

## Offshore release data – trends in underlying causes

Maria Koutsoudaki <sup>a</sup>, Brian Bain <sup>b</sup>, Nijs Jan Duijm <sup>a,b</sup>, Igor Kozine <sup>a</sup>

<sup>a</sup>Technical University of Denmark DTU, Dept. of Management Engineering

<sup>b</sup>DNV GL Oil & Gas

Risk analysis for hydrocarbon hazards in the offshore oil & gas industry depends on data relating to loss of containment events. The UK HSE Hydrocarbon Release Database (HCRD) is one of the main sources of that information. Recent examination of the HCRD shows a decrease in the annual number of releases. This raises the question whether the decrease is due to specific causes, because this would affect whether the latest release rates would be applicable to all installations or only to certain categories e.g. newly built installations.

To this aim, a study was carried out to determine whether significant trends are apparent when categorizing releases by specific cause. The data in the HCRD was processed in order to distinguish between the main causal factors: “Equipment”, “Design” and “Procedure”. It was necessary to set up clear schemes to translate the recorded data on causes into the above three categories in an unambiguous way.

The assessment looked at relative trends, i.e. it was investigated whether the relative contribution of some causes as compared to all releases, had changed over time. This avoided the necessity to consider changes in e.g. population data (number of installations and components) and generally provide more robust conclusions.

The main conclusion is that the relative contribution of “Procedures” as a cause for release has significantly decreased. “Design” seems to lead to a reduction in releases too, despite appearing to be improving at a slower rate than the procedures. Finally, “Equipment” was improving at the slowest rate, if at all, until 2003. Since then, it has been improving at a noticeable rate. Sensitivity assessments support that these findings are significant and robust.

The conclusions suggest that, when considered over the period for which data was available, improvements in offshore safety have been mainly driven by improvements in management, covering elements like procedures, competence and compliance.

### Introduction

Risk analysis for the offshore oil and gas industry is dependent on information from historic loss of containment events. Nowadays, the Hydrocarbon Release Database (HCRD), based on reporting from the offshore operators in the UK-sector of the North Sea, has become the standard source of release frequencies for offshore quantitative risk assessment (QRA) (Spouge, 2006). Recent examination of the HCRD shows a decrease in the annual number of releases (Bain, 2017). The population of equipment has generally grown over the same period, so the frequency of incidents based on equipment appears to have been falling at an even faster rate (Bain, 2017). This raises the question: Do all underlying causes improve at the same rate or is the declining of release rates caused mainly by the improvement of a specific underlying cause or a fraction of them? The answer to this question is important in decision-making over risk assessments of offshore installations and, to find it, an analysis of the HCRD from 1993 up until 2014 was conducted.

The first step of the analysis was to review all entries of the HCRD, especially those that referred to the failure modes that resulted in the release incident. Reporting criteria have changed during the HCRD’s years of operation; an incident which was reported in the past may not meet the current criteria. For this reason, two different datasets were analyzed in the present project: The first dataset included all accidental releases ever reported (“All” dataset), and the second dataset included only the accidental releases meeting the current guidelines (“Reportable” dataset) (Oil & Gas UK, 2015).

A classification algorithm that could uniquely categorize the various HCRD incidents regarding their cause was derived; it was based on the reporting method of the various failure modes of the incidents.

The algorithm was then used to classify the incidents in the two datasets; plotting the number of incidents within each category indicated that leaks due to all causal categories were declining with time. However, there is some uncertainty in the population data so it could be that this change is due to the number of installations in operation. Hence, to find relative trends, the annual number of incidents in each category divided by the identified annual incidents versus time were plotted. This step was very important as it had the potential to reveal a possible shift in the causes of incidents. Indeed, certain patterns appeared to emerge and an appropriate statistical method (regression analysis) was used to test the results.

The paper is organized as follows. Section 1 describes the history and “Cause of Leak” data of the HCRD, while Section 2 presents the logic behind the creation of the two analyzed datasets. Section 3 presents the basic mathematics of the statistical analysis; while Section 4 explains the classification algorithm used and provides the results. Section 5 is an alternative analysis of the data by using running averages and Section 6 expands on the interpretation of the obtained results and conclusions based on them.

### History of HCRD & “Cause of Leak” data

#### History of the HCRD

At the time of the Piper Alpha disaster (July 1988), there was a scarcity of information concerning the loss of containment events in the offshore sector and, in response to a recommendation from the Cullen Enquiry which followed the disaster, the

Hydrocarbon Releases Database was created (Bruce, 1994). The aim was for the industry to learn from past mistakes and improve safety by having a better understanding of the causes of leaks, so that preventive maintenance could be undertaken (Goff, 2016).

Hence, in April 1991, the Health and Safety Executive, Offshore Safety Division (HSE-OSD) issued two new reporting forms:

- i) the OIR/9B in which the basic incident data were reported, and submission of which was a legal requirement by the Reporting of Incidents Diseases and Dangerous Occurrences (RIDDOR) and
- ii) the OIR12 in which the supplementary data were reported on a voluntary basis (Bruce, 1994) (Bain et al, 2016). Despite the submission being voluntary, the offshore industry effectively regarded it mandatory and compliance was high (Bain et al, 2016).

The first completed forms were received by HSE-OSD in early October 1992, so the start date of the HCRD was decided to be the 1st of October 1992 (Bruce, 1995).

Relatively soon, it became apparent that there was not enough guidance as to what size of release was considered reportable or not. Thus, in 1996, the HSE provided the earliest clarification to the requirements under RIDDOR in OTO 96 956 “Revised guidance on Reporting of Offshore Hydrocarbon Releases” (HSE, 1996). Still, the criteria for reporting were subjective enough to result in inconsistency in the severity of events which operators considered reportable (Bain et al, 2016). This resulted in further guidance from Oil & Gas UK (OGUK) who, in 2008 and in collaboration with the HSE, issued the “Supplementary Guidance for Reporting Hydrocarbon Releases, Issue 1”, where the first actual mass limitations for which releases were considered reportable under RIDDOR were provided (OGUK, 2008) (Bain et al, 2016). However, in 2014, the limitations were revised again (“Supplementary guidance on the RIDDOR Reporting of Hydrocarbon Releases”) (Bain et al, 2016).

