FracBots: The Next IoT in Oil and Gas Reservoirs

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Abstract— **Fracture Robots (FracBots) technology is a game-changing technology that has, been developed to revolutionize upstream operations. FracBots are magnetic induction (MI)-based wireless sensor nodes that have the inter-node wireless communication, sensing and localization estimation capabilities. FracBots are miniature devices that can operate as wireless underground sensor networks (WUSNs) inside hydraulic fractures to collect and communicate important data and generate real-time mapping. A large number of FracBots is deployed to establish FracBot-to-FracBot connectivity, making the technology the first IoT (Internet of Things) to generate and exchange data inside the reservoir without human intervention. In addition, a novel artificial intelligence (AI) framework is designed for the real-time sensor selection for subsurface pressure and temperature monitoring, as well as reservoir evaluation. The framework encompasses a deep learning technique for sensor data uncertainty estimation, which is then integrated into an integer-programming framework for the optimal selection of sensors to monitor the reservoir formation. The results are rather promising, showing that a relatively small numbers of sensors can be utilized to properly monitor the fractured reservoir structure.**

Keywords- Wireless underground sensor network; magnetic induction communication; FracBot network; 4IR; artificial intelligence; formation evaluation; robotics; reservoir mapping.

I. INTRODUCTION

Sensing deep in the reservoir has always been a major objective to enhance reservoir formation understanding and optimize the recovery from the reservoir. In the early days of the oil and gas industry, determination of reservoir formation properties was based on assumed geological formations and structures encountered on the surface [1]. Furthermore, retrieved rock cuttings assisted in getting a better understanding of the reservoir formation, however, this information is limited to a small area and may not be representative of the reservoir formation as a whole or taking into account the heterogeneity in the reservoir. Another challenge for mature reservoirs is to determine the sweep efficiency in the reservoir, where besides production information and some surface reservoir monitoring, such as seismic or electromagnetics, there is no overall in-situ reservoir monitoring system available [2, 3]. As the reservoirs are dynamic, permanent monitoring of the reservoir is crucial to determine the saturation flow and the fracture channels. Hence, an in-situ monitoring of the reservoir becomes quintessential in order to overcome the existing challenges of limited information away from the wellbores.

The 4th industrial revolution (4IR) has become a major transformer of the upstream petroleum industry. Major advances were already achieved in enhancing production, performing real-time monitoring of wells and reservoirs and also forecast potential reservoir risks and workover requirements [4, 5, 6]. Several advances were also achieved in performing maintenance and installation operations remotely via the help of 4IR technology [7]. The main objective is to improve productivity and cost-effectiveness of the operations, as well as enhance safety. This allows to conduct maintenance in a much shorter time period and also allows to conduct the operations around the clock.

Enhancing production from and monitoring reservoirs are critical components for ensuring the effectiveness of oil and gas operations and maintain its sustainability. For this, sensing is an essential area that allows to monitor the reservoir in real-time and investigate its evolution. Continuous sensing further allows monitor the behavior of a reservoir over time and forecast its future production potential. Conventional surface sensing covers an extensive area of the reservoir. However, the resolution and challenge connected to the multiple solutions of the inverse problem represent a significant problem. The challenge arises primarily from the lack of direct measurements and observations in the reservoir. Furthermore, challenges arising from placing large measurement equipment downhole for an extensive period of time may render this approach. While surface sensing enables to cover an extensive area and deduce easier the correlations between different measurements, as well as the causes and effects, subsurface sensing operations are significantly more challenging. This is due to the lack of direct measurements and observations of the reservoir structure and formation, as well as challenge to place measurement equipment downhole [8,9]. In order to overcome this challenge related to the lack of direct measurements, a more direct approach to sensing in the form of subsurface reservoir sensors is essential.

Miniaturized downhole sensors have been developed in recent years, allowing to achieve permanent downhole sensing that is both robust and efficient [9, 10]. Reference [11] presented a temperature insensitive pressure sensor based on fiber-optics that has a size of only 125 micrometers. The authors demonstrated the ability to measure pressure levels over a significant range with minimal temperature effects, which may make these sensors applicable for downhole sensing. Similarly, reference [12] presented a fiber-optic FabryPerot gas refractive index sensor for high temperature applications. The miniaturized sensor allows to measure up to 800 degrees Celsius, outlining the feasibility of high temperature permanent downhole monitoring with low power consumption.

