HyDiLLEch: a WSN-based Distributed Leak Detection and Localisation in Crude Oil Pipelines

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Abstract One of the major failures attributed to pipeline transportation of crude oil is oil leakages and spills. Hence, it is monitored via several classical leak detection techniques (LDTs), which are more recently implemented on centralised wireless sensor networks (WSN)-based leak detection and monitoring systems (LDMS). However, the LDTs are sometimes prone to high false alarms, and the LDMS are sensitive to single points of failure. Thus, we propose HyDiLLEch, a distributed leakage detection and localisation technique based on a fusion of several LDTs. In this work, we implemented HyDiLLEch and compared it to the individual LDTs in terms of communication efficiency and leakage detection and localisation accuracy. With HyDiLLEch, the number of nodes detecting and localising leakages increases by a maximum of four to six times, thereby eliminating single points of failures. In addition, we improve the accuracy of localisation in nodes physically-close to the leak and maintain an average of 96% accuracy with little to no communication overhead.

1 Introduction

Oil leakages and spills (OLS) in pipelines occur due to ageing infrastructures, corrosion, and most commonly third-party interference. OLS has both economic and environmental effects. Some of them include the annual loss of up to 10 billion USD in the United States [1], pollution of water and land re-

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sources, fatal accidents caused by resulting explosions, etc. Therefore, several measures are put in place to help monitor, detect and predict such failures in a timely manner.

These measures can be broadly categorised into *human-based* and *non-human-based* leakage detection and monitoring systems (LDMS). The human-based LDMS comprises the use of community-based surveillance, security personnel, specialised helicopters, etc., for detecting and localising leakages. Although they work, their drawbacks include long delays, high cost, inefficiency, etc. This is ascertained with the recorded loss of crude oil from the pipeline network of Shell Nigeria to the tune of 11000 barrels per day in 2018 due to failures, an increment of nearly 550% compared to the previous year [2]. The non-human-based (sensorised) LDMS, on the other hand, detect leakages via the supervisory control and data acquisition (SCADA), fibre optic or copper installed along the length of the pipeline. More advanced sensorised LDMS include the use of multisensory network, i.e Wireless Sensor Networks (WSN), which employ various detection techniques and are considered to be more efficient than others [3, 4].

However, existing works such as [5] proposed WSN-based LDMS that are centralised, making them susceptible to Single Point of Failures (SPOF). This is in addition to other constraints (energy consumption, robustness, etc.) associated with WSNs accompanied by sensitivity, accuracy, high false alarm rates, etc. [6] related to the used leak detection techniques (LDTs). Together, these challenges might explain the limited adoption of sensorised LDMS for pipelines, as shown in [7].

Thus, in this article, we present HyDiLLEch: a fusion of several detection techniques suitable for resource-constrained networks. HyDiLLEch is aimed at improving the resilience to failures (communication, node, third party interference, etc.) by removing the SPOF associated with centralised systems in a distributed manner. We examine its efficiency in terms of *accuracy* of localisation, *energy consumption*, and *communication overhead* compared to the classical LDTs. The remainder of this article is structured as follows. In section 2, related work is discussed. In section 3, we detail some required hydraulics background. Our contribution is presented in section 4 and discussed in section 5. We conclude and present future works in section 6.

2 Related Work

Sela *et al.* [8] worked on a robust placement of sensors in a pipeline network using robust mixed integer optimisation (RMIO) and robust greedy approximation (RGA) as enhancement of the nominal versions. In most cases, RMIO and MIO outperformed the other versions in the conducted test. [9] worked on fault detection in water pipelines using an approximate solution of the minimum set cover problem by adopting the minimum test cover approach.

Both works are based on the assumption that a single sensor can detect failures in multiple pipelines, making them robust to node failures.

Rashid *et al.* [6] used machine learning for leakage detection and classification in pipelines. They compared several machine learning algorithms like the support vector machine (SVM), K-nearest neighbour (KNN) and Gaussian mixture model (GMM), and SVM outperformed the rest in terms of sensitivity, specificity, and accuracy for leak size estimation. They, however, did not consider leakage localisation. Another work based on artificial neural networks (ANN) is that of Roy [10]. He proposed the use of ANN, consisting of input, hidden and output layers as an optimisation tool for accurate leakage detection in pipeline networks. While results from conducted experiments showed improved accuracy in leak detections, ANN may not be suitable for resource-constrained networks like WSNs.

