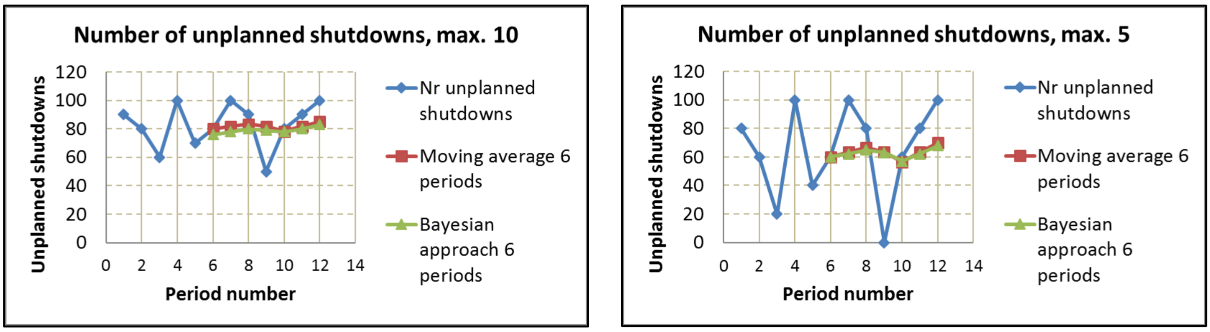


Figure 3: Example of a fluctuating indicator metric and the calculated rolling average over six periods, with at *left* a maximum number of shutdowns assumed per period of 10 and at *right* of 5. The Bayesian approach over six periods produces besides roughly the same averages and standard deviation values (Table 1). The trend seems slightly improving but this is within ± 1σ of 12-14 per 100 not convincing.

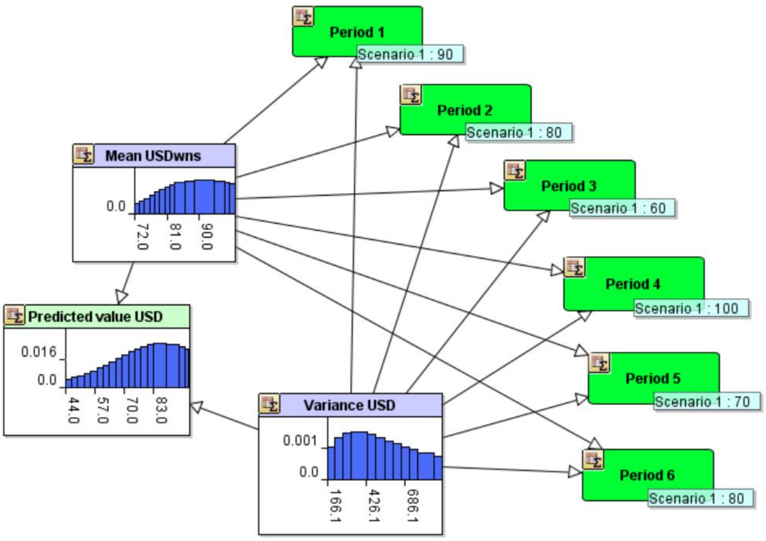


Figure 4: Bayesian network calculating mean and variance over the first six periods of counted unplanned shutdowns (USD) by means of Fenton and Neil's, 2013 AgenaRisk software. (Calculation of μ and σ can also be accomplished via the classical frequentist method, but the Bayesian network method is more convenient and more realistic by including aleatory (randomness) uncertainty due to outcome ranges.

Suppose we have a set of data collected over 12 equal time periods as shown in Table 1. Given the nature of the indicator, unplanned shutdowns, taken from the array of indicators mentioned by CCPS, 2010, it is worth to have a closer look. Suppose in the case considered, physically no more than 10 shutdowns over a period can occur. (Calculation showed that conclusions are not very sensitive to this assumption; halving the maximum to 5 shutdowns shows at the same scale that the trends are stronger). Converting into percentages and calculating a moving average is rather obvious and simple. Results of averaging even over six periods given in Table 1 still show some fluctuation, as appears from Figure 3, and do not reveal a clear trend. By averaging we disregard information, though, namely the degree of fluctuation in the distribution properties of the subsequent unplanned shutdown numbers, i.e., mean and standard deviation. The uncertainty information expressed in the standard deviation shows that within ± 1σ no clear trend can be concluded. This uncertainty analysis will be helpful in later decision making after determining the effect of metrics on the risk level.