In general, microseismic and tiltmeter surveys are ones of many technologies available to characterize reservoir hydraulic fractures but they are expensive, approximate, and time consuming. Moreover, they are conceptual approaches that do not unfortunately provide useful information about the inner workings of hydraulic fractures. However, reference [10] presented innovative wireless sensors for the mapping of hydraulic fractures in subsurface reservoirs. The results outline the ability to accurately map fractures with a hybrid solution of electromagnetic and magnetic conduction wireless communication in order to overcome excessive path losses within the reservoir environment. Communication losses between the sensors represent a major challenge in addition to the power requirements of the sensors, requiring that there is sufficient proximity between the wireless sensors such that the data is adequately transmitted. These advancements lead to the feasibility of downhole sensing in the reservoir with data transmission being conducted wirelessly [6]. Powering these downhole sensors for long period to maximize the sensing duration in the downhole environment is a major challenge. All sensors do not require to operate at the same time due to the connectedness of the reservoir and partial redundancy of the downhole sensors. This operational feature helps to achieve the objective of maximizing data acquisition while minimizing overall power consumption. However, this objective leads to the problem of selecting the minimal number of sensors while achieving the target objective of the most accurate downhole sensing. These selection schemes can typically be classified in coverage schemes, target tracking and localization schemes, single mission assignment schemes and multiple missions assignment schemes [7]. Coverage schemes are selection schemes that ensure the sensing coverage of the location or the targets of interest, while target tracking and localization schemes focus on the selection of sensors for target tracking and localization purposes. The mission assignment schemes focus on the selection of sensors for a single or multiple mission that have to be accomplished.

In this work, we review the FacBot technology and demonstrate a novel intelligent sensor selection framework for the optimization of sensor selection in real-time for flow and fracture monitoring. We generated a platform for FracBot development including software and hardware elements. To this end, we have contributed in five areas as follows: first, we developed a novel cross-layer communication framework for MI-based FracBot networks in dynamically changing underground environments, and thoroughly modeled the efficiency and performance of the network. Second, we developed a novel magnetic induction (MI)-based localization framework that exploits the unique properties of the MI field to determine the locations of the randomly deployed FracBot nodes in hydraulic fractures. Third, we developed an accurate energy model framework of a linear FracBot network topology that gives feasible FracBot transmission rates while respecting the constraints of a realistic energy harvesting paradigm. All together, these elements demonstrate that important new capabilities including 3D mapping of a hydraulic fracture and on-going measurement of reservoir parameters in-situ are possible using wireless underground sensor networks (WUSNs). Fourth, we designed, developed, and fabricated MI-based FracBot nodes. To validate the performance of our solutions in our produced prototype of FracBot nodes, we developed a physical MI-based WUSN testbed. Finally, we develop a novel intelligent sensor selection framework for the optimization of sensor selection in real-time for flow and fracture monitoring. The objective of the framework is to maximize longevity of the operations while maintaining measurement accuracy and flow detection ability.

II. FracBots System

A typical oil reservoir environment with a hydraulic fractures has been described in Figure 1 displaying the tentative placement of the FracBots. The research challenges of current wireless sensor networks (WSNs) are addressed to position wireless underground sensor nodes (FracBots) in cracks during the hydraulic fracturing procedure in order to be capable to work efficiently in underground settings. A short system lifetime, trouble in launching wireless signals, and high path loss are included in these challenges [13]

The structure design of the MI-based FracBot network has been illustrated in Figure 1, which has two layers:

- FracBot (sensor nodes): They are small nodes placed into the fracture throughout the hydraulic cracking process. The nodes positions are roughly uniform and linear inside the fracture because the fracture is extremely narrow. The FracBots are wireless nodes that have powerless source, but they are charged from EM radiation transferred wirelessly from the base station located at the wellbore.
- The base station: It is made up of a big dipole antenna at the wellbore, is linked to an above-ground connection.

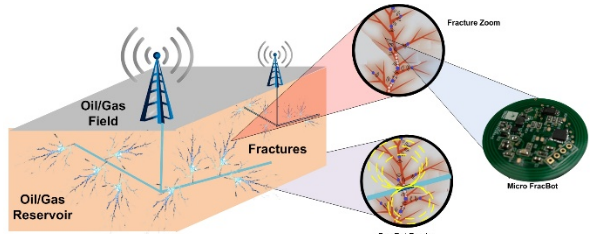

Figure 1. The structure of the FracBots network.

A. FracBot Architecture

FracBots are active micro-wireless sensors injected inside the hydraulic fracture during the hydraulic fracturing process. The FracBot node is furnished with a processor, a transceiver, an antenna, a sensing unit and a harvesting unit. It harvests energy transmitted from the base station, which permits it to execute sensing tasks and to wirelessly communicate collected data back to the base station using MI-based communication.