In October 2014, as a direct result of the Deepwater Horizon oil spill (April 2010), the “Commission implementing regulation (EU) No 1112/2014” was introduced by the European Union (EU). To comply with the requirements of this regulation, the OIR/9B and OIR12 forms were replaced with the “Reporting of an Oil and Gas Incident Form” (ROGI) which is now in use. The OGUK guidance was further revised to include the EU reporting criteria (OGUK, 2015).

Loss of containment incidents now require to be reported if they meet either the criteria for a RIDDOR reportable incident or those of the EU. A convenient way to summarize all these regulations for natural gas and crude oil releases is presented in Figure 1 (Bain et al, 2016). A timeline of the HCRD history with respect to reporting guidance is presented in Figure 2.

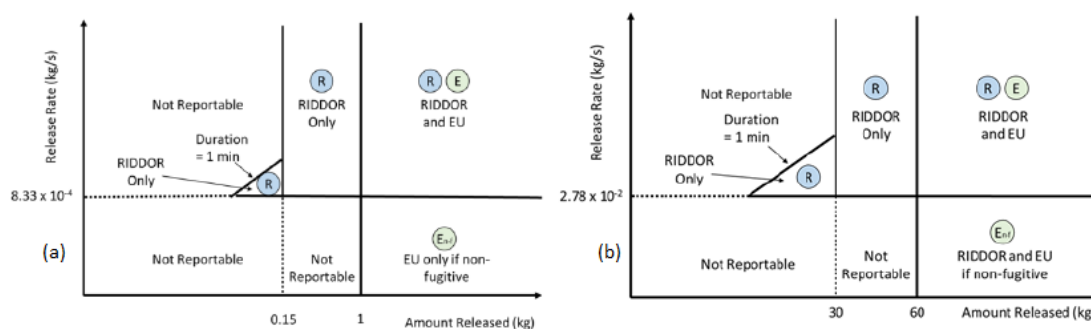
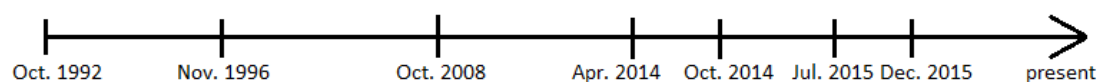


Figure 1:

RIDDOR and EU reporting criteria for (a) gas releases and (b) oil releases (Bain, 2017)



Oct. 1992: Beginning of HCRD.

Nov. 1996: HSE publishes the “Revised guidance on Reporting of Offshore Hydrocarbon Releases”.

Oct. 2008: OGUK publishes the “Supplementary guidance for Reporting Hydrocarbon Releases, Issue 1”.

Apr. 2014: OGUK publishes the “Supplementary guidance on the RIDDOR Reporting of Hydrocarbon Releases”.

Oct. 2014: EU publishes the “Commission implementing regulation (EU) No 1112/2014”.

Jul. 2015: OGUK & HSE issue the ROGI reporting form.

Dec. 2015: OGUK publishes the “Supplementary guidance on the Reporting of Hydrocarbon Releases”.

Figure 2: Timeline of the HCRD history

### “Cause of Leak” data

The “Cause of leak” part of the OIR12 reporting form is presented in Figure 3. To identify whether there is a trend in the underlying causes of HC releases in the offshore UK sector up until 2014, the data arising from the entries in this part were analyzed; the causes of failures are divided into four main categories; “Design”, “Equipment”, “Operation” and “Procedural”, and each category has one or more sub-categories (HSE, 2010). It should be noted that the reporting personnel can identify more than one of the categories as contributor to the failures, thus the reporting form is not requiring a unique categorization. The ROGI reporting form (HSE, 2017) has retained the same four main categories (“Design”, “Equipment”, “Operation” and “Procedural”).

**CAUSE OF LEAK CHECK LIST** (SEE “CAUSE OF LEAK”. ITEM 13. ON PAGE 3)

(Please indicate those items which come nearest to identifying the cause of the leak)  
(Choose one parameter from each of the following categories, and tick appropriate boxes)

**(a) DESIGN:**

- FAILURE RELATED TO DESIGN  
 NO DESIGN FAILURE

**(b) EQUIPMENT:**

- CORROSION: INTERNAL  EXTERNAL   
 MECHANICAL FAILURE FATIGUE  WEAROUT   
 EROSION  
 MATERIAL DEFECTS  
 OTHER (Specify)   
 NO FAILURE IN THE EQUIPMENT ITSELF

**(c) OPERATION:**

- INCORRECTLY FITTED  
 IMPROPER MAINTENANCE INSPECTION  TESTING  OPERATION   
 DROPPED OBJECT OTHER IMPACT   
 LEFT OPEN  
 OPENED WHEN CONTAINING HC  
 OTHER (Specify)   
 NO OPERATIONAL FAILURE

**(d) PROCEDURAL:**

- NON - COMPLIANCE WITH PROCEDURE PERMIT TO WORK   
 DEFICIENT PROCEDURE  
 OTHER (Specify)   
 NO PROCEDURAL FAILURE

Figure 3: “Cause of leak” part of OIR12 reporting form (HSE, 2010)

**Creation of the two datasets**

Data from the OIR/9B and OIR12 reporting forms are collated in the HCRD work sheet (in Excel format) provided by HSE in their website (HSE, 2016). The “Offshore Hydrocarbon Releases 1992 – 2016” file (hsr1992-2014.xls) contains all the information reported until December 2015.

For the present study, it was decided that the 1992 data year should be left out as the bigger part of the year is missing (since the start date of the HCRD is the 1st of October 1992). Furthermore, the deliberate releases that were reported due to them accidentally igniting were also excluded (Bain, 2017).

However, due to the changing regulations concerning the HCRD as to which incidents were considered reportable, a second, better-defined, more consistent dataset was necessary. Thus, a filtered set, based on mass released and release rate criteria shown in Figure 1 was created; this set excluded the incidents that wouldn’t be reported by current criteria. Furthermore, to make the second dataset as consistent as possible, all incidents falling in the “reportable only if non-fugitive” regions of Figure 1, have been assumed as non-fugitive and were thus, included in the second dataset. So, two sets of data were analyzed in the present project:

1. 4528 accidental releases that comprise the “All” dataset and
  2. 3277 accidental releases that fulfil the current RIDDOR or EU criteria that comprise the “Reportable” dataset.
- As a result, the “All” dataset had the advantage of including a greater number of incidents, whereas the “Reportable” dataset had the advantage of consistency. The number of incidents versus year for both datasets is presented in Figure 4.

