Journal of Loss Prevention in the Process Industries 60 (2019) 96–105

Contents lists available at ScienceDirect

Journal of Loss Prevention in the Process Industries

journal homepage: www.elsevier.com/locate/jlp

Operational data-driven prediction for failure rates of equipment in safety instrumented systems: A case study from the oil and gas industry

Lin Xie[a], Solfrid Håbrekke[b], Yiliu Liu[a], Mary Ann Lundteigen[a,*]

[a] Norwegian University of Science and Technology, Trondheim, Norway
[b] SINTEF Digital, Trondheim, Norway

ARTICLE INFO

Keywords:
Safety instrumented system
Data collection
Failure rates
Data-driven models

ABSTRACT

Safety instrumented systems are frequently deployed to reduce the risk associated with industrial activities, such as those in the oil and gas industry. A key requirement for safety-instrumented systems in standards like IEC 61508 and IEC 61511, is that the safety functions and their equipment must fulfill the requirements of a given safety integrity level. A safety integrity level formulates a maximum tolerated probability of failure on demand, which must be confirmed in design as well as follow-up phases. The equipment's failure rates are important inputs to this analysis, and these figures assumed from design must be re-estimated and verified based on the operational experiences with the equipment at the specific facility. A thorough review of reported failures from six Norwegian onshore and offshore oil and gas facilities indicates that equipment of similar type experience different failure rates and different distribution of the occurrence of failure modes. Some attempts have been made to identify the underlying influencing factors that can explain the differences, however, so far the utilization of data-driven methods have not been fully explored. The purpose of this paper is two-fold:1) demonstrate how data-driven methods, i.e. principal component analysis and partial least squares regression, can be used to identify important influencing factors, and 2) propose a framework for predicting the failure rates based on the reported failures. The framework is illustrated with a case study based on the data collected from the six facilities.

1. Introduction

Safety instrumented systems (SISs) are frequently used to reduce the risks associated with industrial activities in many industries, e.g. at process and nuclear power plants, and at oil and gas facilities (Rausand, 2014). A SIS is characterized as a system that relies on electrical/electronic/programmable electronic (E/E/PE) technologies to detect abnormal situations. SISs perform one or more safety instrumented functions (SIFs) to protect the equipment under control (EUC) against the occurrence of hazardous events (IEC61511, 2016). An industrial facility usually is equipped with several SISs, such as process shutdown (PSD) system to stop production in case of process upsets, and emergency shutdown (ESD) system to reduce the escalation of uncontrolled events like leakages by depressurizing and removing electrical ignition sources. A SIS generally consists of three main subsystems: sensor(s) (e.g. level transmitters, gas detectors, and push buttons), logic solver(s) (e.g. programmable logic controller and industrial computer) and final element(s) (e.g. shutdown valves, and circuit breakers). As illustrated in Fig. 1, the sensors detect possible abnormal situations, and the logic solvers activate, and the final elements take actions according to the sensor inputs.

The standards for SISs, e.g. IEC 61508 and IEC 61511, state that the SIFs performed by SISs must fulfill the requirements of specified safety integrity levels (SILs) (IEC61508, 2010; IEC61511, 2016). Each SIL defines the maximum tolerated (average) probability of failure on demands (PFD). The PFD of a SIF must be estimated in design, using generic (often field-based) failure rates or those provided by manufacturers, and then re-estimated in operation using reported failures from the facilities where the SIF is installed (Rausand, 2014). A failure rate is defined as an average frequency of failure, i.e. a number of failures per unit of time (ISO14224, 2006). Failure rates can generally be classified into three groups: generic, manufacturer-provided and user-provided failure rates, depending on how they have been derived (Rausand, 2014).

In oil and gas industry, *Generic failure rates* for SIS equipment performing SIFs are presented in databases and handbooks, like Offshore and Onshore Reliability Data (OREDA, 2015), Safety Equipment Reliability (EXDIA, 2007) and Reliability Data for Safety Instrumented

* Corresponding author.
E-mail address: mary.a.lundteigen@ntnu.no (M.A. Lundteigen).

https://doi.org/10.1016/j.jlp.2019.04.004
Received 26 November 2018; Received in revised form 14 March 2019; Accepted 4 April 2019
Available online 09 April 2019

Nomenclature

SIS	safety instrumented system
PSD	process shutdown
ESD	emergency shutdown
FTO	fail to open
LCP	leakage in closed position
DOP	delayed operation
OTH	other
PCA	principal component analysis
PLSR	partial least squares regression
DD	dangerous detected
DU	dangerous undetected
PC	principal component
SIF	safety instrumented function
SIL	safety integrity level
GLM	generalized linear model
Cox	proportional hazards model
HC	hydrocarbon
T	score matrix
P, Q	loading matrix
X	explanatory variable
V	eigen value
Y	response variable
$\tilde{E}$, $\tilde{F}$, $\tilde{F}^*$	residuals from decomposition
NIPALS	nonlinear iterative PLS algorithm
$\lambda_{DU,i}$	failure rate of DU failure, corresponding to failure mode i
θ_{ij}	weight of influencing factor j, corresponding to failure mode i
σ_{ij}	score of influencing factor j, corresponding to failure mode i
λ^*_{DU}	predicted failure rate
LT	level transmitter
PSV	pressure safety valve
DU_YES	revealed DU failure
DU_NO	no revealed DU failure
PDS	reliability data for safety instrumented system
SAR	safety analysis report
P&ID	process and instrument diagram
SRS	safety requirement specification

Systems (PDS data handbook[1]) (SINTEF, 2013a). OREDA databases and handbooks rely on failures reported in operation from multiple operating companies, while e.g. PDS data handbook relies on a combination of OREDA data, expert judgment, and manufacturer information. Generic failure rates are mainly applied in reliability analysis during the design phase before the designers have decided on what equipment to purchase. *Manufacturer-provided data* is meanwhile based on analyses of specific products, laboratory testing and collected data, typically during the warranty period. It is often seen that manufacturer-provided failure rates are lower than what is experienced in operation (SINTEF, 2013b). *User-provided failure rates* are based on aggregated time in service and the number of reported failures at one or more specific facilities owned by the same operating company. The standards and regulations, such as IEC61508, IEC 61511, ISO 14224 and GL070, have given certain requirements with respect to the failure rates (GL070, 2004; IEC61508, 2010; IEC61511, 2016; ISO14224, 2006). IEC 61508 states that the failure rates used in a reliability analysis should have at least a confidence level of 70% (IEC61508, 2010). The uncertainty of the estimated failure rates is required in OREDA to be presented as a 90% confidence interval with a lower limit and an upper limit (OREDA, 2015). In order to fulfill 90% confidence, a guideline proposed by SINTEF[2] suggests that operational hours times the number of failures should exceed $3{\cdot}10^6$ hours (Hauge and Lundteigen, 2008). In addition, when the upper 95% percentile is approximately three times the mean value or lower, we may use the estimated failure rates based on operational experience (Hauge and Lundteigen, 2008). In this context, many oil and gas facilities invest time and resources to record failures to obtain estimated failure rates.