B. Network Architecture

Fractures dimensions are nominally millimeters wide and some meters high, can reach up to 100 m long. The FacBots are assumed for current purposes to be almost static and uniform in the fractures. Therefore, a static network scheme for the FracBot system in the fracture is envisioned as described in Figure 2. This indicates that energy is transmitted and collected in a single-hop energy method while sensed data is communicated in a multi-hop mode. We suggest a three-stage operational arrangement based on the structure design described earlier.

1) A single-hop emitted energy phase: The base station releases energy through a crack and communicates with the FracBot sensors. The base station is situated at the wellbore and provided with high power communication antenna which permits the use of low frequency RF to emit EM waves and transmit the energy via the fracture environment to the MI-based FracBots spread out in the hydraulic fracture.

2) A multi-hop MI-based transmission phase: The FracBots gather essential energy through harvesting, sense related reservoir parameters, and use the MI communication technique to communicate quantities to the nearby neighbor sensor, and by successive repeating, the uplink with the multi-hop communication path is utilized to communicate the information to the base station.

3) A backbone communications phase: In this phase, the base station collects the sensing information from the FracBots in the fracture and then sends the information via an aboveground gateway.

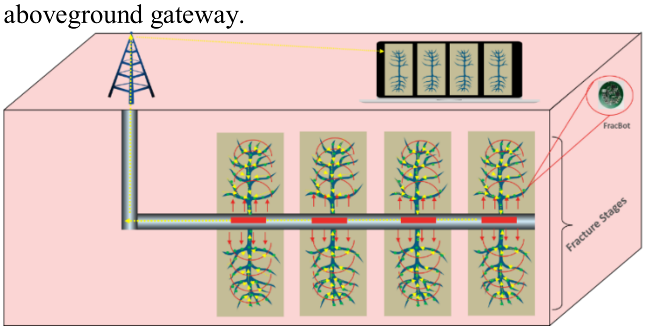

Figure 2. The FracBots network.

III. WIRELESS FRACBOT NETWORKS ENERGY

A wireless channel model in hydraulic fracture is described for both MI communications and energy transmission. The suggested FracBot network comprises of two types of channels described as follows:

A. Downlink Wireless Channel Model

To radiate energy and communicate information to the FracBots in the fracture, the base station antenna emits EM waves at low MHz frequency. The EM waves are affected by harsh environment, and numerous fluids including oil/gas and water in the fracture. The key ingredients surrounding the fracture are reservoir rocks, as displayed in Figure 1. Thus, the fluids and substances influence the downlink path loss as in Eq. (1) [14].

$$L_{DL} = 10\, log\left(\frac{N^2\omega^2\mu_2^2 l^2 r^4 k_2^2 sin^2\theta}{64 R_c R_i d_{DL}^2}\left[\frac{1}{k_1^2 d_{DL}^2}+1\right] e^{-2d_{DL}/\delta}\right) \quad (1)$$

Where θ is the angle of the coil positions, N is the coil number turns, Rc is the resistance of the coil antenna, and r is the radius of the coil. k1, k2 are the wavenumbers inside and outside the fracture, l is the length of the base station antenna, δ is the skin depth inside the fracture, Ri is the input resistance of the base station antenna, μ2 is the reservoir and rocks effective permeability, w is the angular frequency, and d is the distance between the base station and the FracBot. We use the following values throughout this paper. The reservoir rock has similar to that of air (i.e., μ2 = μ0 = 4 × 107 [H/m]). As explained later using magnetic permeability, the permeability μ1 inside the fracture, if occupied with magnetic proppants, is assessed in Eq. (3). We used the following parameters to calculate the permeability. The ratio of ppara and pferro are 30% and 10%, respectively, the proportionality constant ĉ is 0.993, and the magnetic susceptibilities χferro is χFe3O4 ≈ 5 × 10−4 for temperatures under 853[K]. The material employed to yield the high-μ proppants can regulate this effective permeability. The effective permittivity inside the fracture is set to be ε1 = 3.5ε0 (crude oil) while the permittivity of the matrix / reservoir and rock is set to be ε2 = 2ε0 (sand and clay mixture). If we primarily suppose absolute oil production, the conductivity outside the fracture is set to be σ2 = 0.001 S/m, while the effective conductivity in the fracture is low, on the order of σ1 = 10−4 S/m. A base station transmitting power of 50 watts with 20 m dipole antenna are used. Ri = 75Ω is the input resistance. The operating frequency is 10 MHz for the antennas (the dipole and the coils), 5 mm radius and 10 as the number of turns of the coils. The coil resistance is Rc = 0.2 Ω. The minimum received power is Pr = −100 dBm and the converting rate of the energy at the FracBot sensor is η = 80%.