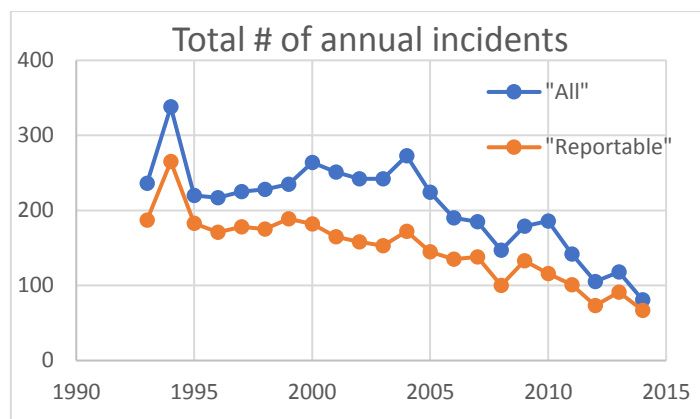


Figure 4: Number of annual incidents for the “All” and “Reportable” datasets

It can be seen that there has been a significant reduction in the rate of incidents occurring over the period covered by the analysis.

## Regression analysis theory

### Simple linear regression analysis

Since the aim was to examine whether there is a relation between the number of incidents in a category and time, simple linear regression statistical analysis was used. It determines a linear relationship between two variables of a dataset (time and number of incidents), and then parameterizes it. A linear relationship between  $n$  pairs of measurements  $(x_1, y_1), (x_2, y_2), \dots (x_n, y_n)$ , is represented by a “regression line” that is representative of the general trend of the data:

$$y = \alpha_0 + \alpha_1 * x \quad (1)$$

To calculate the intercept  $\alpha_0$  and the slope  $\alpha_1$ , the method of least squares is used (Heumann, 2017).

A measure of how well the regression line fits the points is the criterion for the goodness of fit,  $R^2$  (Heumann, 2017):

$$R^2 = \frac{\sum[(\alpha_0 + \alpha_1 x_i) - \bar{y}]^2}{\sum(y_i - \bar{y})^2} \quad (2)$$

### Two-sided hypothesis $t$ -test

After acquiring the equation of the regression line (equation 1), it is also important to test whether its slope,  $\alpha_1$  is statistically significant. Since there is only one independent variable (variable  $x$ ) and only one assumed dependent variable (variable  $y$ ), a  $t$ -test can be used to examine whether there is a statistically significant relationship between the two variables or not (Montgomery, 2013).

Thus, the effort is to disprove the null hypothesis,  $H_0$  that usually states that the slope is equal to zero:  $H_0: \alpha_1 = 0$ .

As a result, the alternate hypothesis,  $H_1$  is:  $H_1: \alpha_1 \neq 0$ .

This translates to a two-tailed  $t$ -test and the null hypothesis will be rejected if its probability (P-value) is less than the significance level, taken as 5%. Thus, there is statistical evidence that the slope is not zero. Instead, if the P-value of the slope is bigger than the significance level, then the null hypothesis is not rejected, meaning there is no statistical evidence that there is a relationship between the two variables.

## Classification algorithm

### Presentation of classification algorithm

As seen already, the taxonomy used in the HCRD has four primary categories “Design”, “Equipment”, “Operation” and “Procedural”. However, very often, a combination of two or more factors is responsible for a release, and thus, it is difficult to apportion the failure to a single cause. For example, some failures, classified as corrosion failures, are caused by overstressing the pipeline in corrosive environment (de la Mare, 1980). To allow for this, an algorithm that will manage the unique classification of all the incidents is required.

Furthermore, after a careful analysis of the HCRD entries, it appeared that the “Operation” category was often not considered a causal factor on its own as on many occasions it was combined with either the “Procedural” category or the “Equipment” category. For example, an “Opened when containing HC” entry in the “Operation” category would often be combined with a “Deficient procedure” entry in the “Procedural” category, or an “Improper maintenance” entry in the “Operation” category would often be combined with an equipment failure. For this reason, the classification algorithm was primarily focused on the “Design”, “Equipment” and “Procedural” categories.

Since the main objective was to understand whether the equipment or the management of the installation is more important in deciding which risk assessment data to use, the “Equipment” category was considered the central one for the newly-introduced classification algorithm. Thus, the new classification was based on whether there was an equipment failure or not. This decision led to two meta-categories: The “YESEQUIP” meta-category if there was an equipment failure, and the “NOEQUIP” meta-category if there was not an equipment failure.

The meta-category “YESEQUIP” includes all incidents where equipment failure was a contributing factor and consists of the newly-introduced categories: “DEStoEQUIP”, “PROctoEQUIP”, “BOTHtoEQUIP” and “EQUIP”. “NOEQUIP” includes those incidents where equipment failure was not a contributing factor: “DES”, “PROC”, “BOTH” and “OPER”. All eight categories, along with the two meta-categories, are presented in Table 1.

Table 1: The categories and meta-categories of the newly-introduced classification algorithm

Meta-category	Category	Description
YESEQUIP	DEStoEQUIP	If the equipment failed due to bad design, then the loss of containment incident was categorized as “DEStoEQUIP”. For example, an incident that occurred because the equipment corroded due to wrong materials (bad design), would fall under this category.
	PROctoEQUIP	If the equipment lost containment due to a procedural failure, as for example, a worker forced a pipe into a space which was too small, and this resulted in the fracture of the pipe, then the incident would fall under the “PROctoEQUIP” category.
	BOTHtoEQUIP	If the equipment failed due to both a bad design and a procedural failure, then the incident was categorized as “BOTHtoEQUIP”. For example, an incident that was caused by a bad fitting (bad design) between two pipes, which was ignored by the workers connecting the pipes (quality control), and which resulted in the pipes’ mechanical failure, would fall under this category.
	EQUIP	If the equipment alone had failed and there wasn’t a design or a procedural failure that led to the equipment failure, then the incident was categorized as “EQUIP”. For example, a flange which eroded due to long-term use, would fall under this category.
NOEQUIP	DES	If the design was the cause of the release, then the incident was categorized as “DES”. For example, a leak caused by inappropriate pipe specification, would fall under this category.
	PROC	If the procedure was the cause of the release. For example, if a worker left a valve open in accordance with a procedure, the release would be categorized as “PROC”.
	BOTH	If the release occurred due to both a bad design and a procedural failure, then the incident was categorized as “BOTH”. For example, an incident that was caused by a bad fitting (bad design) between two pipes, which should have been noticed by the workers (quality control), would fall under this category.
	OPER	If the only failure noted was “Operation”, then the incident would be categorized as “OPER”. Such an example would be an incident that happened due to breaking of containment while HC were present in a vessel (“opened when containing HC” entry).