A number of methods can be applied to estimate failure rates. In many applications, failure rates are estimated as the maximum likelihood estimators (i.e. the total number of failures divided by the aggregated time in service) (OREDA, 2015). Estimation of the failure rates should also consider specific operational conditions (IEC61508, 2010). Different models are suggested to analyze the impact of various operational conditions from one facility to another. Physical models considering physical laws like Arrhenius's law, Voltage acceleration and Gunn's law, are used to estimate failure rates (Foucher et al., 2002; Ratkowsky et al., 1982). MIL-HDBK-217 (MIL-HDBK-217F, 1995), Telcordia SR-332 (TelcordiaSR-332, 2001) and IEC 61709 (IEC61709, 2017) propose analytical failure functions of parameters, e.g. temperature, humidity, stress, voltage or electrical intensity. Statistical models can use operational data to investigate the trends of failure rates, such as Cox models (proportional hazards model) and Bayesian models (Becker and Camarinopoulos, 1990; Cox, 1972; Elsayed and Chan, 1990; Kutyłowska, 2015; Newby, 1994). Brissaud suggests a way to predict failure rates with consideration of the influences from design, manufacture or installation etc. (Brissaud et al., 2010). A similar method is suggested by Vatn, taking into account the effects of implementation of risk reduction measures in the prediction (Vatn, 2006). It is noticed that the physical models for estimating failure rates require well-known knowledge about physical mechanism leading to the failures. In this paper, in order to develop a general model, the prediction of failure rates is only based on statistical models.

Most statistical models mentioned above rely on the data for a large group of equipment. The items within a group are assumed to have similar functions and the same failure rates, however, their design (e.g. measuring principle), location, and environment can be different. SINTEF has previously performed a study where it was documented that similar equipment experienced varied failure rates even if the operating environment is the same (Håbrekke et al., 2017). The study has shown that shutdown valves with flow medium gas and hydrocarbon (HC) liquid experience different failure rates. It was also showed that the failure mode, i.e. the type of failure, was influenced by certain parameters. For example, the occurrence of the failure mode “fail to

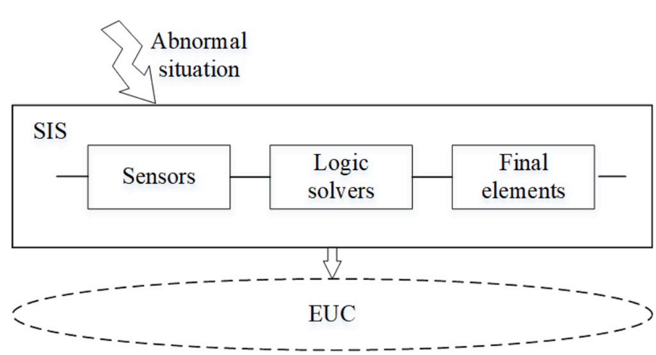

Fig. 1. Role and general configuration of SIFs.

[1] PDS forum is a co-operation between 20 participating companies, including oil companies, drilling contractors, engineering companies, consultants, safety system manufacturers and researchers, with a special interest in SISs, see www.sintef.no/pds.

[2] SINTEF: An independent Norwegian research organization (https://www.sintef.no/en/).

open" (FTO) for the same valves were strongly affected by the temperature of the medium flowing through the valves. The term significant influencing factors were thus introduced for those factors (e.g. design, operating environment, failure mode) with the strongest effects on the failure rates. These factors have been analyzed by using traditional statistical models, however, data-driven methods could also be suitable (Håbrekke et al., 2018). In this paper, data-driven methods refer to the quantitative methods of identifying the correlations based on amounts of data, such as principal component analysis (PCA) and partial least squares regression (PLSR). Those data-driven models based on experienced data are now proposed to be incorporated with the traditional statistical models to predict failure failures of SIS equipment for new facilities in the design phase.

The purpose of this paper is to study the application of data-driven models for failure rate estimation. More specifically, the objectives are to: 1) demonstrate how data-driven methods, i.e. PCA and PLSR, can be used to identify significant influencing factors for the specific failures of SISs, and 2) propose a framework for predicting the failure rates based on the identified factors. The framework is illustrated with a case study from data collected at six Norwegian onshore and offshore oil and gas facilities. The framework is developed for SIS equipment, but can also be applied for other systems or equipment.

The rest of the paper is organized as follows: Section 2 gives some theoretical basis related to predictions of failure rates. Section 3 depicts a framework for prediction of failure rates. Section 4 illustrates the application of the proposed framework based on the data from six different oil and gas facilities. Finally, some conclusions and ideas for further work are discussed.

2. Theoretical basis

This section presents some selected definitions and concepts relating to failures as well as failure rate prediction and elaborates the basic principles of data-driven methods for identifying influencing factors.

2.1. Definitions of the failures

According to IEC 50(191), a failure is defined as "the termination of the ability of an item to perform a required function" (IEC60050, 1990). An item may refer to a system, subsystem, voted group or channel and component. IEC 61508 splits the failures of SISs into four groups (IEC61508, 2010): dangerous detected (DD) failures, dangerous undetected (DU), safe and no part/no effect failures. Both DD and DU failures are dangerous failures that are critical for the functionality of equipment. The difference between DD and DU failures lies in how the two types of failures are revealed. DU failures are latent and only revealed upon real demands, periodic tests, or inspections occasionally, while DD failures are revealed by automatic diagnostics once they occur. Since DU failures cannot be detected immediately and may not be fixed until e.g. the next periodic test, these failures contribute the most to the unavailability of SIS equipment. Hence, DU failures are of concern in most reliability studies and also in this paper.

Other important terms in this paper include "*time to failure*", "*failure cause*", "*detection methods*" and "*failure mode*". Time to failure is often referred to as the time elapsing from when the item is put into operation until it fails for the first time (Rausand and Høyland, 2004). By time to DU failure we mean the time when the item is put into operation until a DU failure on it is revealed. Failure causes include circumstances associated with design, manufacture installation, use and maintenance that have led to a failure (IEC60050, 1990). Detection methods are used to describe how the failures are discovered (IEC61508, 2010). A failure mode is a possible state description of a faulty item, which tells how the inability is observed (Rausand, 2014).

2.2. Influencing factors

Estimation of DU failure rates from operation are often based on generic data and/or user-provided data. In addition, influencing factors that may affect the failure rates should be considered for prediction of failure rates, but it is not mandatory in all generic and user-provided data. Influencing factors are defined as the internal and external parts of a system which act on its reliability or failures (Brissaud et al., 2010). The term of influencing factor is more general than failures causes, and it relates to the indirect explanatory factors, for example, equipment attributes (e.g. sizes, types), operational environment (e.g. temperature, pressure, loads), manufacture activities (e.g. manufacturers, procedures), facility (e.g. location) and maintenance (e.g. test interval) and the activities of the end-user (e.g. general safety culture) (Brissaud et al., 2010; Rausand, 2014). Significant influencing factors are the factors whose effects are the most influencing on the failure rates. Each influencing factor can be broken down into several subcategories. The effects of influencing factors may relate to failure rates. For example, high temperature may lead to a higher frequency of the failures compared to low temperatures.

2.3. Data-driven models for identifying significant influencing factors

In previous analyses of influencing factors, Cox models and generalized linear model (GLM) have been used (Håbrekke et al., 2018). Both of the two models assume underlying failure distributions. For example, GLM is based on binomial distributions, where only two possible states of equipment are considered. A major advantage of these models is the ability to describe the analytical correlations between influencing factors and failure probability. However, both models require high quality data for representing simple statistical correlations, and they are sensitive to the number of factors. When a number of influencing factors are involved with complex interaction and nonlinearity, Cox and GLM models may not be suitable.

