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Human error probability prediction for cargo sampling process on chemical tanker ship under extended SLIM Evidential Reasoning approach.

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***Abstract* –** Cargo sampling, which indicates the condition of the cargo on the ship, is one of the important chemical tanker shipboard operations where human performance is prominent. Any negligence during the cargo sampling process can result in loss of human life, environmental disasters and financial losses. Therefore, evaluating human performance in the cargo sampling process on chemical tanker ships is vital to avoid these. This paper aims to evaluate the contribution of human errors to the cargo sampling process. Hence, the Success Probability Index Method (SLIM) is conducted, incorporating Evidential Reasoning (ER) approach. While SLIM systematically predicts human error probabilities (HEP) considering performance shaping factors (PSFs), ER deals with the uncertain and subjective judgments of experts in the step of rating and weighting PSFs. Based on the presented ER-SLIM model, HEP can be estimated by aggregating the belief degree of the experts and human performance for the cargo sampling process can be evaluated. The outputs of the paper provide a practical contribution to chemical tanker ship owners, health safety environment and quality (HSEQ) managers, maritime safety professionals and, chemical tanker officers in order to minimize the probability of human error in the cargo sampling process, as well as the theoretical background.

Keywords – SLIM, Evidential Reasoning, Cargo Sampling, Chemical Tanker, Human Error

I. INTRODUCTION

On chemical tanker ships, the cargo samples indicate the condition of the liquid cargo. Sometimes liquid cargo may be off specification. The source of this situation may be the shore tank, the shore pipeline or the ship. Contamination by the ship may be due to improper cleaning of cargo tanks or cargo lines or improper storage of the cargo. However, even if the contamination is caused by the shoreside, the ship may encounter a cargo claim. Therefore, proper sampling is important to prove that cargo contamination is not caused by the ship and to avoid exposure to related claims [1]. In addition, a failure in the sampling process can cause health problems and explosions as well as financial losses [1] - [2].

In the literature, although there is no research on the sampling process on chemical tanker ships, there are researches on some specific processes. In these papers, subjects such as tank cleaning [3], gas-freeing [4], cargo loading [5], gas inerting [6], and bunkering [7] were examined. On the other hand, human error is very effective in accidents that occur in maritime transportation [8]. For this reason, some studies in the maritime literature have evaluated human performance by adopting techniques such as Standardized Plant Analysis Risk Human Reliability Analysis (SPAR-H) [9], Human Factors Analysis and Classification System (HFACS) [10], Human Error Assessment and Reduction Technique

(HEART) [11], Cognitive Reliability and Error Analysis Method (CREAM) [12], Success Likelihood Index Method (SLIM) [13].

This paper remedies a gap by calculating the human error probability (HEP) during cargo sampling, one of the critical processes on chemical tanker ships. In this context, the paper presents a robust methodological framework that combines SLIM and Evidential Reasoning (ER). In the paper, SLIM quantifies HEP while ER manages the uncertainty and subjectivity of expert judgments and is applied in the weighting and rating step of performance shaping factors (PSFs). Thus, the HEP values can be estimated and the operational safety level can be increased for the cargo sampling process. Accordingly, the paper is organised as follows. Section 1 gives the motivation for the research including a superficial literature review. Section 2 introduces methods and their integrations. Section 3 carries out a HEP prediction for cargo sampling. Section 4 includes findings and discussions. Section 5 concludes the research.

II. METHODOLOGY

The theoretical background of the methods and their integration are presented in this section.

A. *SLIM*

SLIM is a method developed by Embrey et al. [14] for predicting human error probabilities. It is a practical technique for calculating human error in the domain where lack of error data. In the method, HEP is quantified and predicted for specific tasks, taking into account the PSFs that significantly affect human performance. In SLIM, based on expert judgment, experts select a set of appropriate PSFs. PSFs are weighted and rated using the knowledge and experience of experts. Thus, the Success Likelihood Index (SLI) is elicited. The HEP value is calculated by calibrating the SLI value with human error data [15]. The main steps of the SLIM approach are as follows: i.) PSF derivation, ii.) PSF rating and weighting, iii.) SLI determination, iv.) Converting SLI into HEP [14].