Beushausen *et al.* [11] worked on detecting transient leaks using a statistical pipeline leak detection method through the analysis of the pressure, flow, and modified volume balance of crude oil. Although the system successfully detected some of the transient leaks in the pipeline, localisation error was up to 10km, amongst other challenges. Authors in [12] proposed a non-intrusive leak detection method for fluid pipelines. They estimated the effects of air bubbles in the proposed system's efficiency and evaluated its accuracy and suitability in detection. Also demonstrated in [5] are two leak detection techniques, i.e. the negative pressure wave method and the gradient method. Experimental results showed that both methods could be used to detect and locate leaks. The gradient-based is more energy efficient due to its low sample rate but has slightly lower accuracy compared to the other method.

Whereas these works have considered various aspects of LDMS, the industrial implementation in the midstream is still in the early stages [7]. Research [13] shows that majority of failures in pipelines are caused by vandalism and third-party interference. We have therefore taken into account such situations to propose a decentralised detection and localisation of leakages to address these challenges. To the best of our knowledge, no work has considered distributed leakage detection based on their causal factors.

3 Leakages in Pipelines

Software LDTs such as the pressure point analysis (PPA), the gradient-based method (GM) and the negative pressure wave method (NPWM), amongst others, have proven to be more efficient than others. They are non-invasive LDTs and easy to implement and deploy on existing infrastructure [5]. Therefore, HyDiLLEch is a combination of these techniques. In this section, we give a short reminder about leakages in pipelines and how these techniques work.

Due to frictional resistance, in a transmission pipeline with a steady state, i.e. presenting no leakage, the pressure decreases with distance. Fig. 1 illus-

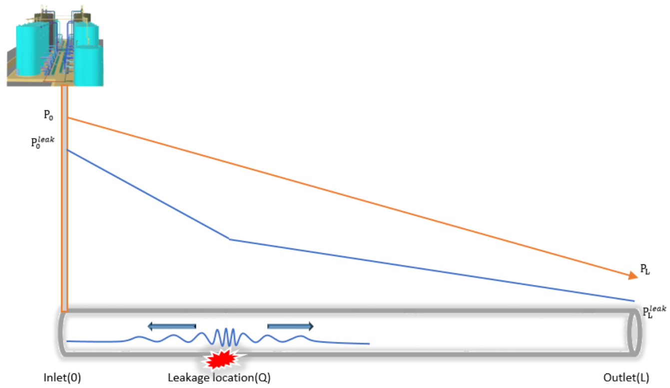

Fig. 1 The pressure gradient distribution in a pipeline before and after leakage

trates the Bernoulli's principle, which shows the pressure gradient changes of the crude oil as it travels along a pipeline. P_0 and P_L are the pressures at the inlet and the outlet of the pipeline, respectively in a steady state. P_0 decreases with distance along the pipeline resulting in a relatively constant pressure gradient (PG) for every measurement points. In a leak case, a negative pressure wave (NPW) - travelling in opposite directions from the point of leak - is generated by the occurrence of a leak [5,14]. This results in different pressures P_0^{leak} at the inlet and P_L^{leak} at the outlet of the pipeline compared to P_0 and P_L.

Methods to detect and localise a leakage include PPA, GM and NPWM, amongst others. PPA is a detection technique used in determining dissipation of flow in pipeline fluid implemented by measuring the pressure at various points along the pipeline using the well known Bernoulli equation (eqn 1).

$$z_a + \frac{P_a}{\rho g} + \frac{V_a^2}{2g} = z_b + \frac{P_b}{\rho g} + \frac{V_b^2}{2g} + E_{ab} \tag{1}$$

where E_{ab} is the energy head loss, $V =$ velocity, $d =$Pipeline's inner diameter, $L =$ the distance from point a to point b,

$P_a =$ pressure at point a, $\rho =$fluid mass density , $g =$ gravitational force and $z_a =$ the elevation at point a.

The GM makes use of the two steady states, i.e. the states before a leak (PG_{0-Q}^{leak}) and after a leak (PG_{Q-L}^{leak}). Given the difference in these pressure gradients as shown in Fig. 1, leakage can be localised with equation (2).

$$\overline{Q} = \frac{L \times dPG_{Q-L}^{leak} + (dp_0 - dp_L)}{dPG_{Q-L}^{leak} - dPG_{0-Q}^{leak}} \tag{2}$$

where $\overline{Q} =$ the estimated leak location, $L =$ the pipeline length, $dp_0 =$ average increment in the pipeline's initial cross-section, $dp_L =$average increment in pipeline final cross-section, $dPG^{leak}_{0-Q}/dPG^{leak}_{Q-L}$ are the average increments in the pressure gradient before/after the leak point.