Figure 3 illustrates the power received at FracBots as a function of the distance between the base station and the FracBots in the hydraulic fracture. The energy transfer framework displays the received power by the FracBots. It indicates that the energy model can overcome the hydraulic fracture environment restrictions. For instance, at a distance of 30 m from the base station, the received power is about -50 dBm, it is adequate to power the very low power wireless FracBots.

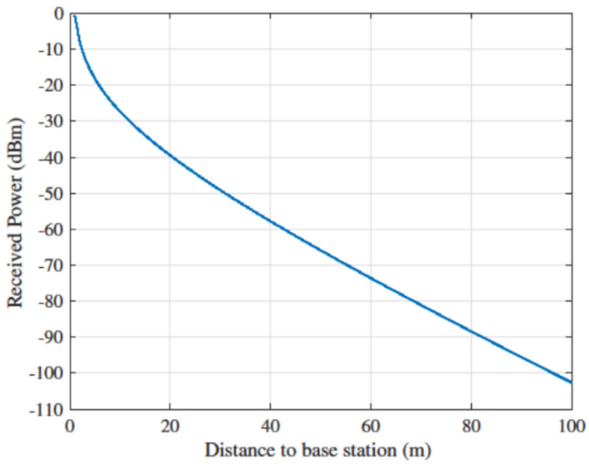

Figure 3. Power received by FracBots from the base station.

B. Uplink MI Channel Model

To send and transmit collected data by the FracBot sensors to the base station in the multi-hop mode, the uplink channel between two adjacent FracBots is employed as presented in Figure 2. The MI technique, to propagate signals and accomplish constant channel settings through the small size of the coils, utilize the near magnetic field of coils. MI communication is extremely appropriate for underground environments. The distinctive MI-based channel formed in the fracture medium is covered by the uplink channel capacity. Reference [15] attains this capacity:

$$C_{UL} = f_U \, log_2\left[1+\frac{2\pi^2 P_t M^2 f_U^2}{R_c^2 N_{noise}}\right] - f_L \, log_2\left[1+\frac{2\pi^2 P_t M^2 f_L^2}{R_c^2 N_{noise}}\right] \quad (2)$$

Where fL is the lower frequency of the channel bandwidth, fU is the upper frequency of the channel bandwidth, Nnoise is the noise power, and Pt is the transmission power. This uplink channel capacity demonstrates the impacts of the hydraulic fracture environment to calculate a feasible data rate via the MI-communication link among the FracBot nodes.

Through the intermediate FracBot nodes, a multi-hop route forms between the FracBot nodes transmitter and the base station. A magnetic field is created between the transmitter and receiver coils, as proposed in [16]. The quality of the MI communication is impacted by the magnetic permeability of the medium which is the key environmental element. The resistance of copper coil will alter with respect to the variable temperatures in hydraulic fracture, particularly, while the permeability of matrix and water is similar to that of air (i.e., μ0 = 4 × 107 [H/m]) at room temperature. Depending on the composites of the underground magnetic content, the medium permeability also behaves differently. The effects of medium permeability and temperature are governed as [16]:

$$\mu = \mu_0(1+x) = \mu_0\left(1+p_{para}\frac{\hat{c}}{T}\right)+p_{ferro}x_{ferro} \quad (3)$$

$$R = 2\pi r N R_0\left[\alpha_{Cu}(T-T_{0)}\right] \quad (4)$$

Where, μ0 is the air permeability, R is the coil resistance, χ and χferro are the magnetic susceptibilities of the medium and ferromagnetic contents, respectively. ĉ is a constant, pferro and ppara are the ratio of ferromagnetic and paramagnetic composites, respectively, T [K] is the actual hydraulic fracture temperature, T_0[◦K] is the room temperature, α_{Cu} = 3.9 × 10−3 [K] is the copper coil's temperature coefficient and R0 [Ω/m] is the resistance of a unit length of coil at room temperature. Stokes theorem is used to obtain the self and mutual inductance is analytically.

$$M(T,\sigma) = \frac{\mu\pi N^2 r^4 \delta(d,\sigma)\cos\theta}{4d_{DL}^3} \quad (5)$$

Where, δ(·,·) is attenuation caused by the skin depth effect and σ [S/m] is the medium conductivity. Between the two MI transceivers, the path loss of MI communication can be described as

$$L_{UL}(d,f_0,\theta,T,\sigma) = \frac{2(2R^2+\omega_0^2 M^2)}{\omega_0^2 M^2} \quad (6)$$