B. *Evidential Reasoning*

ER based on Dempster-Shafer (D-S) evidence theory was first proposed in 1994 [16] – [17]. The ER method, which can address the problems of D-S theory, has evolved over time [18] – [19]. The approach can overcome issues raised by subjectivity and uncertainty. It can also produce consistent results by aggregating information from different evidence.

Let's assume that L experts carry out the evaluation process. Thus, the set of experts is denoted as $E = \{e_1, e_2, \ldots, e_i \ldots e_L\}$. Suppose a set of evaluation grades set $H = \{H_1, H_2, \ldots, H_n, \ldots, H_N\}$ make up a model. Accordingly, an expert can consider N different evaluation grades. Also, the evaluation of e_i is mathematically represented as follows [18].

$$S(e_i) = \{(H_n, \beta_{n,i}), n = 1, \ldots, N\} \qquad i = 1, \ldots, L \tag{1}$$

where $\beta_{n,i}$ states H_n's belief degree and $\beta_{n,i} \geq 0$, $\sum_{n=1}^{N} \beta_{n,i} \leq 1$. In addition, the weight of each piece of evidence is considered in the ER and the weight set of the evidence is $w = \{w_1, w_2, \ldots w_i, \ldots w_L\}$. Consequently, the belief distribution $(H_n, \beta_{n,i})$ and weight (w_i) of the piece of evidence e_i are specified in the ER [18].

C. *Integration of Methods*

This section presents how the ER and SLIM approaches are integrated to predict HEP. The applied approach consists of seven steps: Task analysis, scenario definition, PSF derivation, PSF rating, PSF weighting, SLI determination, and HEP calculation.

First of all, the tasks of the process under consideration are systematically defined. For this, hierarchical task analysis (HTA) is conducted, in which the main tasks and subtasks of the process are determined [20]. Secondly, the scenario is defined by expressing the conditions of the operating environment. The scenario includes many conditions such as morale, weather conditions, fatigue, experience, etc. Thus, HEP can be predicted sensitively. In the third step, experts derive PSFs that affect human performance. PSFs are crucial for accomplishing tasks. Ergonomics, time availability, workload, and complexity are just a few examples of PSFs. In the fourth step, PSFs are evaluated by experts on a linear scale of 1-9. When evaluating PSFs, experts indicate their belief in values between 1 and 9 as a percentage. The highest rate is 9 while the lowest rate is 1. Different experts may have different evaluations of the PSFs rating. Therefore, the ER approach is used in the paper to deal with the subjectivity and uncertainty of expert judgments and to aggregate expert judgments [18].

According to the ER approach, if an expert's (e_i) degree of belief in H_n is $\beta_{n,i}$, the basic probability mass is as in Equation 2:

$$m_{n,i} = w_i \beta_{n,i} \tag{2}$$

where w_i denotes the experts' weight. Then, the belief degrees of the experts are aggregated by applying Equations 3-5.

$$m_{n,I(i+1)} = K_{I(i+1)}\big(m_{n,I(i)}m_{n,(i+1)} + m_{n,I(i)}m_{H,(i+1)} + m_{H,I(i)}m_{n,(i+1)}\big) \tag{3}$$

$$K_{I(i+1)} = \left[1 - \sum_{t=1}^{N} \sum_{j=1, j\neq t}^{N} m_{t,I(i)}m_{j,i+1}\right]^{-1} \quad i = 1, \dots, L-1 \tag{4}$$

$$\beta_n = \frac{m_{n,I(L)}}{1 - \bar{m}_{H,I(L)}} \tag{5}$$

where β_n states the normalized belief degree of the nth evaluation degree, $K_{I(i+1)}$ is the normalizing factor and $m_{n,I(i+1)}$ is the aggregated basic probability mass. After the aggregated belief degrees are determined, aggregated ratings (AR) are calculated using Equation 6.

$$AR = \sum_{n=1}^{N} u(H_n)\beta_n \tag{6}$$

where $u(H_n)$ denotes the utility of H_n. The evaluation grade set has nine elements, i.e. $H = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$. There are nine elements in the valuation grade set. Accordingly, values from 1 to 9 are assigned for the nine utility degrees.