We can obtain those properties rather easily by applying Bayes' theorem as explained in many textbooks on statistics, but because of the further procedure we refer here to the book by Fenton and Neil, 2013, on the application of Bayesian networks. The theorem states that prior knowledge is updated with relevant new evidence by multiplying a prior distribution with a distribution of new evidence conditional on the prior to produce an updated – posterior – distribution. Hence, a "parent" Bayesian network node represents the prior distribution and a "child" likelihood node the new evidence, which updates the prior node to the predicted posterior distribution[2]. This is done both for μ and σ priors resulting in posterior distributions for the mean and the variance model parameters. A convenient point value estimate for the standard deviation is the square root of the mean, median, or mode, depending on skewness, of the variance distribution. Without software the required convolution operation is not feasible, but with Bayesian network software shown in Figure 4, installed on an ordinary laptop, it is easy. One must make some assumptions though. The first assumption is that the metric number sequence is a random draw from a normal distribution truncated at values 0 and 100. The second assumption is that at the start of the monitoring the mean and the variance distributions are uniform with all values equally likely [(0, 100) and (0, 1000), respectively], meaning no specific prior knowledge beyond the ranges is available. (The greater the range, the greater the prior uncertainty). For the next calculation shifting one period, as priors the previously obtained results are taken. If over the last six periods mean, μ, and standard deviation, σ, are determined, one obtains the point value representative results: μ = 83 and σ = 12, see also Figure 3 (Prior uniform [0,100] range coefficient of variation - cov, σ/μ = 0.58; the posterior cov = 0.14, hence dispersion is diminished considerably). The choice of six periods for averaging is arbitrary, and other ensembles can be selected. The iteration with BNs differs initially from the mean by the rolling average calculation, although it of course remains amply within the uncertainty limits, but the outcomes later converge quickly to the moving average. Input data for five example indicators under the heading Conduct of Operations and results are collected in Table 2.

Table 2: A sample of mock-up input data and calculation results of the indicator Conduct of Operation

Indicator Conduct of Operation	Period	1	2	3	4	5	6	7	8	9	10	11	12	Weight
Number of labor hours per unit of product		3.2	4.0	5.2	1.8	3.6	4.8	2.7	3.3	5.6	3.7	2.8	2.4	
Max. number/period = 8, equivalent to 0%		60	50	35	78	55	40	66	59	30	54	65	70	
Moving average over 6 periods							53	54	55	55	51	52	57	
Application Bayesian network	μ						53	54	55	55	51	52	56	0.1
	σ						21	10	7	6.5	6	5	4	
Number of nuisance and always on alarms		120	70	135	55	85	75	95	72	109	44	88	65	
Max. number/period = 200, equivalent to 0%		40	65	33	73	58	63	53	64	46	78	56	68	
Moving average over 6 periods							55	57	57	59	60	60	61	
Application Bayesian network	μ						55	57	57	59	60	60	61	0.2
	σ						21	10	10	4	5	5	6	
Number of times workers challenged to solve 'What, if"		15	22	40	12	16	10	5	7	25	10	16	9	
Max. number/period = 50, equivalent to 0%		70	56	20	76	68	80	90	86	50	80	68	82	
Moving average over 6 periods							62	65	70	75	76	76	76	
Application Bayesian network	μ						61	63	66	69	71	73	74	0.2
	σ						22	10	10	10	10	10	10	
Number of unplanned shutdowns		1	2	4	0	3	2	0	1	5	2	1	0	
Max. number/period = 10, equivalent to 0%		90	80	60	100	70	80	100	90	50	80	90	100	
Moving average over 6 periods							80	82	83	82	78	82	85	
Application Bayesian network	μ						76	78	80	79	78	80	83	0.4
	σ						17	15	14	14	14	13	12	
Staff turnover rates (%)		2.5	4	1.5	2	3.6	5	2.2	1.3	3.1	1.8	2.6	2.8	
Max. number/period = 5%, equivalent to 0%		50	20	70	60	28	0	56	74	38	64	48	44	
Moving average over 6 periods							38	39	48	43	43	47	54	
Application Bayesian network	μ						33	35	41	38	43	46	53	0.1
	σ						21	10	11	11	11	11	11	