Thus, the estimated uplink channel bandwidth is achieved by

$$B_{UL}(T,\sigma) = \frac{R(\sqrt{2}-1)}{\mu\pi^2 r N^2} \quad (7)$$

The lowest transmitting power amount needed to facilitate inter-communication among FracBots over the MI-based channel in hydraulic fracture is displayed in Figure 4. The required transmission power rises dramatically as the distance between the two FracBot nodes rises, as a result of the complex transmission medium. To assure the MI-link quality, this distance must be optimized. The path loss and the frequency response of MI channels at different temperatures in the hydraulic fracture environment is exhibited in Figure 5. The path loss rises, when the operating temperature and the transmission range rise, resulting in degradation of the quality of the communication link.

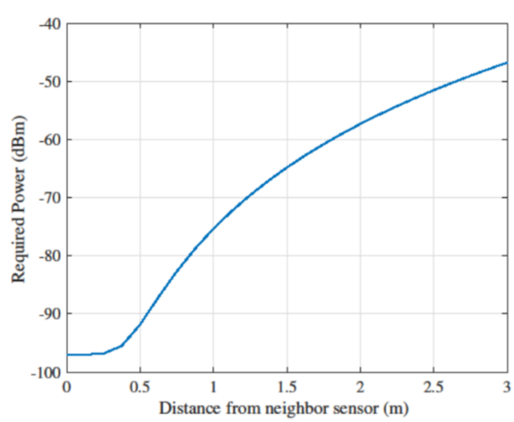

Figure 4. Required power to transmit data from FracBot to neighbor FracBot.

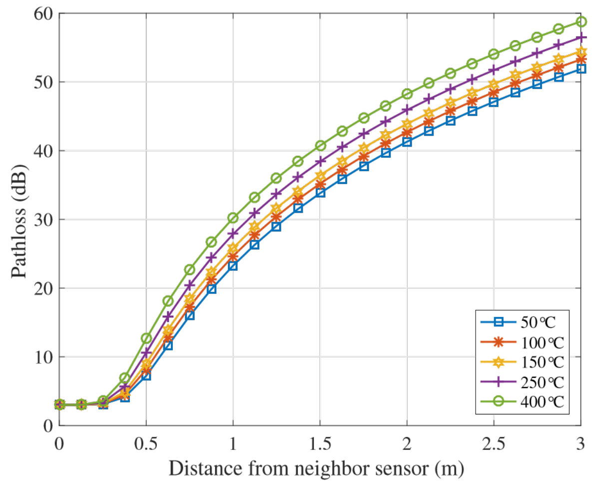

Figure 5. Path loss of magnetic induction at different hydraulic fracture temperatures.

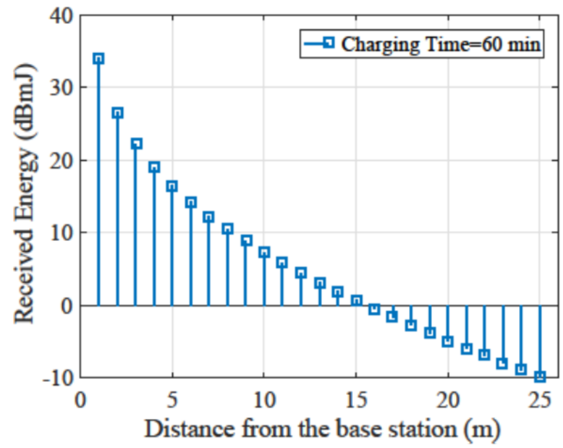

Figure 6. Harvested energy in FracBots network.

C. Energy Consumption and Energy Harvesting Model

To charge the whole FracBot network, the downlink energy charging functions in one-hope fashion. The size of FracBot nodes is very minor which restrict the battery capacity due to the very narrow fracture. Hence, the very low size battery is not able to keep sufficient power for the FracBots to operate the communication and conduct sensing tasks. Due to this limitation, to store the harvested energy for the FracBot operations, the battery is replaced by ultra-capacitor. Accordingly, as the size of sensed information transmitted by FracBots is determined by the collected energy, it is essential to acquire precise energy model for charging and consumption process. To model the energy harvesting from the base station installed in the oil well, the recent results for an energy transfer model were implemented [16]. As a function of the distance from the Base station to a particular FracBot, the equivalent path loss can be calculated for the downlink channel by [14]:

$$E_i^h = T_i^c \eta_i P_{TX} L_{DL}\left(\sqrt{l^2 + \left(\sum_{i=1}^{n} d_j\right)^2}\right) \quad (8)$$

Figure 6 shows the collected energy over the distance between the base stations and the FracBots in the hydraulic fracture in a one-hour charging time. The power received by the FracBot nodes overcoming the hydraulic fracture conductivity constraints is revealed by the wireless energy charging model. For example, the harvested energy is around -10 dBmJ at a 25 m distance from the base station that is sufficient to charge the very low power MI-FracBots.