It is important to note that the OPER category was the only one where incidents with “Operation” failures were considered. Meaning, if neither “Equipment” nor “Design” nor “Procedural” failures were reported, then and only then was the “Operation” category taken into consideration. As a result, and also due to the “Operation” category being often combined with the “Procedural” category or the “Equipment” category, many of the operational causes were absorbed by the rest of the categories.

The logic of the newly-created classification algorithm can be easily summed up in the following table (Table 2).

Table 2: Logic of newly-introduced classification algorithm

Meta-category	Category	Equipment	Design	Procedural	Operation
YESEQUIP	EQUIP	X	-	-	Disregarded
	DEStoEQUIP	X	X	-	Disregarded
	PROctoEQUIP	X	-	X	Disregarded
	BOTHtoEQUIP	X	X	X	Disregarded
NOEQUIP	OPER	-	-	-	X
	DES	-	X	-	Disregarded
	PROC	-	-	X	Disregarded
	BOTH	-	X	X	Disregarded

Due to the structure of the classification algorithm, six categories can be used to create three bigger categories:

- I. If DES<sub>to</sub>EQUIP and DES are summed, the bigger category “DES\*2” is created.
- II. If PROC<sub>to</sub>EQUIP and PROC are summed, the bigger category “PROC\*2” is created.
- III. If BOTH<sub>to</sub>EQUIP and BOTH are summed, the bigger category “BOTH\*2” is created.

Concerning the details of the classification algorithm, the incidents with entries from the OIR12 reporting form were all included except for the particular case of incidents with “Other (Specify)” entries in the “Equipment”, “Procedural” or “Operation” categories. In such cases, incidents that had entries which indicated a degree of uncertainty as to the cause (such as “Other – Not known” or “Other – Awaiting investigation”, etc.) were dismissed as Unknown. Instead, the simple “Other” entries were included. Furthermore, in the “Procedural” category, the “Other – Quality control” entry that was often encountered was also included.

Boolean algebraic formulae (3-10) were used to *Table 3: The Boolean codes of the possible HCRD entries*

express the combination of the categories to unambiguously classify the combination into one aggregated category. In Table 3 the equivalences between the possible HCRD entries and their codes are presented. The symbol  $\wedge$  is used for the logical “and” operator.

$$\text{EQUIP} = B \wedge C \wedge H \quad (3)$$

$$\text{DES}_{\text{to}}\text{EQUIP} = A \wedge C \wedge H \quad (4)$$

$$\text{PROC}_{\text{to}}\text{EQUIP} = B \wedge C \wedge G \quad (5)$$

$$\text{BOTH}_{\text{to}}\text{EQUIP} = A \wedge C \wedge G \quad (6)$$

$$\text{DES} = A \wedge D \wedge H \quad (7)$$

$$\text{PROC} = B \wedge D \wedge G \quad (8)$$

$$\text{BOTH} = A \wedge D \wedge G \quad (9)$$

$$\text{OPER} = B \wedge D \wedge E \wedge H \quad (10)$$

Thus, the classification algorithm doesn't differentiate:

a) between different equipment failures (e.g.: corrosion and mechanical wear out), and

b) between inappropriate procedures and staff competence and compliance.

Possible HCRD entries	Codes	
Failure related to design	A	
No design failure	B	
Corrosion internal	C	
Corrosion external		
Mechanical failure		
Mechanical fatigue		
Mechanical wearout		
Erosion		
Material defects		
Other equipment failure	D	
No failure in the equipment itself		
Incorrectly fitted		E
Improper maintenance		
Improper inspection		
Improper testing		
Improper operation		
Dropped object		
Other impact		
Left open		F
Opened when containing HC		
Other operational failure		
No operational failure		
Non-compliance with procedure	G	
Non-compliance with permit to work		
Deficient procedure		
Other – Quality control		
Other procedural failure		
No procedural failure	H	

### Results of classification algorithm

After implementing the classification algorithm on both sets of data, the numerical results are presented in Tables 4 and 5. Moreover, the number of annual unknown incidents (noted with “Unknown”), as well as the percentage of annual unknown incidents (noted with “Unknown/Total”) are also presented.

Table 4: Results of the classification algorithm for the “All” dataset.

Year	Unknown	EQUIP	DES <sub>to</sub> EQUIP	PROC <sub>to</sub> EQUIP	BOTH <sub>to</sub> EQUIP	PROC	DES	BOTH	OPER	Total	Unknown/Total (%)
1993	15	100	22	19	1	54	5	4	16	236	6.36
1994	13	150	33	30	5	55	8	15	29	338	3.85
1995	19	85	17	22	3	39	5	2	28	220	8.64
1996	5	82	22	17	8	37	7	3	36	217	2.30
1997	7	112	17	11	5	37	1	2	33	225	3.11
1998	20	101	22	7	6	30	6	1	35	228	8.77
1999	11	107	24	15	2	31	7	4	34	235	4.68
2000	14	115	23	14	2	40	13	2	41	264	5.30
2001	16	125	20	12	3	41	3	2	29	251	6.37
2002	11	120	23	12	2	43	1	2	28	242	4.55

2003	7	146	13	12	2	38	1	4	19	242	2.89
2004	11	153	36	13	3	38	2	2	15	273	4.03
2005	1	131	25	16	2	20	2	4	23	224	0.45
2006	3	108	22	19	2	23	0	1	12	190	1.58
2007	4	108	16	24	1	17	1	1	13	185	2.16
2008	4	79	12	13	2	13	2	5	17	147	2.72
2009	6	109	9	18	2	26	2	2	5	179	3.35
2010	2	106	11	9	2	27	4	2	23	186	1.08
2011	2	77	8	10	2	24	1	2	16	142	1.41
2012	6	46	11	15	3	13	2	2	7	105	5.71
2013	0	62	8	13	1	18	4	3	9	118	0.00
2014	5	37	1	15	2	9	1	3	8	81	6.17
Total	182	2259	395	336	61	673	78	68	476	4528	4.02

Table 5: Results of the classification algorithm for the “Reportable” dataset.