More flexible models, such as those data-driven models, can be alternatives. PCA and PLSR are therefore introduced to investigate the correlation between many factors simultaneously. These models enable us to extract the most important information in order to understand the correlations that may exist between factors. PCA and PLSR have been applied for root cause identification, fault detection, and quality monitoring in many cases (Li et al., 2016; Qin, 2012; Tidriri et al., 2016). Here we will adopt them for understanding the essential relationships between the influencing factors and DU failures. Details regarding PCA and PLSR are found in the Appendix.

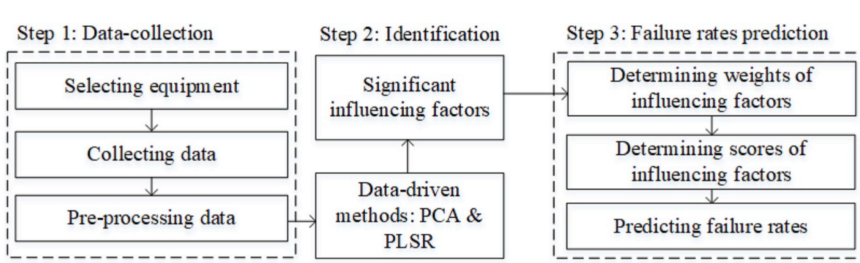

Fig. 2. Framework for predicting failure rates.

3. Framework of failure rate prediction

In this section, we propose a framework to predict failure rates of SIS equipment at a new facility based on experiences from comparable facilities. The framework clarifies the correlations between operational data and influencing factors, and thereby provides more preciseness in failure rates prediction for selected equipment. As illustrated in Fig. 2, the framework consists of three main steps: 1) data-collection, including a selection of equipment, collection, and pre-processing data; 2) identification of significant influencing factors to find out hidden correlations; and 3) failure rates prediction by determining the weights and scores of the factors.

3.1. Step 1: data-collection

The purpose of this step is to collect and interpret, classify and clean data. It is required to collect data concerning both failures and influencing factors. The failure data were obtained from failure notifications and maintenance records, ranging from time to DU failure, failure causes, and failure modes to detection methods. The data reflecting the states of influencing factors were related to equipment attributes, operational environment and maintenance activities, etc. Equipment attributes are used to describe equipment relating to manufacturer's data and design characteristics.

To limit the scope of the analysis, experts from manufacturers, oil and gas facilities and engineering companies within the PDS project have suggested some typical types of SIS equipment relevant for analysis. The selected groups of equipment should be accompanied by sufficient data to obtain the required statistical confidence. The recommendation is limited to four groups: shutdown valves (i.e. ESD and PSD valves), process safety valves (PSVs[3]), level transmitters (LTs), and gas detectors. In terms of their safety functions, shutdown valves can close and isolate related segments on demands, PSVs can be open on a predefined setpoint to relief pressure, LTs measure the level in a vessel or tank, and gas detectors discover the presence of gas and initiate an alarm at specified concentrations.

To assure the quality of the data, pre-processing of data is needed. Each failure maintenance notifications is reviewed and classified according to failure causes, failure modes, and detection methods. The failures were registered by operators and maintenance personnel, including both random hardware failures and systematic failures. It is suggested that systematic failures can be in failure rates estimations (SINTEF, 2013a). However, some reoccurring failures due to specific problems, such as icing problems and hydrate design problems have been removed to avoid invalid the impacts on the overall results. Such problems at one facility may not necessarily occur at other facilities. The classifications of equipment are predefined according to the suggestions of the experts. For example, the valves whose diameters are less than one inch are categorized into a separated group, since they are normally water-based and low-risk valves. Some assumptions are necessary in case of lack of data, for example, the valves installed in one particular system are assumed to share the same medium as the flow medium within the valves is not given.

3.2. Step 2: identification of significant influencing factors

The purpose of this step is to investigate the correlations between failures and influencing factors, and to identify significant influencing factors based on the data-driven models. Significant influencing factors are referred to as the factors that highly affect the performance of equipment.

PCA has been selected to identify gross correlations in data, and give an overview of the distribution of the DU failures, correlations between DU failures (e.g. occurrence of DU failures, failure modes) and influencing factors (e.g. equipment attributes, maintenance, environmental factors). As shown in Fig. 3, PLSR is applied to find quantitative correlations between equipment performances (e.g. time to DU failure) and the same influencing factors. PCA models are concerned with the occurrence of DU failures and failure modes, while PLSR models are mainly related to time to DU failure. Both models contribute to the identification of significant influencing factors, and investigate more on the correlations between failures and factors.

3.3. Step 3: failure rates prediction

The purpose of this step is to predict failure rates of SIS equipment at a new facility based on experiences from comparable facilities. A user-provided failure rate for DU failures is denoted as λ_{DU}. This failure rate can be split into i groups according to different failure modes:

$$\lambda_{\mathrm{DU}} = \lambda_{\mathrm{DU},1} + \lambda_{\mathrm{DU},2} \ldots + \lambda_{\mathrm{DU},i} \tag{1}$$

where $\lambda_{\mathrm{DU},i}$ is the failure rate according to the failure mode i. θ_{ij} ($j = 1,2\ldots k$) denotes the weight of the significant influencing factor j, meaning its importance to the failure rates $\lambda_{\mathrm{DU},i}$. The weight θ_{ij} can be determined based on either the analysis in step 2, such as regression coefficients and correlation analysis or the experience from the experts.

Then, the score σ_{ij} for the influencing factors can be determined by comparing the new conditions and existing conditions. The scores represent the impact of the significant influencing factors. For example, when $\sigma_{ij} = 1$, the influencing factor j is supposed to be in the medium state according to failure rates $\lambda_{DU,i}$. When $\sigma_{ij} > 1$, the impact from influencing factor j is more hostile than the existing condition. When $\sigma_{ij} < 1$, the impact is considered more benign than the existing condition. Similar studies have been discussed by many authors (Brissaud et al., 2010; Rausand, 2014; Vatn, 2006). The predicted failure rates are then estimated by:

$$\lambda_{\mathrm{DU}}^{*} = \sum \theta_{ij} \cdot \sigma_{ij} \cdot \lambda_{\mathrm{DU},i} \tag{2}$$

Failure rates are then obtained by using Equations (1) and (2).

4. Case study

In this section, a case study is used to illustrate the proposed framework for the prediction of failure rates. The content of this paper is based on the works of the PDS project. We focus on the shutdown valves and use the analysis of equipment attributes as examples. Other influencing factors like the operational activities of the end-user or maintenances, may also have important influences on the failure rates.

4.1. Step 1: data-collection

The data stem from the six offshore and onshore facilities in the Norwegian oil and gas industry, involving 12788 equipment items and more than 13000 failures. A number of influencing factors can be taken into account, but we mainly focus on equipment attributes here since they are demonstrated important in explaining the variance of experienced reliability performance of the SIS equipment.