[2] To be more precise for the case shown in Figure 4, the prior distribution of the prior node becomes the posterior distribution of the same node from conditioning with the overlap of observed variables likelihood values presented as "scenarios" This can also be described as co-occurrence with the prior and normalized by the total probability of the observed variable, P(OV). A point value representation of the posterior, shown as n/N (part n on total N), is the fraction of the P(OV) given overlap of the likelihood with the prior, where the sample space of the observed variable is reduced by the overlap with the prior.

Indicator aggregation

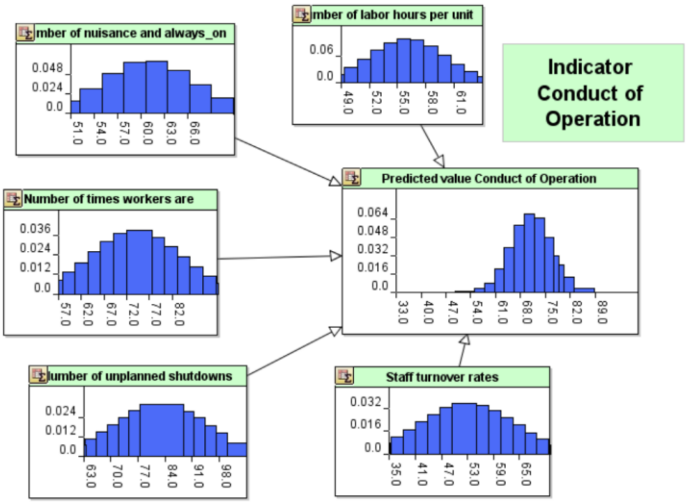


Figure 5: Aggregation of five sub-indicators to a higher level indicator.

For the aggregation technique, guidance was borrowed from the one proposed by Hassan and Khan, 2012. To compare, the metrics should first all be converted to the same scale of 0 to 100. For this, a maximum estimate shall be made. This can be determined by physical factors as we have seen with the unplanned shutdowns, but as it is all relative the maximum can also be an estimate or a target value. Because indicators aggregating to one at a higher level will have different importance, weight factors also shall be attached. Based on perceived contribution to the value of the aggregated metric, experts shall attribute these weight factors. Example weight factors are given in Table 2.

Aggregating one level higher can easily be performed by applying a Bayesian network. The indicators averaged over 7-12 periods as shown in Table 2 last column are aggregated to Conduct of Operation (CoO), as shown in Figure 5. The weight factors are embedded in the central result node. The mean and standard deviation result for CoO is $\mu = 71$ and $\sigma = 6$ (cov = 0.08). The dispersion is relatively small thanks to the six period averaging. The population mean value will be within a 95% confidence interval of 71 ± 12.

Besides the CoO indicator there are quite a few other useful indicators. CCPS, 2010 suggests on the level of Conduct of Operations 20 others. If a different system is followed, e.g., that of HSE or ISC, in principle the same aggregation problem will appear albeit at a smaller scale. Hassan and Khan, 2012 aggregate in a third and a fourth aggregation stroke to three major ones: personnel, operational, and mechanical integrity indicators for consideration by top management.

Relating metrics to operational risk level

In the last few years there have been several attempts to correlate process signals with risk level. For this purpose, based on HAZOP results, a Dynamic Bayesian network is constructed. With process variable observables and a relation between deviating values and risk level, it is demonstrated that for the operator hidden causes of abnormal process situations can be traced and potential causes with ordered probabilities to prioritize actions for reducing risk of upset outcomes, see e.g., Hu et al., 2015 and Naderpour et al., 2015. Process safety performance indicators have however longer-term influences on risk level and are because of the human and organizational characteristics more difficult to couple to quality of risk control and safety level. However, relative quantification produces a gain as it helps to identify trends to guide risk management and to measure possible "drift to disaster". As put forward by Leveson, see e.g., Leveson and Dulac, 2005, or in relation with safety indicators Khawaji, 2012, System dynamics models describe the process cycles that are active, but quantification of the time constants involved is difficult and therefore its predictive power will be limited. To this end Dynamic BNs present a better perspective. Human reliability analysis makes more and more use of BNs (Mkrtchyan, 2015) as expert elicitation results including uncertainty can be incorporated in the nodes, while on the other hand bowties describing technical cause-effect chains can be easily converted into BN. So, it is obvious to seek a solution in that direction. Vinnem et al, 2012, reported encouraging results with offshore maintenance work. Due to the close Norwegian cooperation institutes, universities and industry, they had historical data available to validate the results. Vinnem's work shows the efficacy of measuring organizational factor influences to identify trends and prioritize actions.

