Data Fusion for Subsea Oil Spill Detection Through Wireless Sensor Networks

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***Abstract*—This work studies the impact of Wireless Sensor Networks (WSNs) for oil spill detection in subsea Oil&Gas applications. The case study is the Goliat FPSO where one WSN with passive acoustic sensors is assumed to be installed on each subsea template to monitor the manifold. Sensors take local binary decisions regarding the presence/absence of a spill by performing an energy test. A Fusion Center (FC) collects such local decisions and provides a more reliable global binary decision. The Counting Rule (CR) and a modified Chair-Varshney Rule (MCVR) are compared. An objective function derived from the Receiver Operating Characteristic (ROC) is used for threshold design. The considered methodology requires the knowledge of the involved subsea production system, in particular of its hotspots whose failure could cause an oil spill.**

***Index Terms*—Data fusion, leak detection, oil spill, subsea production system, wireless sensor network**

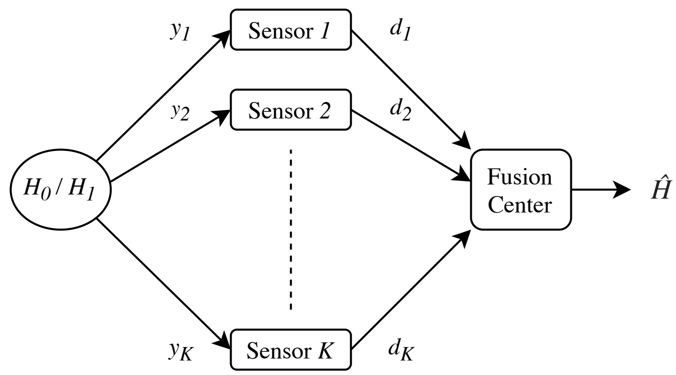

Fig. 1. Wireless Sensor Network

I. Introduction

The Oil&Gas industry over the last few decades has developed new technologies for the exploitation of offshore resources that were once technologically inaccessible or economically unfeasible. One of these is the use of Subsea Production Systems (SPS) which can be connected to a close fixed platform, a floating system, or directly to the shore. This allows the oil extraction in deep waters which are normally out of range of standard fixed platforms, as well as exploiting fields more efficiently due to the versatility of such systems [1]. On the other hand, one of the disadvantages related to this technology is that the presence of a SPS in deep water makes the detection of oil spills less effective resulting in delayed production shutdowns with a consequent risk for workers' safety and the environment. For this reason, the presence of a Leak Detection System (LDS) able to quickly detect oil spills is of critical importance.

Current technologies rely on both internal methods (based on measurements of process variables) and external methods (monitoring the SPS's surrounding environment). More specifically, an underwater oil spill is known to cause an acoustic signal that can be sensed via passive acoustic sensors [2], [3]. Although the use of WSNs for leak detection has been considered mainly in the monitoring of Oil&Gas pipelines [4], [5], recent works have focused on monitoring of a SPS through a WSN [6]–[8]. This work investigates the use of Wireless Sensor Networks (WSNs) as an external method for leakage detection and illustrates results on a realistic case-study based on the Goliat FPSO. This approach has the advantage of being able to detect (and eventually localize) oil spills with a small number of sensors and limited power consumption.

The remainder of the paper is organized as follows. Sec. II provides a system overview, including assumptions related to signals characterizations. Data processing for leak detection is described in Sec. III, which includes local detection at sensor location and global detection at the Fusion Center (FC). Numerical results on the considered case study are presented in Sec. IV in terms of Receiver Operating Characteristic (ROC). Finally, conclusions and further works are addressed in Sec. V.

II. System Model

A. Wireless Sensor Network Model

The proposed WSN architecture (see Fig. 1) is made of K acoustic sensors[1] used to detect the presence ($\mathcal{H}_1$) or absence ($\mathcal{H}_0$) of an oil spill. The kth sensor (where $k = 1, \dots, K$) individually performs a test on the received amplitude y_k and takes a local decision $d_k = i \in \{0, 1\}$ if $\mathcal{H}_i$ is declared. The local decisions are collected and combined at the FC for a global decision $\widehat{\mathcal{H}} \in \{\mathcal{H}_0, \mathcal{H}_1\}$. Such a system is extremely energy efficient when On-Off Keying is considered for decision reporting from the sensors to the FC.