The data regarding the failures and equipment attributes is derived from maintenance notifications, work orders and relevant documentation, such as safety requirement specifications (SRSs), process and instrument diagrams (P&IDs), safety manuals and safety analysis reports (SARs) and manufacturer specifications. Discussions with technical advisors and process engineers have also been included. For example, the flow medium for shutdown valves in the separation and stabilization system has been checked in P&ID manually and discussed with the experts. Some failure records are illustrated in Table 1. Shutdown

[3] PSVs are non-instrumented equipment, but they are considered for the data collection since some reliability handbooks for SIS include data for such equipment.

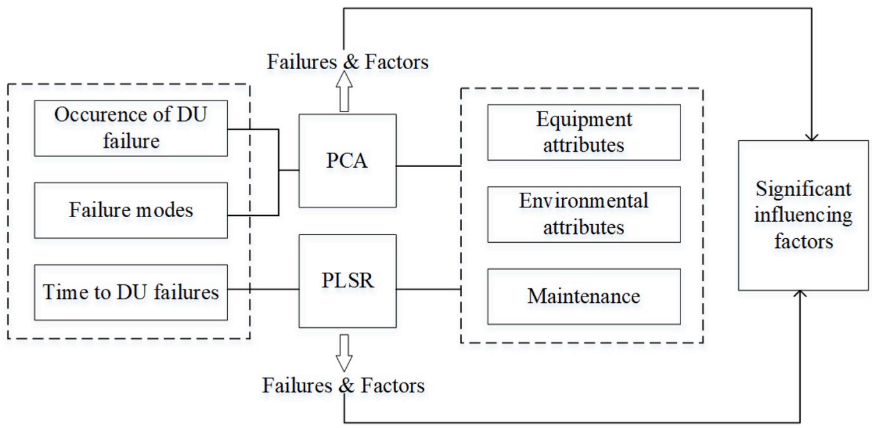

Fig. 3. Flowchart for identifying significant influencing factors.

Table 1
Examples of failure notifications.

Comp.	Notification	Functional loc.	Failure mode	Detection method	Description	Comments
PSD valve	*	*	FTC	Proof test	The valve fails under function test	Valve went to 40% opening at closing. Rust actuator and spring.
ESD valve	*	*	DOP	On-demand	Error of feedback	The too long closing time during the function test
PSD valve	*	*	DOP	Proof test	Check opening and closing time for valve	Closing time is 56 s
…	…	…	…		…	…

valves mainly have three types of DU failure: fail to close (FTC), leakage in closed position (LCP), and delayed operation (DOP) (ISO14224, 2006).

Table 2 and Table 3 present a summary of the failure data and equipment attributes. The equipment attributes, i.e. manufacturers, size, flow medium and type of the shutdown valves, are included in the analysis.

Table 4 illustrates an example of the shutdown valves used in data analysis. For example, No. 1 valve has survived and No. 4 valve has failed during the surveillance time.

4.2. Step 2: identification of significant influencing factors

PCA and PLSR are possible methods to identify significant influencing factors for shutdown valves in this section. The results are visualized by the software called "The Unscrambler X", but it should be noted that similar analyses can also be realized in Matlab or R.

Each possible influencing factor is defined as a variable. The samples here are shutdown valves, which are distributed in the variable space. By application of PCA, a set of possibly correlated variables are converted into a set of linear uncorrelated variables. Then, the dimension of the multivariate variables is reduced to principal components (PCs) with a minimal loss of information. The samples are projected by using PCs with the largest explained variance. Fig. 4 shows the correction loadings plot. The explained variance now tells us how much information attribute to each of the PCs when high dimensional space is converted to low dimensional space. In Fig. 4, PC1 contains 12% of the variance and the PC2 contains 10% of the variance. The loading plot is used to understand the correlation between the variables, as illustrated in Fig. 4. "DU_NO" stands for a situation where DU failures are not revealed, while "DU_YES" stands for a situation where DU failures are revealed during surveillance time. There is a distinction between "DU_NO" and "DU_YES" along PC2. The valves with DU failures are allocated in third and fourth quadrants, illustrating the distribution of DU failures. The score plot indicates how the samples are distributed along with PCs. By comparing Figs. 4 and 5, we can recognize the correlation between the grouped influencing factors and DU failures. In Fig. 5, the extremely large and large valves are also distributed in the third and fourth quadrants, meaning they are more likely to be subject to DU failures than the rest of the valves. The valves with gas and chemical flow medium are more exposed to DU failures compared to the other valves.

By introducing failure modes, e.g. DOP, FTC, LCP, in the analysis, the variance of PC1 and PC2 rises to 17% and 14% respectively. As shown in Fig. 6, failure mode DOP is close to "extreme" and "gas", meaning that the failure mode DOP and extreme large-sized valves with gas flow medium are clustered. This implies that these valves are more exposed to DU failures with the failure mode DOP.

Fig. 7 and Fig. 8 show the analysis results from the PLSR analysis. The predicted plot is used to describe the correlations between time to DU failure and the influencing factors. R-squared gives the goodness-of-fit of the model. Time to DU failure is poorly predicted in Fig. 7 since R-squared is rather small and there is a big deviance between predicted regression lines (red validation line and blue calibration line) and target line (black reference line). Fig. 8 illustrates the weight regression coefficients providing information about the importance of the influencing factors. The influencing factors with a large regression coefficient play an important role in the regression model. In this case, some influencing factors like size (e.g. extremely large), flow medium (e.g. water, multiphase) and type of valves (e.g. ball and gate) can still be

Table 2
Failure data for the four groups of equipment.

Equipment Group	No. of equipment	Total operational time (hours)	No. of DU failures	Experienced failure rates (per 10^6 hours)
Shutdown valves	1646	$3.7 \cdot 10^7$	292	7.9

Table 3
Equipment attributes for the shutdown valves.

Type	Ball	Controls flow by rotating a perforated and pivoting ball, poor methanol resistance in O-rings and deposits.
	Gate	Opens and closes by lifting or putting a gate out/down of the path of the fluid. Precipitation and abrasion are typical problems.
	Butterfly	Regulates or isolates flow by a damper.
	Others	Other types, e.g. globe valves
Size	Small-sized	0–1 inch
	Medium-sized	1–3 inches
	Large-sized	3–18 inches
	Extreme large-sized	> 18 inches
Flow medium	HC liquid	Oil and condensate (hydrocarbon) liquid
	Diesel	Diesel fuel.
	Chemical	Chemical medium in chemical injection system e.g. H_2S, Oxygen and some in methanol injection system e.g. 90% MEG with 10% water
	Multiphase	A mixture of different flow medium, e.g. a mixture of hydrocarbon, water, and sand
	Water	Freshwater with normal temperature and produced water with high temperature
	Seawater	Used for a fire water system and is characterized by salt
	Gas	HC gas or HC vapor in gas compression and re-injection systems, gas treatment systems, gas export metering systems, heating medium systems, etc.
Manufacturer	Manufacturers	E.g. P, B … (anonymized)

Table 4
Examples for the analyses.

No.	Time (hours)	DU Failures	Type	Dimension	Flow Medium	Manufacturer
1	96456	DU_NO	Ball	Large	HC Liquid	P
2	96456	DU_NO	Ball	Medium	Others	P
3	96456	DU_NO	Ball	Large	Others	B
4	624	DU_YES	Ball	Large	Others	P
5	96456	DU_NO	Ball	Medium	Gas	B
…	…	…	…	…	…	…

Note: " DU_YES " – DU failures are revealed and " DU_NO " – No DU failure is revealed.

found as significant with respect to the failure rates.