In the example network of Figure 6, effects on an initiating event are demonstrated. Reality is complex and there are many interdependencies among defined nodes, and such simplified trials should be thoroughly validated. Progress for this approach, however, requires a concrete case and industry participation.

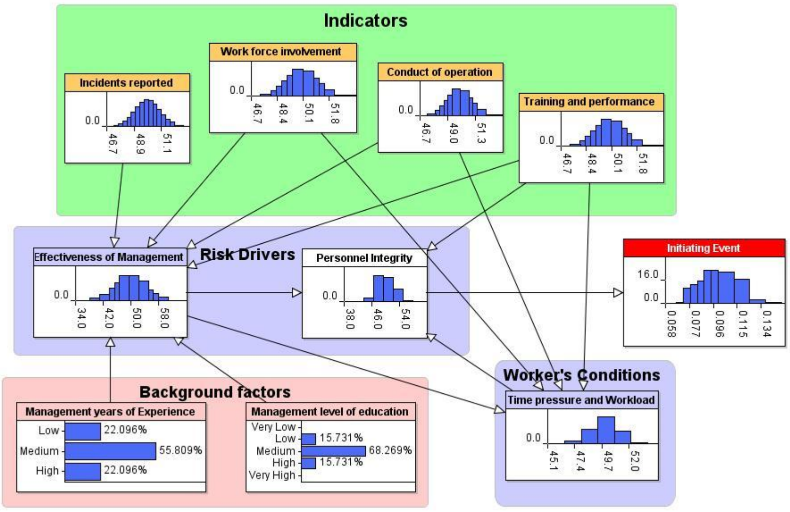
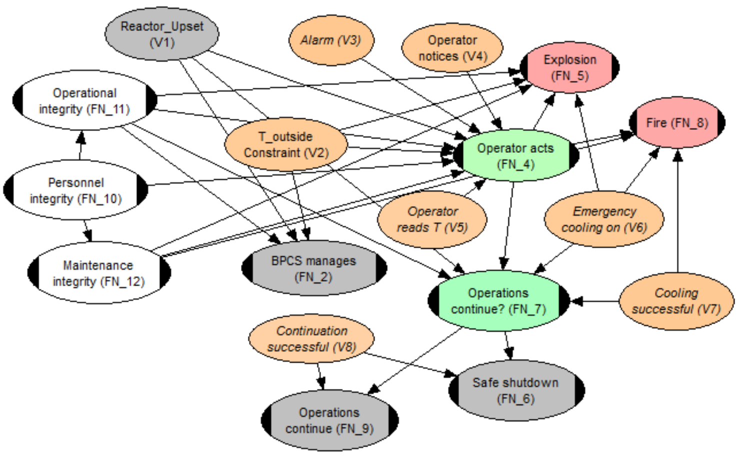


Figure 6: Influences of various indicators on initiating event frequency. Conduct of Operations is assumed to have twice as much weight as the others. For the situation in the figure, all indicators are set at 50 resulting in an initiating event frequency of 0.1 per year. When CoO is given the data calculated above and the BN updated, μ = 71 and σ = 6, the upset event frequency mean decreases from 0.1 to 0.07 per year, showing the sensitivity of initiating event to indicator value.