Year	Unknown	EQUIP	DES to EQUIP	PROC to EQUIP	BOTH to EQUIP	PROC	DES	BOTH	OPER	Total	Unknown / Total (%)
1993	10	81	19	15	0	44	4	4	10	187	5.35
1994	11	110	26	29	4	45	7	12	21	265	4.15
1995	13	71	15	20	2	35	4	2	21	183	7.10
1996	5	59	15	14	8	29	7	3	31	171	2.92
1997	6	88	12	8	3	29	1	2	29	178	3.37
1998	18	70	17	6	6	27	5	1	25	175	10.29
1999	8	77	19	14	2	28	6	4	31	189	4.23
2000	10	80	15	10	2	30	7	1	27	182	5.49
2001	11	75	14	9	2	33	2	1	18	165	6.67
2002	7	75	12	7	2	34	1	2	18	158	4.43
2003	7	81	8	9	1	29	1	3	14	153	4.58
2004	8	87	25	9	1	26	2	2	12	172	4.65
2005	1	79	18	12	2	16	0	3	14	145	0.69
2006	3	71	18	14	2	17	0	0	10	135	2.22
2007	3	80	13	16	1	14	1	1	9	138	2.17
2008	3	47	12	7	2	12	2	5	10	100	3.00
2009	5	71	8	15	2	24	2	2	4	133	3.76
2010	1	63	5	7	2	19	3	2	14	116	0.86
2011	2	46	5	9	2	20	1	2	14	101	1.98
2012	5	30	6	11	3	9	2	2	5	73	6.85
2013	0	48	7	11	1	13	3	3	5	91	0.00
2014	3	32	1	13	2	8	0	3	5	67	4.48
Total	140	1521	290	265	52	541	61	60	347	3277	4.27

It was clear that over the whole period, the EQUIP category contains the greatest number of incidents, whereas the BOTH and BOTHtoEQUIP categories have the least.

The annual number of incidents of all eight categories has been decreasing throughout the period for both datasets. To find a trend in the underlying causes of releases, a more complex analysis was needed. For this reason, the number of annual incidents of each category was divided by the number of annual identified incidents (Total minus the Unknown); this way, the fluctuation of the “share” of each category was acquired and it was now possible to compare them. This approach also offered the advantage of not requiring the equipment population data. The figures for the proportions of all categories, bigger categories and meta-categories versus time were plotted and the figures of EQUIP and PROC categories and of the NOEQUIP meta-category are presented (Figures 5, 6 and 7 respectively).

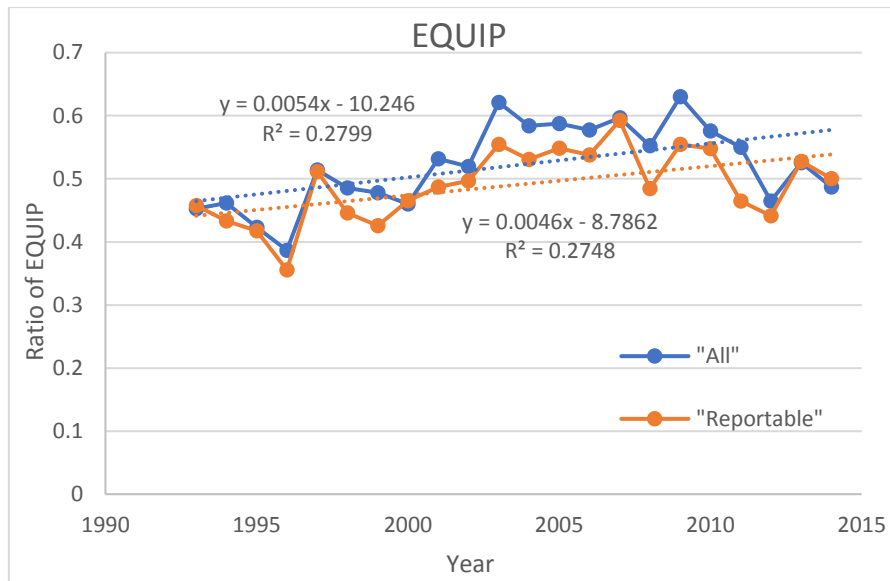


Figure 5: Ratio of EQUIP category divided by the number of identified incidents versus time for both datasets

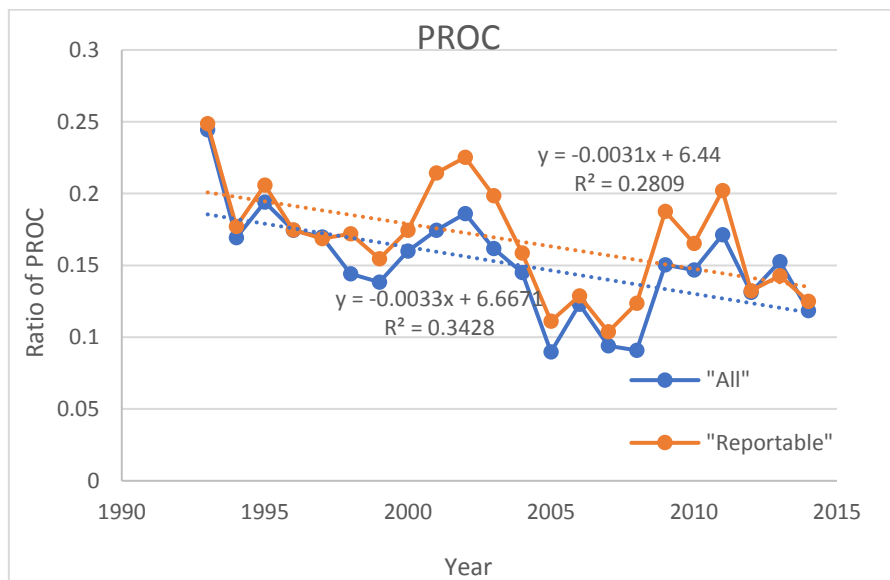


Figure 6: Ratio of PROC category divided by the number of identified incidents versus time for both datasets