To sum up, we conclude that in our case study DU failures are correlated with the most significant influencing factors, e.g. size and flow medium. Extremely large-size and flow medium (i.e. gas) are critical for some particular failure modes like DOP. That is why the two influencing factors, i.e. size and flow medium are mainly concerned in the following subsection.

4.3. Step 3: failure rates prediction

Based on operational experiences, we intend to predict failure rates of the shutdown valves installed a new facility. The user-provided failure rates in our case study are based on 1646 shutdown valves and 292 DU failures in total. The failures rate is estimated as the maximum likelihood estimator by $7.9{\cdot}10^{-6}$. The corresponding confidence interval is given by $[7.2{\cdot}10^{-6},\ 8.9{\cdot}10^{-6}]$. Table 5 lists the DU failures and associated rates λ_l per failure mode for the shutdown valves.

As discussed in the previous section, two significant influencing factors need to be taken into account in predicting failure rates, i.e. size and flow medium of the valves. The weight θ_{ij} reflects the influence on failure rates from each influencing factor according to the failure modes, which is determined by experts based on the analysis results from PCA and PLSR. The score σ_{ij} is determined by comparing new conditions and existing conditions. The relevant assumptions and prediction results are shown in Table 6. Due to changes in operational conditions, the failure rate can be calculated by Eq. (1) and Eq. (2) and the predicted failure rate decrease by 5% to 8.8 per 10^6hour, lower than the predicted result by using Brissaud's method (9.3 per 10^6hour) under the same assumptions. The difference between the two predicted results can be explained by obtaining more information about correlations between significant influencing factors and the failure modes from the

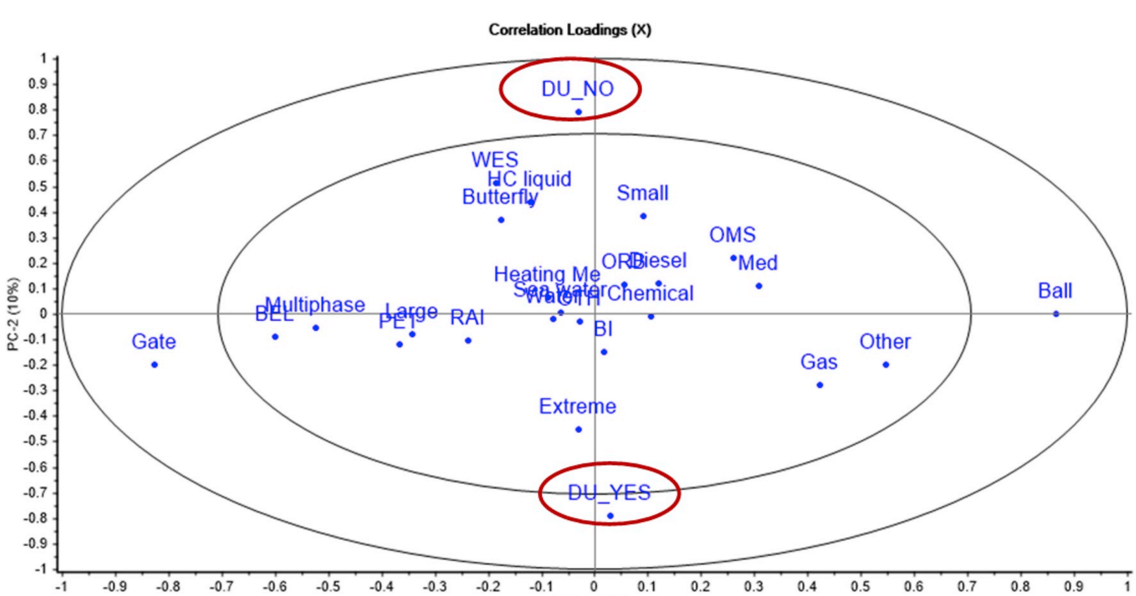

Fig. 4. Correlation loading plot for the first and second PCs in PCA.

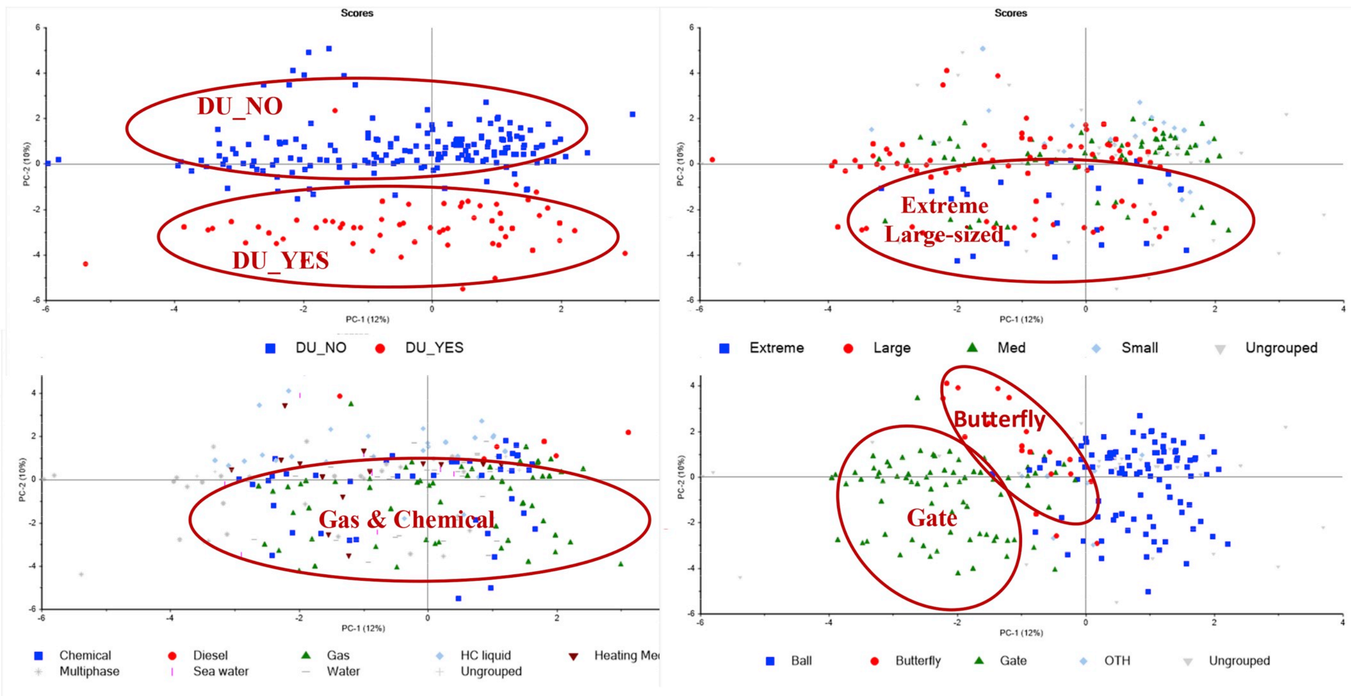

Fig. 5. Score plot of the first and second PCs in PCA.

PCA and PLSR analysis. It is illustrated that changes in the influencing factors may affect some specific failure modes, rather than all failure modes. Thus, it is more reasonably to predict failure rates for the specific failure modes of the shutdown valves.