In the fifth step, the PSFs are weighted to determine their relative importance. Experts assess PSFs on a scale of 0-100 based on their overall impact on tasks [14]. ER is also applied in this step to aggregate expert opinions. In this context, Equations 2-5 apply. In the sixth step, the SLI value is computed using Equation 7 [14]. In Equation 7, n is the number of PSF. R_i specifies the aggregated rating of the PSF. W_i is the weight of PSF.

$$SLI = \sum_{i=1}^{n} R_i W_i \tag{7}$$

Finally, in the seventh step, the SLI values are converted to HEP values with Equation 8. In Equation 8, a and b are constants [14].

$$Log(HEP) = aSLI + b \tag{8}$$

III. Human Error Probability Prediction for Cargo Sampling Process on Chemical Tankers

In this section, HEP values are estimated for the tasks of the cargo sampling process on chemical tanker ships. To achieve this purpose, tasks are derived by using company circulars, expert opinions, and ship's operation manuals for the closed sampling process. Accordingly, Table 1 provides the HTA for closed sampling on chemical tanker ships.

After determining the tasks for the process, a real-shipboard scenario was considered. According to the scenario, closed sampling from the cargo tanks started at 03:00 am after the loading was completed. The operation took about an hour. During operation, the temperature was about 32 ◦C and the humidity was about 80%. The ship's crew were not well rested. No non-conformity was identified in the inspection conducted by the port state control two days ago.

Table 1. HTA of closed sampling for chemical tanker ship.

1	Before sampling
1.1	Ensure the duty officer is ready for the closed sampling.
1.2	Make sure the closed sampling equipment is clean.
1.3	Make sure the crew taking the sample to wear proper and adequate protective gear.
2	During sampling
2.1	Connect the closed sampler to the vapour lock properly and with the valve fully closed.
2.2	Make sure that the sampler is earthed before it is lowered into the tank.
2.3	Take the sample following the manufacturer's guidelines.
2.4	Fully close the vapour lock valve, to disconnect the sampler.
3	After sampling
3.1	Clean the closed sampling equipment.
3.2	Label each sample and store it in the designated compartment.

Then, six PSFs have been derived by experts with extensive knowledge and experience in operations on chemical tanker ships. PSFs are Task complexity (PSF1), Time pressure (PSF2), Training and experience (PSF3), Environmental condition (PSF4), Working condition (PSF5), and Organizational factors (PSF6). Next, five experts with extensive knowledge and experience rate the PSFs on a scale of 1-9. The evaluation results obtained from the experts are aggregated with the

ER approach by using Equations 2-6. Table 2 illustrates the aggregated PSF ratings for all sub-tasks based on evaluations by marine experts.

Table 2. Aggregated ratings for all sub-task.

Task No	PSF1	PSF2	PSF3	PSF4	PSF5	PSF6
1						
1.1	7.37	5.92	7.01	6.16	6.61	7.47
1.2	7.34	5.17	5.77	4.67	5.46	5.63
1.3	6.84	4.43	5.07	5.75	6.28	5.39
2						
2.1	4.73	4.73	4.70	4.65	6.09	6.21
2.2	4.07	3.50	4.54	4.56	5.07	5.08
2.3	3.16	2.98	4.19	3.89	4.74	3.88
2.4	5.66	4.11	5.80	5.51	5.87	6.40
3						
3.1	4.80	3.37	5.95	4.63	6.40	6.84
3.2	4.23	3.36	4.92	4.97	7.36	5.35

In the step of weighing the PSFs, experts assess the PSFs between 0-100. The values assigned by each expert are normalized. The normalized values of the five experts are aggregated using Equations 2-5. The experts' assessments, normalized values and aggregated weight of PSFs are shown in Table 3.