[1] Sound pressure is sensed. Analysis concerning the sampling frequency is not treated in the present work.

B. Signal Model

The model of the received signal at the kth sensor, depending on the corresponding hypothesis (presence/absence of a leakage), is the following:

$$\begin{cases} \mathcal{H}_0: & y_k = w_k \\ \mathcal{H}_1: & y_k = \xi \cdot g(\boldsymbol{x}_k, \boldsymbol{x}_T) + w_k \end{cases}, \tag{1}$$

where $\xi \sim \mathcal{N}(0,\, \sigma_s^2)$ and $w_k \sim \mathcal{N}(0,\, \sigma_{w,k}^2)$ are independent Gaussian random variables representing the emitted sound pressure produced by the leakage at a reference length (ℓ_{ref}) and the Additive White Gaussian Noise (AWGN) at the kth sensor, respectively. Also, $g(\boldsymbol{x}_k, \boldsymbol{x}_T)$ is the Amplitude Attenuation Function (AAF) depending on the distance between the kth sensor and the leakage, whose positions are denoted $\boldsymbol{x}_k$ and $\boldsymbol{x}_T$, respectively. The signal power σ_s^2 and the noise power $\sigma_{w,k}^2$ are assumed to be known (for all K sensors). The AAF, here treated as the contribution of the sea-water absorption and the geometrical spreading, has the following form:

$$g^2(\boldsymbol{x}_k, \boldsymbol{x}_T) = \left(\frac{\ell_{\text{ref}}}{\|\boldsymbol{x}_k - \boldsymbol{x}_T\|}\right)^{k_{\text{sc}}} 10^{(\ell_{\text{ref}} - \|\boldsymbol{x}_k - \boldsymbol{x}_T\|)\alpha 10^{-4}}, \tag{2}$$

where ℓ_{ref} and $\|\boldsymbol{x}_k - \boldsymbol{x}_T\|$ are measured in meters, the seawater absorption coefficient α is measured in dB/km, and k_{sc} is the spreading coefficient. It can be noticed that if $\ell_{\text{ref}} = \|\boldsymbol{x}_k - \boldsymbol{x}_T\|$, then $g(\boldsymbol{x}_k, \boldsymbol{x}_T) = 1$.

III. Leak Detection

A. Local Detection

Given Eq. (1), the *uniformly most powerful* test [9] to be performed by the kth sensor is the energy test [10]:

$$d_k = \begin{cases} 0, & y_k^2 < \tau_k \\ 1, & y_k^2 \geq \tau_k \end{cases}, \tag{3}$$

where τ_k is a local threshold. The local performances, in terms of probability of detection and probability of false alarm, of this test are defined and computed as follows:

$$P_{d,k} = \Pr(y_k^2 \geq \tau_k | \mathcal{H}_1) = 2\mathcal{Q}\left(\sqrt{\frac{\tau_k}{g^2(\boldsymbol{x}_k, \boldsymbol{x}_T)\sigma_s^2 + \sigma_{w,k}^2}}\right), \tag{4}$$

$$P_{f,k} = \Pr(y_k^2 \geq \tau_k | \mathcal{H}_0) = 2\mathcal{Q}\left(\sqrt{\frac{\tau_k}{\sigma_{w,k}^2}}\right), \tag{5}$$

where $Q(\cdot)$ is the complementary cumulative distribution function of the standard normal random variable. However, since the leakage position is unknown, Eq. (4) cannot be used directly. One possibility to overcome the issue is to refer to average performances with respect to the SPS's hotspots[2] and their positions $\boldsymbol{h}_m$ (where $m = 1, \ldots, M$), i.e.

$$\overline{P_{d,k}} = \frac{1}{M}\sum_{m=1}^{M} P_{d,k,m}, \quad \overline{P_{f,k}} = P_{f,k}, \tag{6}$$

[2]The hotspots are those components within the SPS that could be the source of a spill in case of failure.

where $P_{d,k,m}$ is obtained replacing $\boldsymbol{x}_T$ with $\boldsymbol{h}_m$ in Eq. (4). By using the arithmetic mean, Eq. (6) assumes that the hotspots have equal failure rates and that their leakages would cause signals having equal power σ_s^2.