5. Conclusions, discussions and further work

The main contribution of this paper is the proposed framework for identifying influencing factors and predicting failure rates of SIS equipment. The framework combines data-driven models i.e. PCA and PLSR, and statistical models for predictions of failure rates. The methods help us to identify the most important significant influencing factors on failure rates, and to decide on the weights and scores of identified influencing factors based on the analysis results from PCA and PLSR.

Such a framework has been illustrated with a case study involving operational experiences reported for the shutdown valves at six oil and gas facilities. The results suggest that the size and the flow medium through the valves are the most significant influencing factors. The case study also illustrates how the framework is utilized to predict the failure

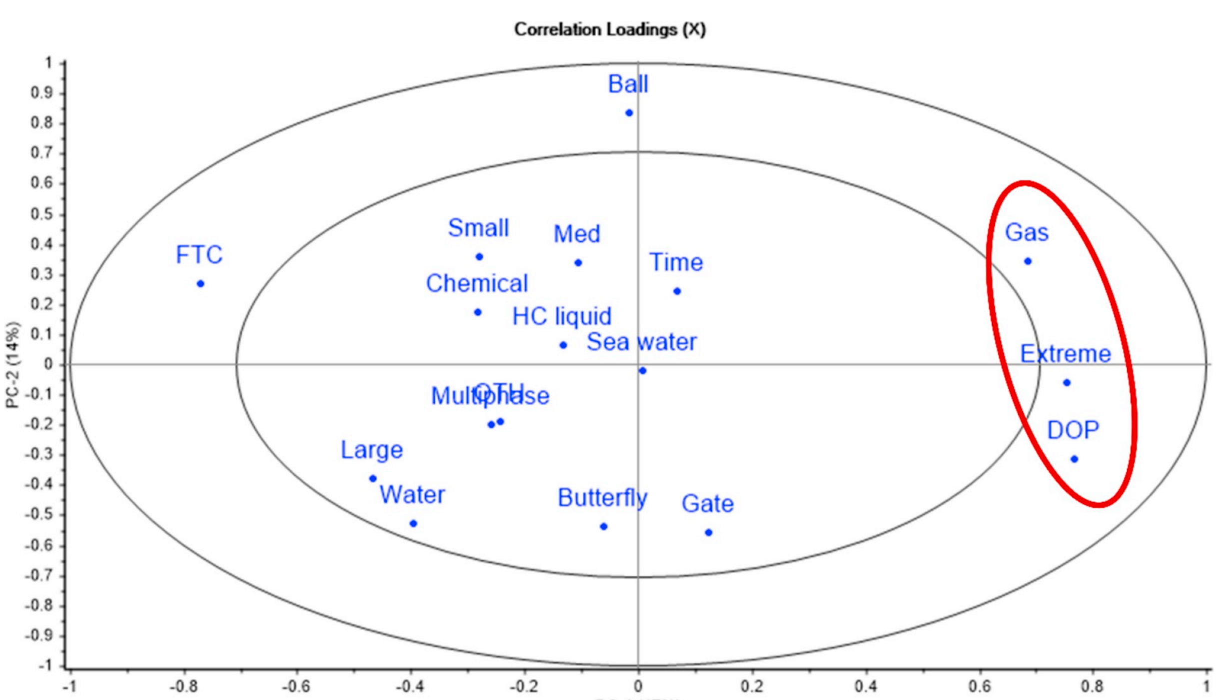

Fig. 6. Correlation loading plot of the valves in PCA with failure modes.

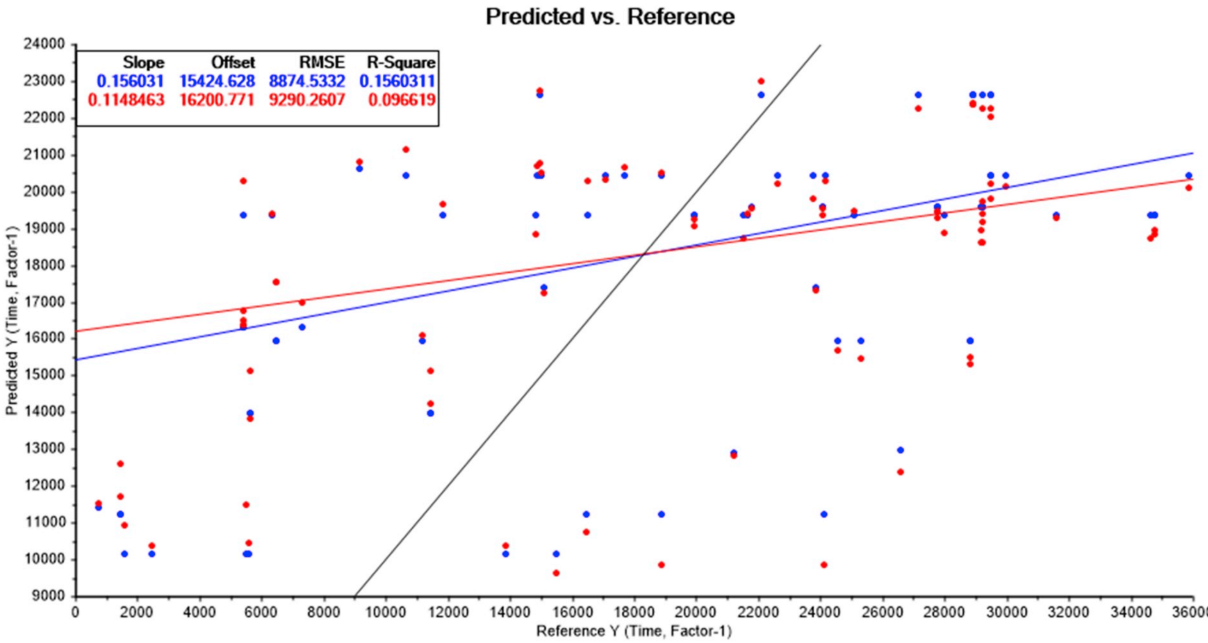

Fig. 7. Predicted plot of the shutdown valves in PLSR.

rates for equipment at a new facility. It can be the basis for reliability improvement programs, optimizing maintenance programs and suggesting subcategories within equipment groups. Prediction of failure rates is the start of risk assessment and the calculation of PFD (Famuyiro, 2018).

Many factors will affect the accuracy of the analysis. The biggest challenge comes from the quality of data, such as lack of data, missing information. Another limitation is the choice of predefined categories for equipment (i.e. attributes) and failures (e.g. failure modes). The selection of these categories strongly depends on the experts' opinion and the information available in the data. The data applied in the case study to identify significant influencing factors is restricted to time to DU failure. This time may be underestimated since DU failures are not revealed immediately. Constant failure rates are also assumed in this paper, which only applies to the failures during the useful life period of operation. Thus, we have disregarded any changes in failure rates during early life and end-of-life.

Table 5
Failure distributions and corresponding failure rates.

Failure mode	No. of DU	Weights	Failure rates $\lambda_{DU,i}$ (per 10^6 hour)
DOP	152	52.0%	4.1
FTC	101	34.6%	2.7
LCP	16	5.5%	0.4
OTH*	23	7.9%	0.6
Total	292	100%	7.9

Note*: OTH represents other failure modes and unknown failure modes.