The NPWM, on the other hand, makes use of the arrival of the NPW front at the sensor nodes. The NPW speed c can be calculated with (eqn 3). But, the amplitude of the wave attenuates with distance. Thus, (eqn 4) gives us the maximum detectable distance of the wave front from the point of leakage.

$$c = \frac{1}{\sqrt{\rho(\frac{1}{K} + \frac{d}{Y.w})}} \tag{3}$$

$$A_b = A_a * e^{-\alpha D} \tag{4}$$

where ρ = Fluid density, K = Fluid's modulus of elasticity, d = Pipeline's inside diameter, Y = The Young's modulus and w = Pipeline's wall thickness, A_b = the amplitude at sensing point b, A_a = the initial amplitude i.e at sensing point a, α = attenuation coefficient and D = the distance between two sensing points.

Each of the techniques mentioned above has some limitations. For example, the accuracy of the GM is tightly coupled with the accuracy of the sensor nodes. The NPWM is dependent on the ability to accurately detect the wave front, which reduces the detecting distance. The NPWM is also less power-efficient than the GM due to its higher sampling rate [5]. Using PPA to detect leakages in transient states and localise leaks is impossible without combining it with other changes resulting from the leak [15].

Therefore, we propose combining these LDTs (PPA, GM and NPWM) by taking advantage of their various strengths to improve the accuracy and sensitivity of leakage detection and localisation while minimising their individual weaknesses.

4 Contributions

We propose a distributed architecture based on several sensors deployed on the pipeline with a mesh connection that enables pre-processing of information among geographically close sensors. This allows distributed detection and localisation of leakages at the sensor level. For the communication aspect, we propose the use of a LPWAN in short and long-range communication and cellular network as a backhaul as they are more widely deployed.

Based on this architecture, we introduce *HyDiLLEch*, an LDT based on the fusion of PPA, GM, and NPWM. It aims to minimise false positives and improve accuracy through a distributed algorithm by defining appropriate distance between nodes and interconnecting them until 2-hops. This is achieved through the spatial correlation of data shared among geographically close sensor nodes. The data containing pressure and the NPW information is shared with neighbouring sensors in a single-hop or double-hop manner.

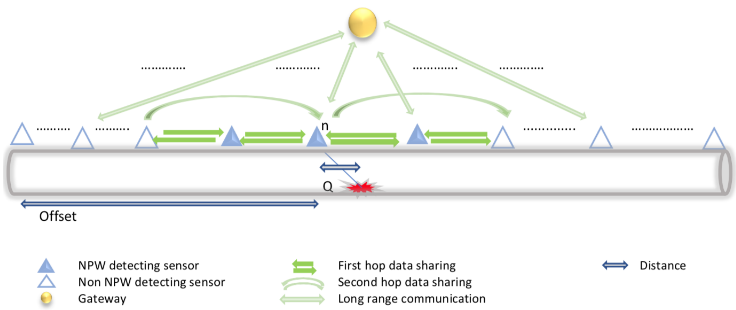

Fig. 2 Detection and localisation of leakages

Detection and localisation are implemented locally, i.e. on the sensors using this *partial information* shared amongst the nodes.

Propagation-based node placement: Some of the factors that affect the performance and efficiency of an LDMS is the placement of sensors on a pipeline. Several approaches exist based on the maximum communication range [16], the definition of the shortest distance between the event and a sensor [8, 9], or the placement of nodes only at the key junctions [1]. By our side, we assume that leakage events are stochastic in nature, cannot be predetermined and may occur at any point in the pipeline. Also, researches [2,13] shows that over 90% of leakages are caused by third party interference and vandalism, where the mean value of the failure rate is 0.351 per km-year. Hence, we propose the deployment of several sensors along a pipeline segment with two constraints :

- The distance between sensors must be less than half the sensor's maximum communication range to ensure a two-hop interconnection.
- The distance between sensors and event source must be sufficiently small to make small leakage events detectable by at least three nodes considering the amplitude of the NPW (eqn 4). This is to ensure detection and localisation in the event of node failure.