IV. FracBot Functionalities

The basic functions have been developed. First, we have developed an innovative cross layer communication model for Magnetic Induction networks in altering underground environments, coupled with selections of coding, modulation and power control and a geographic forwarding structure. Second, we have developed an innovative MI-based localization framework to capture the locations of the randomly deployed FracBot nodes by exploiting the exceptional properties of the MI-field.

A. Environment-Aware Cross-layer Communication Protocol

We present a distributed cross-layer framework for MI-based WUSNs [18]. A cross-layer framework is recommended for WUSNs in oil reservoirs as an alternative of taking the classical layered protocol method which is the 7-layer Open Systems Interconnection model (OSI Model). To improve MI communication in WUSNs, it is executed in a distributed manner to jointly enhance the communication functionalities of different layers. Our solution attains optimal energy consumption and high throughput efficiency with low computational complication, and also fulfills the quality of service (QoS) requirements of diverse applications. These properties qualify our solution as a valuable for practical applications. The cross-layer solution framework includes the following:

1) Evaluation for the major environment facts of underground reservoir affecting the transmission qualities of MI-based communication.
2) Three-layer protocol stack for WUSNs in oil reservoir.
3) Cross-layer framework to conjointly enhance communication functionalities of various layers.
4) Distributed Environment-Aware Protocol (DEAP) proposal to realize the projected cross-layer framework.

Figure 7 demonstrates the protocol stack for environment-aware cross-layer protocol design and its key contributions. Firstly, the distributed cross-layer framework accounts for environment information of oil reservoirs that influences the MI-based communications qualities. MI channel models are established to consider the effects of the physical layer functionalities. The effects of temperature, electrical conductivity, magnetic permeability, and coil resistance are studied. This is to capture their effects on the MI-communication parameters, such as the path loss, the bandwidth, and the interference. Second, the protocol stack consists of three-layer stacks: a data link layer, a network layer and a physical layer. The communication functionalities for each layer of a protocol stack are recognized, for example, medium access control (MAC), routing algorithms, modulation and forward error coding, and the statistical quality of service (QoS) comprising of transmission reliability and packet delay. These parameters are analyzed to find out their effects on MI-based communications. Third, the proposed cross-layer framework addresses all functionalities of each protocol layer. To optimize MI communication in WUSNs, it is executed in a distributed manner to jointly optimize the communication functionalities of various layers. Finally, DEAP is recommended to comprehend the cross-layer framework and solve its optimization problem in a disseminated manner. The DEAP process comprises a distributed power control, an evaluation of a multiple access scheme for a data link layer and a two-phase decision process for executing a routing algorithm for the network layer.

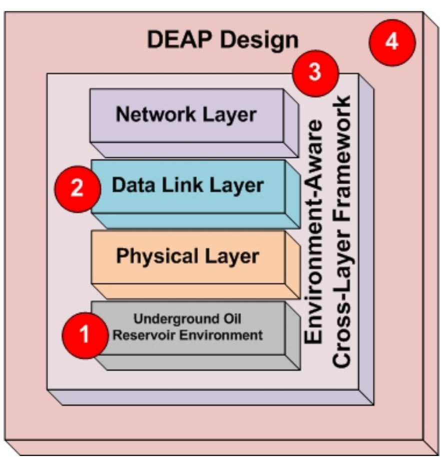

Figure 7. Protocol stack of environment-aware cross-layer protocol design.

Thus, the DEAP achieves both optimal energy savings and throughput gain concurrently for practical application and provides statistical QoS guarantee. Evaluation findings indicate that cross-layer framework outclasses the layered protocol solutions with 6 dB throughput gain and 50% energy savings. Furthermore, the distributed framework comprises of two-rounds per node decisions that involves single-hop neighbor data and has uncomplicated computation process. As a result, consistent and effective communication is recognized by the distributed cross-layer design for MI communication in the challenging underground environments.