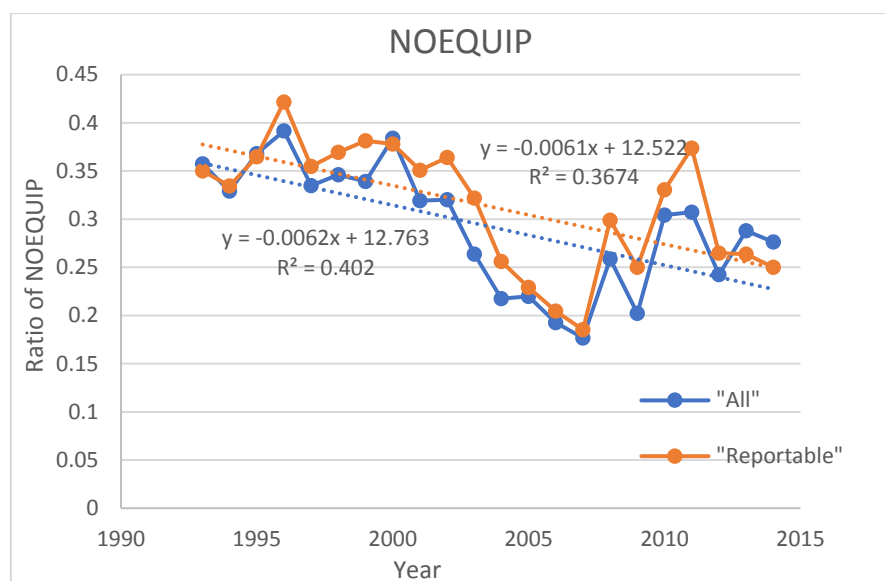


Figure 7: Ratio of the NOEQUIP meta-category divided by the number of identified incidents versus time for both datasets

It was revealed that for both data sets, the ratio of the EQUIP category to the identified incidents was increasing (positive slope), whereas for PROC, DES and OPER categories, it was decreasing (negative slope). As a result, the regression line of the ratio of the NOEQUIP meta-category had a negative slope, whereas of the YESEQUIP meta-category a positive slope.

The statistical significance of the slopes of the regression lines was then tested. To avoid confusion, and state one null and one alternate hypothesis that corresponded to all categories, the slopes were tested with a two-sided  $t$ -test. So, for all the slopes, the null hypothesis was that the slope was equal to zero:  $H_0: \alpha_1 = 0$  and the alternate hypothesis was that the slope was different from zero:  $H_1: \alpha_1 \neq 0$ . The significance level was decided to be 0.05 and the results are presented in Table 6.

For both datasets, the EQUIP category has P-values quite smaller than 0.05, meaning there is statistical evidence that the slopes of the regression lines are indeed positive. Hence, it appears that the equipment has been improving at the slowest rate when considered over the whole period of analysis.

Since the DES\*2 for both datasets and the DESStoEQUIP for the “All” dataset have statistically significant negative slopes, whereas the DES category for both datasets and the DESStoEQUIP for the “Reportable” dataset have P-values greater than 0.05, it was concluded that the design has partly contributed to the reliability improvement.

Furthermore, for both datasets, for the categories PROC and OPER, there is statistical evidence that the slopes are negative. Meaning, that reduction in the rate of loss of containment incidents in offshore installations has been more pronounced for those incidents relating to procedural problems.

Table 6: The slopes of the category ratios & their P-values for both the “All” and “Reportable” datasets. The P-values that are less than 0.05 (meaning the slopes are statistically significant) are noted with a bold font.

	“All”		“Reportable”	
	Slope, $\alpha_1$	P-value	Slope, $\alpha_1$	P-value
EQUIP	0.005374	<b>0.011356</b>	0.004630	<b>0.012265</b>
DESStoEQUIP	-0.001967	<b>0.030511</b>	-0.001784	0.096914
PROCtoEQUIP	0.002868	<b>0.026325</b>	0.002956	<b>0.024801</b>
BOTHtoEQUIP	-0.000050	0.870171	0.000291	0.493067
PROC	-0.003252	<b>0.004199</b>	-0.003131	<b>0.011182</b>
DES	-0.000556	0.208004	-0.000617	0.171864
BOTH	0.000264	0.499732	0.000568	0.237311
OPER	-0.002680	<b>0.041183</b>	-0.002914	<b>0.040824</b>
DES*2	-0.002523	<b>0.013301</b>	-0.002401	<b>0.040969</b>
PROC*2	-0.000384	0.804649	-0.000174	0.907996
BOTH*2	0.000213	0.688165	0.000859	0.215147
YESEQUIP	0.006224	<b>0.001532</b>	0.006094	<b>0.002789</b>
NOEQUIP	-0.006224	<b>0.001532</b>	-0.006094	<b>0.002789</b>

The two datasets were also analyzed with two more, “stricter” classification algorithms that also followed the logic presented in Tables 1 and 2. These algorithms were “stricter” in the sense that neither were accepting the “Other” entries and, furthermore, one of them was never disregarding the “Operation” category. Both of those algorithms led to similar conclusions

as the presented classification algorithm, especially concerning the EQUIP and PROC categories and the YESEQUIP and NOEQUIP meta-categories. However, the PROCtoEQUIP category had negative slopes instead of positive (Koutsoudaki, 2018), thus, it was concluded that the statistical significance of the slopes of the PROCtoEQUIP category is probably random.

### Review of Data Using Running Averages

An alternative way of viewing trends would be to use running averages. In this approach the number or proportion of incidents is averaged over a period of a number of years in order to smooth out the stochastic variation in the number of incidents reported in a given year and reveal the general trend. This is a less precise mathematical treatment but has the advantage of showing whether changes in the rate of incidents occurring have been consistent over the period or have themselves varied with time. In this study an averaging period of 5 years was considered appropriate for this purpose.