In this work, we consider a linear and uniform deployment of sensors on the pipeline. We limit the number of collaborations among the sensors to a maximum of 2-hops. This allows us to minimise the various interferences resulting from such collaborations and optimising the energy consumption for all the sensors. Therefore, 2-hops data sharing represents additional information from two upstream nodes and two downstream nodes (Fig. 2).

Leakage detection: In HyDiLLEch, leakage detection is implemented by making use of PPA to pre-estimate the expected pressure at every sensor node location. According to equation (1), we can find the pressure gradient PG_{0-L} for a pipeline. Thus, the pressure gradient in a steady state at every point for a horizontal pipeline can be estimated as follows:

$$PG_{0-L} = (\frac{P_0}{\rho g} - \frac{P_L}{\rho g})\frac{1}{L} \tag{5}$$

A threshold is set to accommodate the difference between the real value and possible calibration errors from the sensor readings. The first step in detecting leakage is by comparing the sensed pressure and the pre-estimated pressure threshold. A difference between these values represents a possible leakage. Then we check the pressure values to determine the pressure gradient on both side of the current node i ($PG_{(i-1)-(i)}$, $PG_{(i)-(i-1)}$) and finally, we check for the arrival of the NPW front. Thus, we can correctly detect the presence of leakages and reduce false positives.

Leakage localisation: Each node detecting a leakage does its localisation estimation by two methods. The first one is GM, using pressure gradients and equation (2), while the second is considering the time of arrival of the NPW front [17]. It can be calculated by:

$$\overline{Q} = node\text{'}s\ offset + c \times \delta t \tag{6}$$

where c is the negative wave speed estimated by equation (3), δt the difference in arrival time of the signal at the upstream and downstream nodes and *node's offset* is the distance between the nodes multiplied by the detecting node's index.

Algorithm 1 HyDiLLEch (Double-Hop)

{Initialisation while no leakage}
Form Neighbourhood
Get PG in steady state
Set upper, and lower threshold values for PG
for ever do
    Get pressure data from neighbours
    Calculate local gradients $PG_{(i-1)-(i)}$, $PG_{(i-2)-(i)}$, $PG_{(i)-(i+1)}$ and $PG_{(i)-(i+2)}$
    Detect NPW
    if local PG is outside the threshold *and* NPW detected, share NPW data **then**
        Try to localise using GM data (equation 2)
        Try to localise using NPW data (equation 6)
    else
        No leak detected
    end if
end for

Finally, HyDiLLEch is defined with a neighbourhood of 1-hop (2 nodes) or 2-hops (4 nodes) to deal with a possible node failure - respectively referred to as HyDiLLEch-1 and HyDiLLEch-2. Algorithm 1 shows the main structure of the 2-hops version.

Both versions result in an increment in the number of sensor node detecting and localising leakages (NDL) with relatively high localisation accuracy. The results of the simulation are discussed next in the following section.

5 Simulations and Results

Metrics used to determine the efficiency of LDTs include *accuracy* of leakage localisation, *sensitivity* to leaks, amongst others. In this work, we focus on these two metrics to determine the efficiency of HyDiLLEch compared to the classical LDTs, including the energy consumption and communication overhead due to the distributed approach of our LDT.

Using NS3, we simulate crude oil propagation and leakages on a horizontal transmission pipeline for a single-phase laminar flow within industrially-defined operational criteria. The pipeline properties, such as the length, material, etc., are those of existing long haul transmission pipelines sourced from the Department of Petroleum Resources (DPR) of Nigeria. Tables 1 and 2 outlines the simulation parameters.

Material	Carbon steel
Pipeline Length (L)	$20km$
Wall thickness (w)	$0.323m$
Inside diameter (d)	$0.61m$
Height/elevation (z)	$0m$
Oil kinetic viscosity	$2.90mm^2/s$
Temperature	$50°C$
Oil density (ρ)	$837kg/m^3$
Inlet pressure (P_0)	$1000psi$
Reynolds no (R_e)	1950
Velocity (V)	$2m/s$
Molecular Mass (m)	229
Oil elasticity (K)	$1.85 \times 10^5 psi$
Carbon steel elasticity (Y)	$3 \times 10^6 psi$
Gravitational force (g)	$9.81m/s^2$
Constant (e)	2.718
Coefficient of friction (λ)	0.033
Wave speed (c)	$14.1m/s$