B. *FracBots Localization Framework*

We introduce a MI-based localization for FracBots in the hydraulic fracture [19]. We suggest an innovative MI-based localization solution, which uses the spinoff of magnetic induction communication (received magnetic field strength (RMFS)) and the promising features of MI channel. By using RMFS, it guarantees the accuracy, simplicity, and ease of the localization scheme. MI-based communication is very appropriate for oil reservoirs due to its distinctive multi-path and fading-free propagation features. Unknown sensor locations are provided by the MI-based localization in randomly-deployed wireless sensor systems in underground environments. By capitalizing on the unique features of the magnetic induction communication including fading-free and multi-path propagation features, it generates approximate distances, between two neighboring nodes and between nodes and base stations, with very accurate RMFS measurements. Our solution develops an MI-based localization framework to integrate Weighted Maximum Likelihood Estimation (WMLE) and Semidefinite programming (SDP) relaxation techniques to generate very accurate localization in underground environments. It mutually applies both fast initial positioning and fine-grained positioning to attain high positioning precision in WUSNs to provide a rapid and precise positioning in different noise systems (low and high) while sustaining high computational efficiency under various underground environment situations. Our localization framework is summarized as follows:

1) RMFS measurements for designing localization in hydraulic fracture.
2) Localization framework for WSNs in hydraulic fracture.
3) Quick early positioning by varying Direction Augmented Lagrangian Method (ADM).
4) High resolution positioning from Conjugate Gradient Algorithm (CGA).

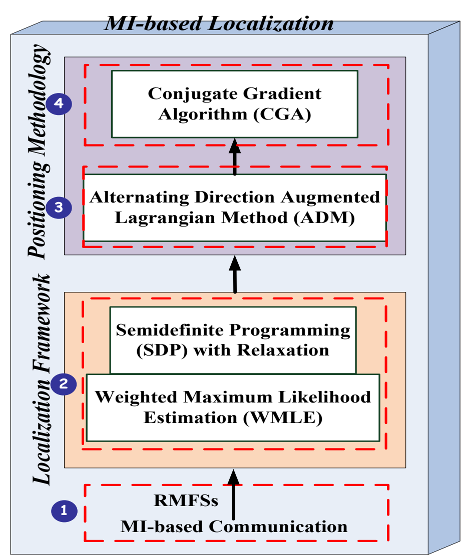

Figure 8. MI-based localization system.

Figure 8 displays the structure of MI-based localization system. The first step is to attain the approximate distance from received magnetic field strengths (RMFSs) via the developed channel models. Next, the localization framework is formulated as the problem creation of combined WMLE and SDP reduction for precise FracBot positioning from noisy distance estimations. Third, an efficient initial positioning is gained from a fast algorithm, called ADM, to provide approximate but useful location results. According to the initial results, a fine-grained positioning obtained from the powerful Algorithm (CGA) is finally fed to improve localization accurateness in a time-efficient way.

V. FracBot Nodes and Testbed

The key component of WUSN is the sensor node; mainly in reservoirs monitoring and hydraulic fracture mapping. Thus, we develop a miniaturized FracBot node to validate the feasibility and capability of using MI-based communication in underground environments. Particularly, we design and realize a FracBot node that can be used to gather useful data about hydraulic fracture such as temperature, pressure, chemistry composition and other variables. The FracBot is designed based on major electronic components including Microcontroller (MCU) and RFID/NFC chip. This chip launches the communications among the FracBots using Near Field/MI-based technique. The key design concepts are:

1) Low energy requirements (feasibility and implementation in aggressive environments).
2) MI communication (RFID/NFC technology with passive/active sensors).
3) Multi-purpose FracBots (support several sensing applications).
4) Hardware miniaturization (hardware is designed in small footprint).

To implement these key design concepts, we create a design roadmap to proficiently develop the FracBot node in terms of hardware and software as described in Figure 9.

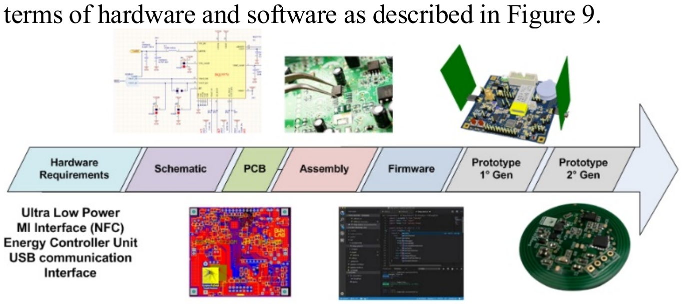

Figure 9. Roadmap of the FracBot design.

The roadmap skeletons the steps of design after determining the idea and requirements. Component selection is a broad process, requiring picks from a wide-range of available products, and it directives how the remaining phases proceed. Prototyping and software development is extremely constrained, encompassing the development of a model sensor node and associated software. Prototype design is first achieved in a schematic diagram and then as a printed circuit board. Then, the firmware and software are executed. After this stage, a completed circuit has been prepared to the final step which is testing and verification.