We define the reference Signal-to-Noise ratio (SNR) and the sensing SNR at the kth sensor respectively as

$$\Gamma_{\text{ref},k} = \frac{\sigma_s^2}{\sigma_{w,k}^2}, \quad \Gamma_k = \frac{\Gamma_{\text{ref},k}}{M}\sum_{m=1}^{M} g^2(\boldsymbol{x}_k, \boldsymbol{h}_m). \tag{7}$$

B. Global Detection

The FC assesses the presence of a leakage based on a test statistic (Λ) depending on the local decisions d_k:

$$\widehat{\mathcal{H}} = \begin{cases} \mathcal{H}_0, & \Lambda < T \\ \mathcal{H}_1, & \Lambda \geq T \end{cases}, \tag{8}$$

where T is a global threshold.

Two different fusion rules are considered for computing the test statistic at the FC: (i) the Counting Rule (CR), and (ii) a modified version of the Chair-Varshney Rule (MCVR). MCVR is adapted to work using the mean performances in Eq. (6). More specifically, the corresponding test statistics are computed as follows:

$$\Lambda_{\text{CR}} = \sum_{k=1}^{K} d_k, \tag{9}$$

$$\Lambda_{\text{MCVR}} = \sum_{k=1}^{K}\left[d_k \ln\left(\frac{\overline{P_{d,k}}}{\overline{P_{f,k}}}\right) + (1 - d_k)\ln\left(\frac{1 - \overline{P_{d,k}}}{1 - \overline{P_{f,k}}}\right)\right]. \tag{10}$$

Global system performances for each fusion rule are expressed in terms of *Global Probability of Detection* and *Global Probability of False Alarm* at the FC, defined as $Q_d = \Pr(\Lambda \geq T|\mathcal{H}_1)$ and $Q_f = \Pr(\Lambda \geq T|\mathcal{H}_0)$, respectively. It is worth noticing that Q_d will depend on the position of the leakage, then the same approach used in the previous section for local performances is considered:

$$\overline{Q_d} = \frac{1}{M}\sum_{m=1}^{M} Q_{d,m}, \quad \overline{Q_f} = Q_f. \tag{11}$$

C. Threshold Selection

Local thresholds τ_k are hyper-parameters that ideally should be optimized based on the global performance. Such a task does not exhibit an easy solution, then sub-optimal solutions are usually considered. Here we consider to select the thresholds based on the optimization of the Youden Index (J) [11]:

$$\tau^* = \arg\max_{\tau} J(\tau) = \arg\max_{\tau}\{P_d(\tau) - P_f(\tau)\}. \tag{12}$$

In Eq. (12), the variables τ, P_d, and P_f are replaced with τ_k, $\overline{P_{d,k}}$, and $\overline{P_{f,k}}$ (respectively T, $\overline{Q_{d,k}}$, and $\overline{Q_{f,k}}$) when tuning the sensors (respectively the FC).

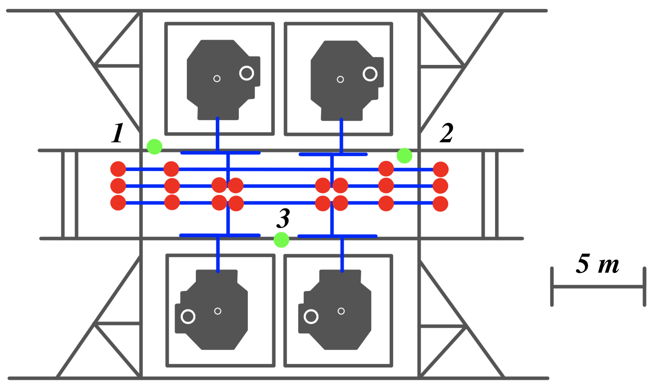

Fig. 2. Goliat's subsea template: the grey elements are the structure and the Christmas Trees, the blue lines are the main streamlines, the green dots are the sensors, and the red dots are the hotspots

IV. Case Study (Goliat FPSO)

The Goliat FPSO is a production platform located in the Norwegian Barents Sea relying on eight subsea templates. Each template has its manifold monitored by three passive acoustic sensors as part of the external LDS [12], [13]. Twenty hotspots (corresponding to the main valves and connections) have been highlighted in Fig. 2. Hotspots and sensors are assumed to be at the same height.