Table 1 Pipeline and oil characteristics

Number of sensors	21
Number of gateways	1
PHY/MAC model	802.11ax Ad hoc
Transmit power	80dBm
Transmit distance	20km
Error model	YANS
Propagation Loss	Log-distance
Path Loss (L_0)	$46.67dB$
Reference distance (d_0)	$1m$
Path-Loss Exponent (σ)	3.0
Packet size	$32bytes$
Data rate	$1Kbps$
Distance between sensors	$1Km$

Table 2 Network simulation parameters

These parameters enable us to calculate the values of the NPW speed using equation (3). Expected pressure (P_L) at the pipeline's outlet in a steady state is firstly estimated by the Bernoulli equation defined in equation (1). The resulting value is then used to determine the pressure gradient using equation (5). As a preliminary work, all tests are conducted in ideal conditions, i.e. no communication or node failures and results are discussed in the following subsections.

5.1 Localisation Accuracy

In our first simulations, we implemented two LDTs (NPWM and GM) in a centralised way [18]. While they both localise the leakage at an average of 99%

and 98%, respectively, with different variance, the centralised detection and localisation make them susceptible to SPOF and less robust to other types of failures, i.e. communication failure and others outlined in section 3. In this section, we explain how HyDiLLEch performs relative to this drawback.

Both single-hop (HyDiLLEch-1) and double-hop (HyDiLLEch-2) versions of HyDiLLEch were simulated, and the results are represented in Fig. 3 and 4 respectively. The number of NDL are *four* for HyDiLLEch-1 and *six* for HyDiLLEch-2, a significant increment compared to *one gateway* in the centralised version. These sensors, which are represented as N_{1-6} in Fig. 3 and Fig. 4, make use of the spatially correlated data (pressure gradient and negative pressure wave arrival) received from neighbouring sensors.

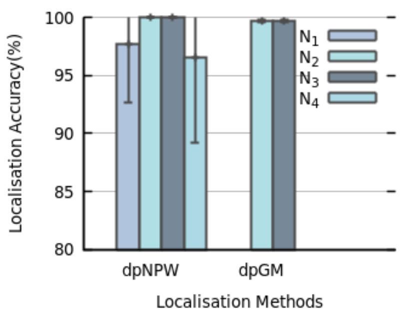

Fig. 3 Single-hop HyDiLLEch

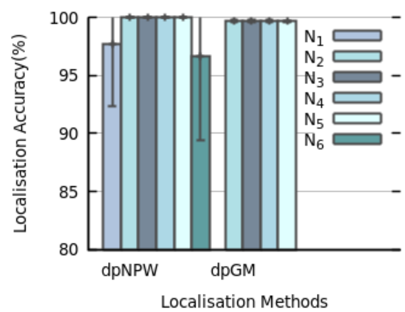

Fig. 4 Double-hop HyDiLLEch

Thus, in HyDiLLEch-1, the average localisation accuracy on all four nodes is above 96%, with nodes N_2 and N_3 maintaining the highest accuracy of about 99%. HyDiLLEch-2 has similar results with two additional NDLs. Nodes physically-close to the leak -N_2, N_3, N_4, N_5- are also maintaining the highest accuracy of about 99%.

Note that from Figures 3 and 4, we have several nodes localising using different principal information (dpGM or dpNPW). The hybrid method is kept loosely coupled to allow robustness of detection and to improve fault tolerance in cases where one or more performance influencing factors such as noise, communication failure, node failures, etc. is particularly detrimental to one of the localisation techniques. The choice of the most accurate estimated leak location will be made through a consensus algorithm to be implemented in the data and service layer in our future work.

5.2 Communication Efficiency

To compare the communication efficiency of the LDTs, we consider the cost of communication by the number of packets used by each LDT. We also evaluate their energy consumption based on the sampling rate and the radio energy consumption of the net devices. Obtained results are discussed next.

Communication Overhead: Fig. 5 shows the number of packets exchanged between the sensors and the gateway (for NPWM and GM -based on the total number of packets needed to localise) and amongst the sensors for HyDiLLEch-1 and HyDiLLEch-2. The GM has the lowest number of exchanged packets compared to NPWM and the two versions of HyDiLLEch. As expected, data correlation among neighbours increased the overhead in the number of packets in HyDiLLEch. Thus, HyDiLLEch-1 relative to GM has an overhead of about 50% with a corresponding 200% increment in the number of NDL. HyDiLLEch-2 has approximately 60% overhead with a 400% increment in the number of NDL as well. On the contrary, both versions of HyDiLLEch requires a lower number of packets when compared to NPWM packets with an even higher increment of 400% and 600% in the number of NDL respectively.