The data for “All” and “Reportable” was analyzed and a number of graphs were produced. In producing these, an estimate of the actual number of incidents in each year was obtained by redistributing the incidents of unknown cause into the categories in the same proportions as for the incidents of known category. Hence, for example, in 2001 there were 16 incidents of unknown cause out of a total of 251 reported incidents. Of the 235 with reported causes, 125 were in the EQUIP category which accounted for 53.2%. Assuming that this proportion is also true of the 16 “unknown” incidents then a notional 8.5 should also have been given this category resulting in an adjusted estimate of 133.5. Similarly, the estimated numbers in the other categories were also increased such that the total matched the total number of reported incidents.

Figure 8 shows the variation of the number of incidents by category for “All” incidents over time while Figure 9 shows the same information expressed as a proportion of the incidents in a given year. Two particular points are apparent with respect to the EQUIP category;

1. The number of incidents per year has fallen significantly. The overall proportion in the EQUIP category has, as identified by the regression analysis above, generally increased over the period. However, when expressed in absolute terms it has fallen.
2. While it is true that the proportion of EQUIP incidents has had an upward trend over the last 20 years, it can be seen that the trend has not been consistent over the period. From 1992 to around 2003, the number of incidents was increasing in absolute terms and this is more pronounced when viewed as a proportion of the total. From 2003 onwards, there is a significant decrease in the number of EQUIP incidents and the rate of reduction is greater than the average for the other categories leading to a decrease in the proportion.

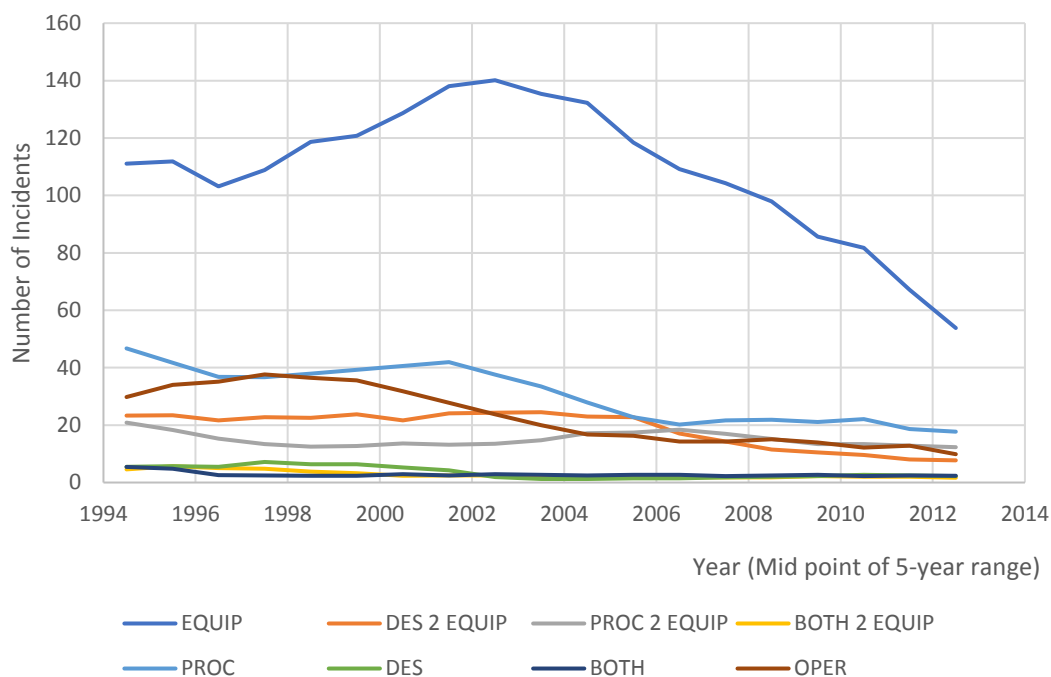


Figure 8: 5-year rolling average versus number of incidents by category

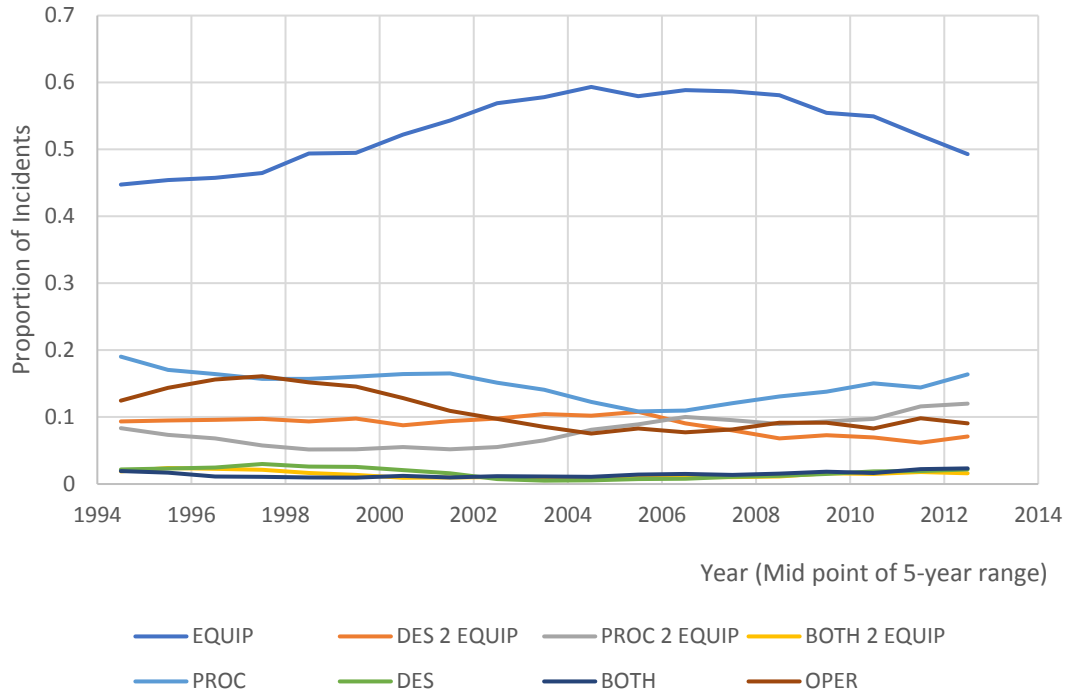


Figure 9: 5-year rolling average versus proportion of incidents by category

Looking in more detail at the YESEQUIP meta-category, a comparison between the “All” and “Reportable” data can be made. In Figure 10, it is shown that what made the YESEQUIP meta-category of the “All” data to increase over the period around 1995 to 2003 is the number of non-reportable incidents. When these are removed to form the “Reportable” data set, the absolute number of incidents in this meta-category actually shows a slight decline rather than the pronounced increase indicated by the “All” data.