Table 3. Aggregated weight of PSFs.

Expert		PSF 1	PSF 2	PSF 3	PSF 4	PSF 5	PSF 6	∑
1	Assigned Weight	80	80	90	85	70	65	470
	Normalized Weight	0.170	0.170	0.191	0.181	0.149	0.138	
2	Assigned Weight	85	90	85	80	75	70	485
	Normalized Weight	0.175	0.186	0.175	0.165	0.155	0.144	
3	Assigned Weight	75	70	80	70	65	65	425
	Normalized Weight	0.176	0.165	0.188	0.165	0.153	0.153	
4	Assigned Weight	80	85	85	80	75	65	470
	Normalized Weight	0.170	0.181	0.181	0.170	0.160	0.138	
5	Assigned Weight	85	90	95	80	80	85	515
	Normalized Weight	0.165	0.175	0.184	0.155	0.155	0.165	
Aggregated Weight		0.172	0.176	0.186	0.167	0.153	0.146	

Then, using Equation 7, SLI values are computed for each subtask of the closed sampling process. Finally, the SLI values are transformed into HEP values by applying Equation 8. Table 4 lists the SLI values and HEP results for each sub-task.

Table 4. Calculated SLI and HEP values for each task.

Task	SLI	Log (HEP)	HEP
1			
1.1	6.74	-2.46	3.51E-03
1.2	5.68	-2.06	8.78E-03
1.3	5.61	-2.03	9.36E-03
2			
2.1	5.14	-1.85	1.40E-02
2.2	4.44	-1.59	2.57E-02
2.3	3.79	-1.35	4.50E-02
2.4	5.53	-2.00	1.00E-02
3			
3.1	5.28	-1.91	1.24E-02
3.2	4.97	-1.79	1.62E-02

IV. DISCUSSION

In the view findings, as shown in Table 4, the highest HEP value for the cargo sampling process was found as sub-task 2.3 (Take the sample following the manufacturer's guidelines). Time pressure and complexity are major factors leading to high HEP. The manufacturer's instructions should be followed when transferring the sample to the bottle using closed sampling equipment. This task can be complicated for the crew as each ship has a different type of sampler. Failure of the task can result in the inhalation of toxic cargo vapors and poisoning. In addition, failure may cause a prolongation of the sampling process. Subtask 2.2 (Make sure that the sampler is earthed before it is lowered into the tank) has the second highest HEP during closed cargo sampling. Closed sampling equipment must be earthed due to static electricity after connections are made. Failure of the task can cause an explosion in the cargo tank. Subtask 3.2 (Label each sample and store it in the designated compartment) has the third highest HEP. After the samples are taken, they are marked on the sample bottle with the necessary information. Samples are stowed in the sample locker in the main cargo area in accordance with the compatibility chart. Failure of the task may result in loss of samples. On the other hand, failure may cause financial losses by not being able to prove the ship's innocence when faced with any problem.

V. CONCLUSION

Cargo sampling is considered as one of the critical processes performed at every port of call of the ship. A failure during sampling may cause serious financial losses, poisoning or explosions, depending on the characteristics of the cargo carried. To minimize all these negative consequences, this paper discusses the role of the human factor during the cargo sampling process. Tasks are determined for the process and HEP values of each task are calculated. To achieve this purpose, SLIM under the ER approach is adopted. The findings show that sub-task 2.3 (Take the sample following the manufacturer's guidelines) has the highest HEP value in the cargo sampling process. Subtask 2.2 and subtask 3.2 are the other tasks with the highest HEP values, respectively. The research's findings emphasize the most important tasks that require attention. The paper contributes to chemical tanker ship owners, health safety environment and quality (HSEQ) managers, maritime safety professionals and, chemical tanker officers for the process.

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