Numerical performances have been obtained via simulation with 10^8 Monte Carlo runs using the software MATLAB. The parameters used for the case study can be found in Table I. The seawater absorption coefficient α in Eq. (2) has been computed using *Francois & Garrison equation* [14], [15], where the underwater speed of sound was obtained using the *updated Chen & Millero equation* [16]. Table II shows the average SNR for each sensor in case of $\Gamma_{\text{ref}} = 13.0$ dB and $\Gamma_{\text{ref}} = 14.8$ dB.

Fig. 3 shows the ROC curves of the LDS in the two SNR cases comparing the two fusion rules. It is apparent how both CR and MCVR perform almost similar in the considered case. The reason is the symmetrical topology of the considered case study. Asymmetrical setups would show the advantage of MCVR over CR. Also, it is worth noticing that the ROC of the MCVR exhibits more flexibility than the CR in terms of global performance since a larger number of possible thresholds is admitted (7 vs. 3 in the specific case study). Also, Table III shows the maximum Youden Index and the corresponding global probabilities of detection and false alarm, to highlights the incremental improvement of MCVR with respect to CR.

V. Conclusions

This work investigated the use of Wireless Sensor Networks (WSNs) for subsea oil spill detection, using Goliat FPSO as a case study. Local sensors' decisions are collected at the FC, where CR and MCVR are considered for data fusion. ROC performances have been obtained through realistic numerical simulations, showing the potential benefit of the considered approach. Future works will include a more extended analysis on the local and global threshold selection as well as the localization of the subsea component responsible for the spill which is crucial for quicker and more efficient maintenance.

TABLE I
Parameters used to simulate a leak scenario

Parameter	Value	Note / Reference
Reference Frequency	2.5 kHz	[17]
Temperature	3.8 °C	[18]
Salinity	3.5 %	[18]
Depth	350 m	[12]
pH	8	[19]
Spreading Coeff. (k_{sc})	1.5	[20]
Ref. Length (ℓ_{ref})	1 m	–
Noise Variance (σ_w^2)	1	$\sigma_w^2 = \sigma_{w,k}^2\ \forall k$
Γ_{ref}	13.0 dB; 14.8 dB	$\Gamma_{\text{ref}} = \Gamma_{\text{ref},k}\ \forall k$

TABLE II
Average SNR at the different sensors

Γ_{ref}	Γ_1	Γ_2	Γ_3
13.0 dB	2.4 dB	3.4 dB	1.4 dB
14.8 dB	4.1 dB	5.2 dB	3.2 dB

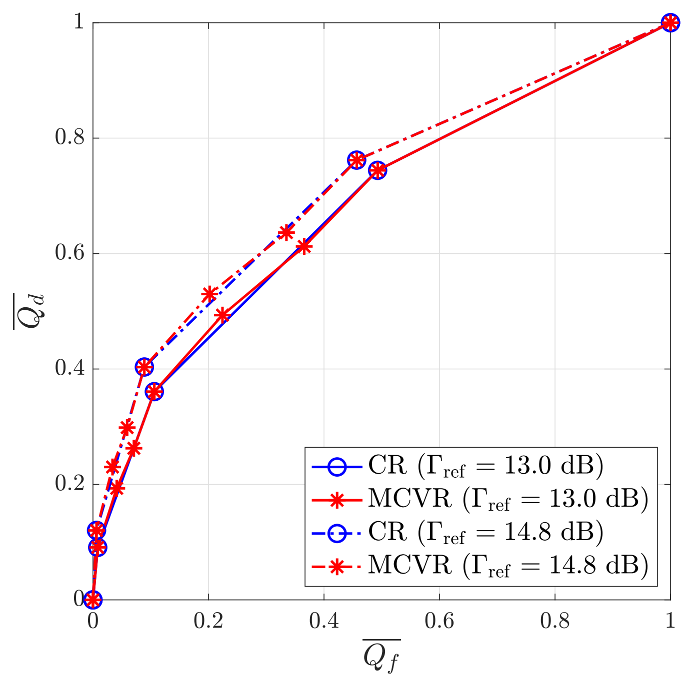

Fig. 3. ROC curves at the Fusion Center

TABLE III
Leak Detection System Performances

Γ_{ref}	Fusion Rule	$J(\Lambda^*)$	$\overline{Q_d}(\Lambda^*)$	$\overline{Q_f}(\Lambda^*)$
13.0 dB	MCVR	0.269	0.493	0.224
	CR	0.255	0.361	0.106
14.8 dB	MCVR	0.328	0.530	0.202
	CR	0.314	0.403	0.089

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