Node	Distribution or equation
Reactor_Upset, /yr	Triangular (0.23-0.70-2.10)
T_outside_constraint	Triangular (0.07-0.20-0.35)
Operator notices	Triangular (0.70-0.85-0.95)
Operator acts	Oprtr notices OR Oprtr reads T
Fire	Oprtr Acts*0.9*EmerCool*0.15
Explosion	T outside constraint - Op.acts
Alarm	Bernoulli (0.9)
Operator reads T	0.5*(1-Operator notices)
Emergency Cooling on	Bernoulli (0.9)
Cooling successful	Bernoulli (0.85)
Continuation successful	Bernoulli (0.8)
Personnel integrity default	1.00

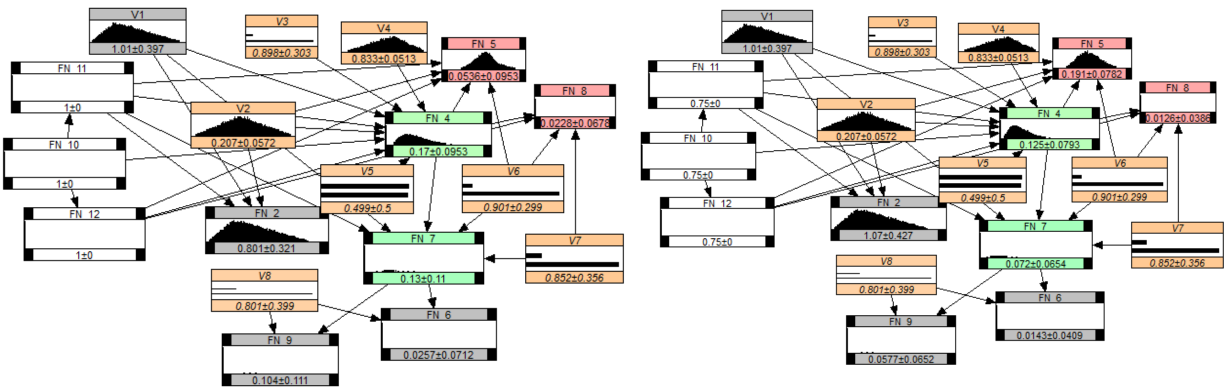


Figure 7: BN representing reactor upset running out-of-control and a barrier to explosion and fire in the form of an emergency cooling initiated by operator action with several degrading reliability factors, modified after Pasman, Knegtering, 2013 and Pasman, 2015, and recalculated with Uninet software. For this case rank correlation has been set to zero. Concerned arcs are not shown. Below are shown the solutions for integrity values set to 1 (*left*), and 0.75 (*right*)

In earlier publications Bayesian networks have been shown serving to demonstrate the effect of personnel integrity on defect causation. An example is presented in Figure 7, which is modified after Pasman and Knegtering, 2013 and Pasman, 2015, and recalculated with different software. The case represents a reactor in which an upset can occur with an estimated triangular distribution with a minimum and maximum limit of respectively 0.2 and 2 occurrences per year and with a mode frequency of 0.7 per year. On average this yields one event per year. In about 20% on average of cases the temperature runs out of the safe range with also using a triangular distribution (a different one, e.g., normal distribution would be just as easy). In the rest of cases the BPCS manages to bring the temperature under control again. If the temperature increases above its upper limit, an alarm sounds with 90% reliability upon which an operator should start an emergency cooling. The operator notices the alarm in 85% of cases with a triangular distribution between 70 and 95%. Alternatively, there is a small chance he/she will pick it up by reading the temperature from the screen. This occurs with a probability of 50% in case alarm is defective or the alarm sounds, but the operator didn't notice it. If the operator does not act, the upset certainly will develop to an explosion. This will also be the case if the operator acts but the emergency cooling fails to start. However, there is a good chance (90%) the cooling will work. In case the cooling is too late a fire breaks out (chance 15%), but if cooling is timely (85%) the reactor may continue producing (80%) or in marginal cases shutdown safely (20%).

The BN does the calculation in a split second and produces as outcomes the full distributions for all sensitive variables. Now, functioning of the reactor system and the cooling is influenced by the personnel integrity level along different routes: directly on the operator acting to start emergency cooling, via operational integrity on upset frequency and operator chance of noticing, and via maintenance integrity on reliability of the alarm and of the emergency cooling. A 25% decrease in personnel integrity increases in this way the probability of explosion by a factor 3.5 from 0.054 ± 0.095 ($= \pm 1\sigma$) to 0.191 ± 0.078 /yr, while at the same time continuing the operation almost halved from 0.104 ± 0.111 to 0.058 ± 0.065 /yr. Of course, all this is just a matter of a model with assumed data, but the model can be developed through collaboration with a company to an industrial case. By modularization the number of nodes can be greatly expanded. This example serves to show how reactor control and risk management can be realized through a Bayesian network of an engineering system in its socio-technical framework. Quantification and predictive methods lower the uncertainty, which we then can handle through risk and uncertainty management of the system and its organization, as exemplified by Figure 7.