Further research should involve the comparisons of the effects of different significant influencing factors on various SIS equipment groups to mitigate DU failures. It is relevant to study other influences,

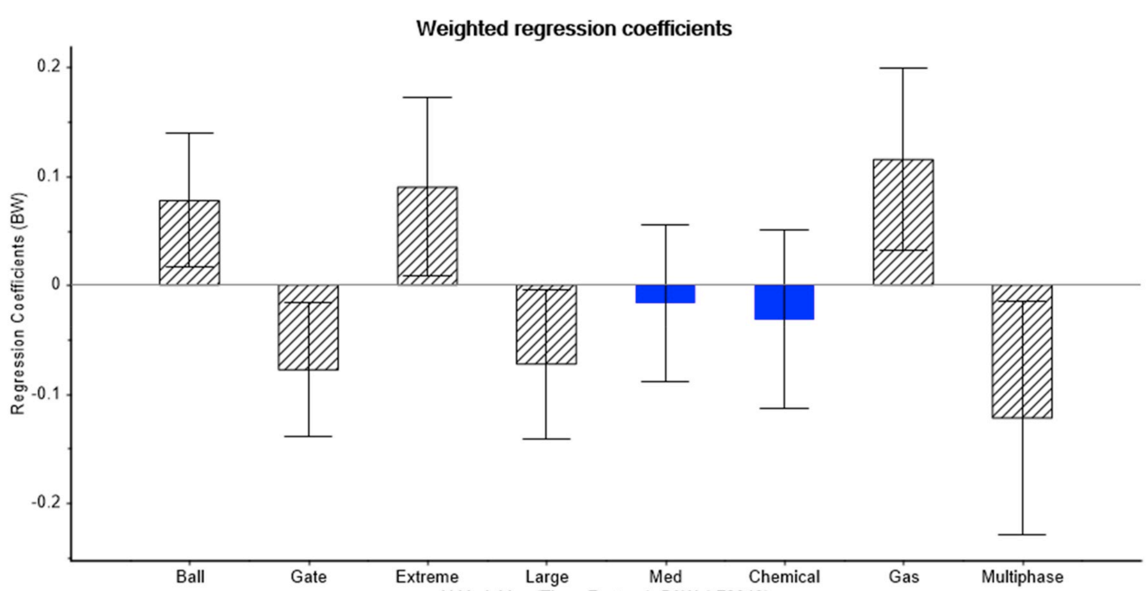

Fig. 8. Weighted regression coefficients of the influencing factors in PLSR.

Table 6
Comparison of the distribution for subcategories.

Brissaud's method					Proposed method in this paper					
λ_{DU}(per 10^6 hours)	Significant Influencing factors	θ_j	σ_j	$\lambda^*_{DU,i}$(per 10^6 hours)	Failure mode	$\lambda_{DU,i}$(per 10^6 hours)	Significant influencing factors	θ_{ij}	σ_{ij}	$\lambda^*_{DU,i}$(per 10^6 hours)
7.9	Size	0.6	1.5	7.1	FTC	4.1	–	–	–	4.1
	Flow medium	0.4	0.7	2.2	DOP	2.7	Size	0.6	1.5	3.2
							Flow medium	0.4	0.7	0.4
					LCP	0.4	–	–	–	0.4
					OTH	0.6	–	–	–	0.6
Prediction				9.3						8.8

such as installation, maintenance and general safety culture, on the prediction of failure rates. Root cause analysis could also be incorporated in the proposed framework from the beginning of the quantification of influencing factors. Other alternative methods, like dynamic principal component analysis and or machine learning, can be considered and their effectiveness needs to be analyzed. Development of a guide for failure rate prediction is also required from an end-users perspective, including validation of predicted values with experienced failure rates. Another issue to be considered is to perform analyses to predict dynamic failure rates in the operation.

Acknowledgment

Thanks to all the participants of the PDS forum (www.sintef.no/pds) that have contributed with data, valuable information, operational experience, expert judgments, and suggestions. Particularly, thanks to SINTEF that have contributed with their knowledge, comments, and discussions. The authors are also pleased to thank the anonymous reviewers for their thoughtful, constructive comments.

Appendix

PCA

PCA is based on the statistic model proposed by Pearson and Hotelling (Hotelling, 1933; Jolliffe, 2011; Pearson, 1901). Such a method can reduce the dimensionality of multivariate to principal components (PCs) with minimal loss of information. In the context of this paper, PCA is used to reduce the dimensionality of the influencing factors, so that significant influencing factors are retained and essential correlation is analyzed more easily.

Influencing factors are defined as the explanatory variables and expressed as $\boldsymbol{X} = [X_1,\ X_2,\ \dots X_n]^T$. Assume m samples of equipment that describe the observed situation relating to various influencing factors and the states of DU failures. '1' represents a situation where a DU failure is detected, whereas '0' represents that there is no DU failures. The matrix $\boldsymbol{X}$ is decomposed into a score matrix $\boldsymbol{T} = [t_1,\ t_2,\ \dots t_n]$ and a loading matrix $\boldsymbol{P}$:

$$\boldsymbol{X} = \boldsymbol{T}\boldsymbol{P}^T + \tilde{\boldsymbol{E}} \tag{3}$$

where $\tilde{\boldsymbol{E}}$ denotes the residual matrix. The score T shows how the DU failures are distributed and how they project along the orthogonal PCs. The loading P reflects the correlations between PCs. Then, the covariance matrix can be expressed as:

$$\boldsymbol{S} = \frac{1}{N-1}\boldsymbol{X}^T\boldsymbol{X} \tag{4}$$

The Eigen-decomposition is performed on $\boldsymbol{S}$ to obtain loading matrix $\boldsymbol{P}$. The Eigenvalues $\boldsymbol{V}$ are denoted as:

$$\mathbf{V} = [\nu_1,\ \nu_2 \dots \nu_l] \tag{5}$$

Then, the ith eigenvalue ν_i, relates to the i^{th} column of the score matrix $\boldsymbol{T}$:

$$\nu_i = \frac{1}{n-1}\,\boldsymbol{t_i}^{\boldsymbol{T}} t_i \tag{6}$$

The highest eigenvalues represent the PCs with the most information and the measurement of the residuals is conducted to contain less covariance.