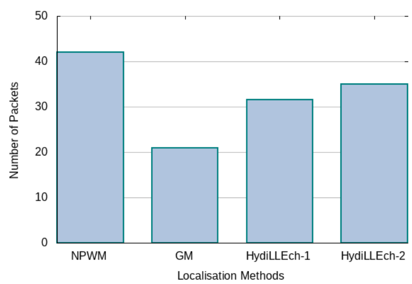

Fig. 5 Communication overhead by number of packets

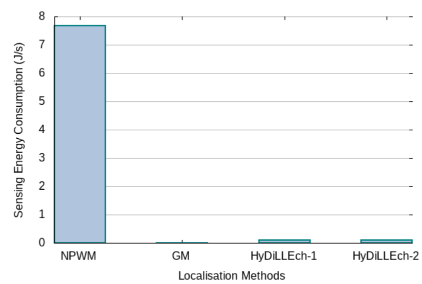

Fig. 6 Sampling energy consumption of the sensors

Energy Consumption: We evaluated the energy consumption of each LDT based on *the sampling rate* of the sensors and *radio energy consumption* by the network duty cycle. Results shown in Fig. 6 reveals the energy consumed per second by the sensors. The high sampling rate of NPWM results in more energy consumption compared to both GM and HyDiLLEch. Combining both techniques in HyDiLLEch allows first determining the offset region before enhancing the location accuracy by the expected time of arrival of the NPW. Thus, we need less than 2% of NPWM sampling rate, allowing us to take advantage of the low energy consumption of GM while maintaining the high localisation accuracy of NPWM.

In the radio energy consumption case, we analyse the rate of change of the energy consumed by the netdevice for every duty cycle. From Fig. 7, the most significant change can be seen during the first and second duty cycles. This is due to the difference in connections required among the participating nodes by each LDT. Once connections are established and as the cycle increases, the energy consumption converges and becomes stable for each of the

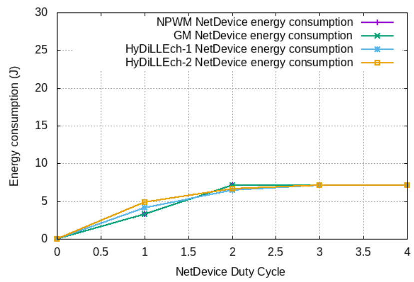

Fig. 7 Radio energy consumption

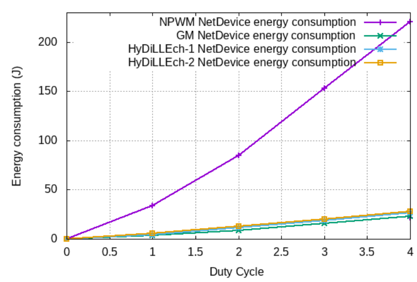

Fig. 8 Cumulative energy consumption

methods. Fig 8, on the other hand, shows the cumulative energy consumption of all the methods. Energy consumption compared to NPWM is reduced by approximately 86% and 83% for HyDiLLEch version 1 and 2, respectively, in the first duty cycle, and increase by $6-7\%$ compared to GM per NDL. Both versions show a more linear rate of change in consumption as the cycle increases, which is very similar to that of GM.

6 Conclusion and Future Works

In this paper, we proposed a new LDT –HyDiLLEch– based on a fusion of several detection techniques using a node placement strategy that allows distributed detection and localisation of small to big-sized leakages.

Simulation results show that HyDiLLEch in both the single and double-hops versions increased the NDLs by four to six times, respectively, thereby eliminating the SPOF problem related to the classical LDTs. In terms of communication efficiency, both versions of HyDiLLEch performed comparatively well with little to no communication overhead. We also showed that the global energy consumption of HyDiLLEch is relatively low compared to NPWM and similar to GM. In our future work, we will examine the fault tolerance and resilience of HyDiLLEch by introducing communication, node, etc. failures to the system. The choice of the most accurate estimated leak location will be made through an asynchronous consensus to be implemented in the data and service layers. Once the data and service layers are implemented, experiments will be carried out on real pipeline networks.

Acknowledgment

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