This BN is constructed by means of Uninet software formerly developed by Roger Cooke and coworkers at Delft University of Technology, see Hanea, (2008), Hanea, and Kurowicka (2008) and Hanea, Kurowicka, and Cooke (2006). It is updated and expanded by Dan Ababei, Lighttwist, Australia (for downloading software, see http://www.lighttwist.net/wp/uninet). Uninet's random variable nodes, which may be assigned arbitrary continuous or discrete distributions, are connected by arcs representing probabilistic influence by (conditional) rank correlations, realized by normal copula. The quantification of such a network involves assigning one dimensional marginal distribution to each node and a (conditional) rank correlation to each arc (0 if uncorrelated; extremes +1 and -1). This rank correlation feature is useful when applying expert elicitation results. The joint distribution is realized by sampling it using the marginal distributions and the (conditional) rank correlations. Uninet strictly separates probabilistic nodes and functional ones, the latter performing the arithmetic operations between variables modeling an empirical multivariate distribution.

Conclusions

Process safety performance indicators and their metrics provide an important "safety health" monitoring means for operator awareness in real time and for the management of complex systems on the longer term. As long as results develop in a favorable direction management can be satisfied. However, if lagging indicators vanish and leading metrics fluctuate, more must be done to interpret the figures. To enable trend analysis, averaging and variance determination shall be performed. A further challenge is the large number of leading indicators required to obtain a fair impression. For examining results at higher levels, indicator aggregation is a requirement. The ensuing desirable objective is linking indicator value to instantaneous risk level.

It is shown how with the aid of Bayesian networks the sketched problems can be solved without losing information. In due time it will be feasible to tie metrics to the risk level of an operation taking into account technical, human, and organizational factors. This approach will require further analysis of how various factors interact and are interdependent, estimation of factor weights, and historical data to validate models, but it promises to enable improved risk and uncertainty management.

References

ANSI/API (2010), American National Standards Institute/American Petroleum Institute (API) recommended practice 754, Process Safety Performance Indicators for the Refining and Petrochemical Industries, First Edition, April 2010

Bhandari, J., Abbassi, R., Garaniya, V., Khan, F. (2015) Risk analysis of deepwater drilling operations using Bayesian network, Journal of Loss Prevention in the Process Industries 38, 11-23

CCPS (2007), Center for Chemical Process Safety. Guidelines for risk based process safety. Hoboken (NJ): John Wiley & Sons; ISBN 978-0-470-16569-0

CCPS (2010), Center for Chemical Process Safety. Guidelines for process safety metrics. Wiley; ISBN 978-0-470-57212-2

COMAH (2012), Competent Authority Workstream 2e, Process safety performance indicators, (Operational Delivery Guide), http://www.hse.gov.uk/comah/guidance/process-safety-performance-indicators.pdf

Fenton, N., and Neil, M., (2013), Risk Assessment and Decision Analysis with Bayesian Networks, CRC Press, Taylor & Francis Group, Boca Raton, FL 33487-2742, USA, ISBN 978-1-4398-0910-5

García-Herrero S, Mariscal M.A., García-Rodríguez J., Ritzel D.O. (2012), Working conditions, psychological/physical symptoms and occupational accidents. Bayesian network models. Safety Science 50, 1760–1774

Hanea, A. M. (2008). Algorithms for non-parametric Bayesian belief nets. PhD thesis, Department of Mathematics, Delft University of Technology

Hanea, A. M., & Kurowicka, D. (2008). Mixed non-parametric continuous and discrete Bayesian belief nets. Advances in mathematical modeling for reliability. IOS Press, ISBN 978-1-58603-865-6

Hanea, A. M., Kurowicka, D., & Cooke, R. M. (2006). Hybrid method for quantifying and analyzing Bayesian belief nets. Quality and Reliability Engineering International, 22, 709-729