PLSR

Similarly, PLSR decomposes $\boldsymbol{X}$ and $\boldsymbol{Y}$ matrices into bilinear structure models consisting of scores and loading matrices. The influencing factors are defined as the explanatory variable expressed by $\boldsymbol{X} = [X_1,\ X_2,\ \dots X_n]^T$. The response variables $\boldsymbol{Y} = [Y_1,\ Y_2,\ \dots Y_n]^T$ represents here the time to DU failures. $\boldsymbol{X}$ and $\boldsymbol{Y}$ project from high dimensional spaces to low-dimensional spaces as follows:

$$\boldsymbol{X} = \boldsymbol{T}\boldsymbol{P}^T + \tilde{\boldsymbol{E}} \tag{7}$$

$$\boldsymbol{Y} = \boldsymbol{T}\boldsymbol{Q}^T + \tilde{\boldsymbol{F}} \tag{8}$$

where $\boldsymbol{T} = [t_1,\ t_2,\ \dots t_l]$ are the score vectors, $\boldsymbol{P} = [p_1,\ p_2,\ \dots p_l]$ and $\boldsymbol{Q} = [q_1,\ q_2,\ \dots q_l]$ are the loading for $\boldsymbol{X}$ and $\boldsymbol{Y}$. $\tilde{\boldsymbol{E}}$ and $\tilde{\boldsymbol{F}}$ are PLS residuals corresponding to $\boldsymbol{X}$ and $\boldsymbol{Y}$. The loading weights of $\boldsymbol{P}$ and $\boldsymbol{Q}$ reflect the correlations between $\boldsymbol{X}$ and $\boldsymbol{Y}$ with the purpose of prediction. Then, the PLSR mode can be rewritten as:

$$\boldsymbol{U} = f(\boldsymbol{T}) + \tilde{\boldsymbol{F}}^* \tag{9}$$

where $\boldsymbol{U}$ is a matrix that represents score vectors when $\boldsymbol{Y}$ projects to $\boldsymbol{T}$. $\tilde{\boldsymbol{F}}^*$ denotes the combined residuals from the decomposition. In this study, the nonlinear iterative PLS (NIPALS) algorithm is used. Once all significant components are extracted, the model can then be used to predict new data using the following relationship:

$$\boldsymbol{Y} = \boldsymbol{T}\boldsymbol{Q}^T + \tilde{\boldsymbol{F}} = \boldsymbol{X}\boldsymbol{B} + \tilde{\boldsymbol{F}}^* \tag{10}$$

where $\boldsymbol{B}$ denotes a matrix of regression coefficients. More details of PLS algorithms can be found in the studies introduced by Geladi and Kowalski (1986) and Hoskuldsson (Höskuldsson, 1988).

References

Becker, G., Camarinopoulos, L., 1990. A Bayesian estimation method for the failure rate of a possibly correct program. IEEE Trans. Softw. Eng. (11), 1307–1310.
Brissaud, F., Charpentier, D., Fouladirad, M., Barros, A., Bérenguer, C., 2010. Failure rate evaluation with influencing factors. J. Loss Prev. Process. Ind. 23 (2), 187–193.
Cox, D.R., 1972. Regression models and life-tables. The Royal Statistical Society: Ser. Bibliogr. 34 (2), 187–202.
Elsayed, E., Chan, C., 1990. Estimation of thin-oxide reliability using proportional hazards models. IEEE Trans. Reliab. 39 (3), 329–335.
EXDIA, 2007. Safety Equipment Reliability Handbook. exida.com, Sellersville, PA.
Famuyiro, S., 2018. Use of combustible gas detectors in Safety Instrumented Systems–A practical application case study. J. Loss Prev. Process. Ind. 54, 333–339.
Foucher, B., Boullie, J., Meslet, B., Das, D., 2002. A review of reliability prediction methods for electronic devices. Microelectron. Reliab. 42 (8), 1155–1162.
Geladi, P., Kowalski, B.R., 1986. Partial least-squares regression: a tutorial. Anal. Chim. Acta 185, 1–17.
GL070, 2004. Application of IEC 61508 and IEC 61511 in the Norwegian Petroleum Industry. Stavanger, Norway. Norwegian Oil Industry Association.
Håbrekke, S., Hauge, S., Hoem, Å.S., Lundteigen, M.A., Xie, L., 2017. Modified generic failure rates for safety instrumented systems based on operational experience from the oil and gas industry. In: Europen Safety and Reliability Conference Proceedings, Portorož, Slovenia.
Håbrekke, S., Hauge, S., Xie, L., Lundteigen, M.A., 2018. Failure rates of safety critical equipment based on inventory attributes. In: Europen Safety and Reliability Conference Proceedings, Trondheim, Norway.
Hauge, S., Lundteigen, M.A., 2008. Guidelines for Follow-Up of Safety Instrumented Systems (SIS) in the Operating Phase. SINTEF, Trondheim, Norway.
Höskuldsson, A., 1988. PLS regression methods. J. Chemom. 2 (3), 211–228.
Hotelling, H., 1933. Analysis of a complex of statistical variables into principal components. J. Educ. Psychol. 24 (6), 417.
IEC60050, 1990. International Electrotechnical Vocabulary. International Electrotechnical Commission, Geneva.
IEC61508, 2010. Functional Safety of Electrical/electronic/programmable Electronic Safety-Related Systems. International Electrotechnical Commission, Geneva.
IEC61511, 2016. Functional Safety-Safety Instrumented Systems for the Process Industry Sector. International Electrotechnical Commission, Geneva.
IEC61709, 2017. Electronic Components–Reliability–Reference Conditions for Failure Rates and Stress Models for Conversion. International Electrotechnical Commission, Geneva.
ISO14224, 2006. Petroleum, Petrochemical and Natural Gas Industries: Collection and Exchange of Reliability and Maintenance Data for Equipment. International Organization for Standardization, Geneva.
Jolliffe, I., 2011. Principal component analysis. In: International Encyclopedia of Statistical Science. Springer, Berlin, Heidelberg, pp. 1094–1096.
Kutyłowska, M., 2015. Neural network approach for failure rate prediction. Eng. Fail. Anal. 47, 41–48.
Li, G., Qin, S.J., Yuan, T., 2016. Data-driven root cause diagnosis of faults in process industries. Chemometr. Intell. Lab. Syst. 159, 1–11.
MIL-HDBK-217F, 1995. Reliability Prediction of Electronic Equipment. U.S. Department of Defense, Washington, DC.
Newby, M., 1994. Perspective on Weibull proportional-hazards models. IEEE Trans. Reliab. 43 (2), 217–223.
OREDA, 2015. Offshore and Onshore Reliability Data Høvik, Norway: OREDA Participants.
Pearson, K., 1901. LIII. On lines and planes of closest fit to systems of points in space. The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science 2 (11), 559–572.
Qin, S.J., 2012. Survey on data-driven industrial process monitoring and diagnosis. Annu. Rev. Contr. 36 (2), 220–234.
Ratkowsky, D., Olley, J., McMeekin, T., Ball, A., 1982. Relationship between temperature and growth rate of bacterial cultures. J. Bacteriol. 149 (1), 1–5.
Rausand, M., 2014. Reliability of Safety-Critical Systems: Theory and Applications. John Wiley & Sons, Hoboken, New Jersey, USA.
Rausand, M., Høyland, A., 2004. second ed. System Reliability Theory: Models, Statistical Methods, and Applications, vol. 396 John Wiley & Sons, Hoboken, New Jersey, USA.
SINTEF, 2013a. Reliability Data for Safety Instrumented Systems, PDS Data Handbook. SINTEF, Trondheim, Norway.
SINTEF, 2013b. Reliability Prediction Method for Safety Instrumented Systems, PDS Method Handbook. SINTEF, Trondheim, Norway.
TelcordiaSR-332, 2001. Reliability Prediction Procedure for Electronic Equipment. Piscataway, N. J: Telcordia.
Tidriri, K., Chatti, N., Verron, S., Tiplica, T., 2016. Bridging data-driven and model-based approaches for process fault diagnosis and health monitoring: a review of researches and future challenges. Annu. Rev. Contr. 42, 63–81.
Vatn, J., 2006. Procedures for updating test intervals based on experience data. In: The 30th ESReDA Proceedings, Ispra, Italy.