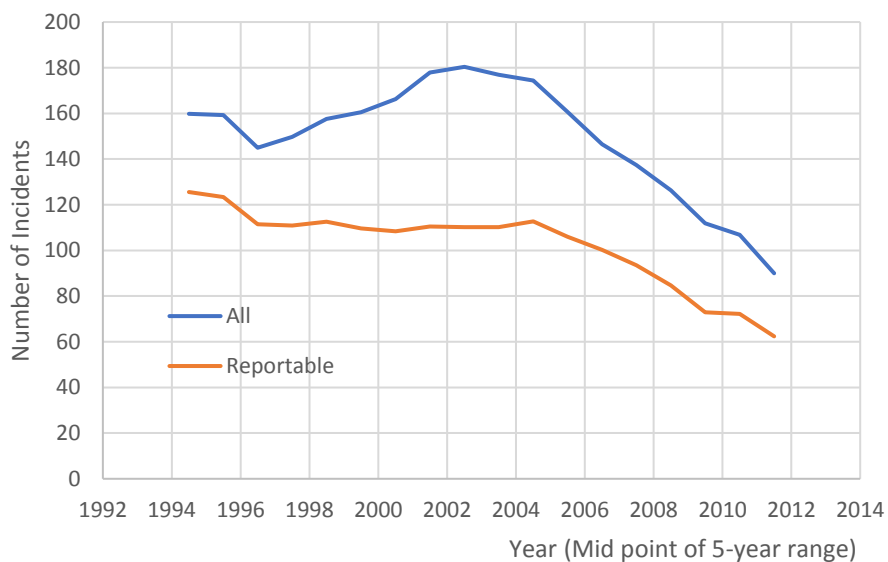


Figure 10: Estimated Number of YESEQUIP Incidents in the “All” and “Reportable” Data Sets (5-year running average)

It can be concluded that all four causal categories have been declining during the last 20 years. In the period until around 2003 the decrease was mostly due to improvements in design, operations and procedures with equipment failures remaining at a consistent level. Since then the downward trend has been more apparent for equipment causes than for other categories.

**Conclusions**

Due to a noted reduction in loss of containment incidents in the offshore UK sector, the aim of the present study was to analyze whether there was a shift in the underlying causes of releases over the HCRD’s years of operation. The conducted analysis

showed that the improvement over the whole period from 1993 to 2014 appeared to be mainly driven by improvement in procedures, hence general management of the oil platforms. Furthermore, the design, despite appearing to be improving at a slower rate than the procedures, still contributed to the noted improvement of reliability. Finally, the equipment failures were improving at the slowest rate, if at all, until 2003. Since then, the equipment too has been improving at a significant rate.

The above results are supported by the several sensitivity assessments, e.g. with respect to strictness of the schemes used to assign release incidents to a causal category, and whether to include “all” data or only the releases that would be reportable under current criteria.

The conclusions of the present study are particularly useful in decision-making over risk assessments concerning offshore installations; in the case of an old oil platform that is managed in a modern way, the question of which risk data to use – older or more recent risk data – is raised. Since improved risk management approaches seem to have decreased the release frequency, it can be justified that the latest data may be used.

## References

- Bain, B., 2017, Updated leak frequency modelling based on the UK Hydrocarbon Release Database, IChemE Symposium Series, 162.
- Bain, B. J., Wakefield, S. and Borresen, R. J., 2016, Improvements in the UK offshore hydrocarbon release database, Risk, Reliability and Safety: Innovating Theory and Practice; Proceedings of ESREL 2016, 2031-2038.
- Bruce, R. A. P., 1994, The offshore hydrocarbon releases (HCR) database, IChemE Symposium Series, 134: 107-122.
- Bruce, R. A. P., 1995, The offshore hydrocarbon releases (HCR) database, IChemE Symposium Series, 139: 563-578.
- de la Mare, R. F., Andersen, O., 1980, Pipeline Reliability, Det Norske Veritas, Report No. 80-0572.
- Goff, R. J., 2016, Learning from the Causes of Failures of Offshore Riser Emergency Shutdown Valves, IChemE Symposium Series, 161.
- Heumann, C., Schomaker, M., Thakur, S., 2017, Introduction to Statistics and Data Analysis: With Exercises, Solutions and Applications in R, Springer International Publishing, 249-295.
- HSE, 1996, Revised Guidance on Reporting of Offshore Hydrocarbon Releases, Report No. OTO 96 956.
- HSE, 2010, “Hydrocarbon Release Report – Supplementary Information” Form OIR12, OIR12 reporting form is available at <https://www.hse.gov.uk/forms/incident/oir12.pdf> – accessed January 2019.
- HSE, 2016, Excel Workbook "hsr1992-2014" available from HSE Offshore Statistics, [cited 2019 January]. Available from: <http://www.hse.gov.uk/offshore/statistics.htm>
- HSE, 2017, “Report of an Oil and Gas Incident (ROGI) Form”, v3.0, ROGI reporting form is available at <http://www.hse.gov.uk/osdr/assets/docs/rogi.pdf> – accessed January 2019.
- Koutsoudaki, M.; 2018, Trends in underlying causes of releases in the Hydrocarbon Releases Database (HCRD), MSc thesis at the Technical University of Denmark DTU.
- Montgomery, D. C., 2005, Design and Analysis of Experiments, John Wiley & Sons.
- Oil & Gas UK, 2008, Supplementary Guidance for Reporting Hydrocarbon Releases, Issue 1.
- Oil & Gas UK, 2015, Supplementary Guidance on the Reporting of Hydrocarbon Releases, Issue 3.
- Spouge, J., 2006, Leak frequencies from the hydrocarbon release database, IChemE Symposium Series, 151: 732-747.