Hassan, J., Khan, F. (2012), Risk-based asset integrity indicators, J Loss Prevention in the Process Industries 25 544-554

Hopkins, A. (2009), Thinking about process safety indicators. Safety Science 47: 460-465 and following articles

HSE (2012), Health and Safety Executive U.K. Developing process safety indicators: a step-by-step guide for chemical and major hazard industries, HSG 254, ISBN:978-0-7176- 6180-0

Hu, Jq., Zhang, Lb., Cai, Zs., Wang, Y., Wang, Aq., (2015), Fault propagation behavior study and root cause reasoning with dynamic Bayesian network based framework. Process Safety and Environmental Protection, 97, 25–36, doi:10.1016/j.psep.2015.02.003

IChemE Safety Centre, ISC (2015), Guidance, Lead Process Safety Metrics – selecting, tracking and learning, www.ichemesafetycentre.org

Khawaji, I.A., (2012), Developing system-based leading indicators for proactive risk management in the chemical processing industry [Master of Science Thesis]. Massachusetts Institute of Technology, http://sunnyday.mit.edu/safer-world/Khawaji-thesis.pdf

Knijff, P., Allford, L. and Schmelzer, P. (2013), Process Safety Leading Indicators—A Perspective From Europe, Process Safety Progress (Vol.32, No.4), 332-336

Leveson, N.G., Dulac, N. (2005), Safety and risk-driven design in complex systems-of-systems. In:1st space exploration conference: continuing the voyage of discovery; Orlando, FL, USA; 30 January -1 February 2005, p. 1-25

Mannan, M.S., Sachdeva, S., Chen, H., Reyes-Valdes, O., Liu, Y. and Laboureur, D.M. (2015) Trends and Challenges in Process Safety, AIChE Journal, 61 (11), 3558-3569, DOI 10.1002/aic.15019

Mkrtchyan, L., Podofillini, L., Dang, V.N. (2015), Bayesian belief networks for human reliability analysis: A review of applications and gaps. Reliability Engineering and System Safety 139, 1-16

Naderpour, M., Lu, J., Zhang, G., (2015), An abnormal situation modeling method to assist operators in safety-critical systems. Reliability Engineering and System Safety 133, 33–47

OECD (2008), Guidance on developing safety performance indicators related to chemical accident prevention, preparedness and response. For industry. Second edition, 2008. OECD Environment, Health and Safety Publications – Series on Chemical Accidents No. 19, Environment Directorate, Organisation for Economic Cooperation and Development, Paris; and the extensive original publication from 2003 OECD Guidance on safety performance indicators, Guidance for industry, public authorities and communities for developing SPI programmes related to chemical accident prevention, preparedness and response. (Interim Publication scheduled to be tested in 2003 – 2004 and revised in 2005), OECD Environment, Health and Safety Publications, Series on Chemical Accidents, No. 11.

OGP (2008), International Association of Oil & Gas Producers, Asset integrity - the key to managing major incident risks. Report No. 415.

Pasman, H.J., Knegtering, B. (2013), What process risks does your plant run today? The safety level monitor, Chemical Engineering Transactions, Vol. 31, 277-282, ISBN 978-88-95608-22-8; ISSN 1974-979.

Pasman, H.J., (2015), Risk Analysis and Control for Industrial Processes – Gas, Oil and Chemicals; A System Perspective for Assessing and Avoiding High Consequence, Low Probability Events, 327-328, ISBN 978-0-12-800057-1

Yuan, Zh., Khakzad, N., Khan, F., Amyotte, P. (2015), Risk-based optimal safety measure allocation for dust explosions, Safety Science 74, 79–92

Vinnem, J.E., Bye, R., Gran, B.A., Kongsvik, T., Nyheim. O.M., Okstad, E.H., (2012), Risk modelling of maintenance work on major process equipment on offshore petroleum installations. J Loss Prev Process Industries 25, 274-92

Weber, P., Medina-Oliva, G., Simon, C., Iung, B. (2012), Overview on Bayesian networks applications for dependability, risk analysis and maintenance areas. Engineering Applications of Artificial Intelligence 25, 671–682