Restricted characteristics are essential for designing an effective node that withstands operations in severe environments with high temperature, and pressure, high path loss and limited energy. Moreover, to improve every component based on their requirements, the very small size is needed as it can protect development time, board space, and cost. The key features of our proposal are a long operating time, ultra-low power, an efficient communication layer, a processing function, and sensing capabilities and energy-harvesting. The concurrent employment of all five characteristics allows the node to operate in a perpetual powered status. The FracBot node will encompass mainly a microcontroller, a temperature sensor, an energy harvesting unit and a transceiver. The feasibility of energy harvesting will be exhibited using this FracBot node.

A. *FracBot node design and development*

The design and development of FracBot node are based on near field communication (NFC) for a physical layer coupled with an energy collecting feature and very low power requirements [20]. Two types of FracBots are created: a FracBot active node and a FracBot passive node. Figure 10 demonstrates the active FracBot prototype, which entails of a microcontroller, an energy management unit (EMU), USB communication, a temperature sensor, a NFC transceiver (passive and active), and a super-capacitor.

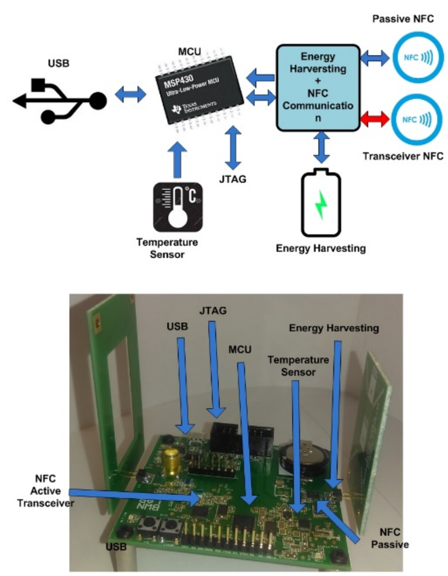

Figure 10. Block diagram and prototype of the FracBot active node.

The FracBot active node has sophisticated functions and consumes minimal energy since the FRAM technology has been exploited. The microcontroller features used in the active node are very low energy, a high processing speed, and several interfaces. In addition, Figure 10 shows a block diagram of the active node featuring the interconnection block of the node, which comprises of the microcontroller, the JTAG interface, the energy harvesting circuit, USB communication, the temperature and the MI transceiver. The JTAG interface permits us to program and access all variables of the code and stop the code from running at a pre-defined point (breakpoints).

The FracBot passive node is a passive node that does not have a transceiver but a transmitter only relaying the data to the active node. Its prototype and diagram are shown in Figure 11. It comprises of the microcontroller, the temperature sensor, the USB interface, and the NFC active tag. The NFC transceiver of the active node can access, through the established link, the NFC tag memory, change the configurations of the nodes and generate energy by harvesting energy output. As shown in the block diagram, the node is capable to launch a bidirectional communication with RFID/NFC transceiver.

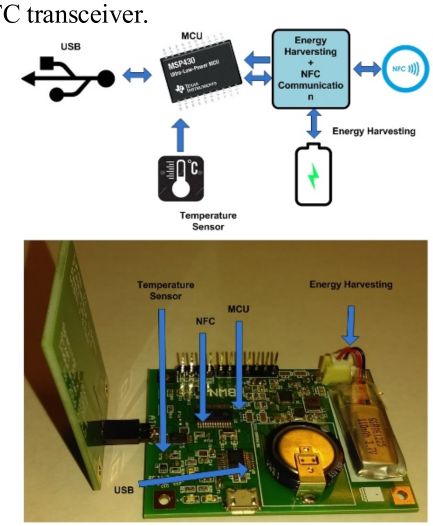

Figure 11. Block diagram and prototype of the FracBot passive node.

B. *FracBot Node Software/ Firmware*

Firmware is a special type of computer software used to control components hardware of electronic devices at low-level. Low power firmware is categorized by the capability to switch between active and low-power modes with the guarantee of the functionalities and operation continuation. This feature contributes in significant energy reduction on microcontroller unit (MCU). The software is optimized according to the advanced control of MCU and all peripherals. The most advanced microcontroller considers efficient power control, instant wakeup, intelligent autonomous peripherals and interrupts in its operation. Inefficient firmware codes are not preferred since they slow the function and require a lot of energy. There are many examples of inefficient firmware properties such as software delay loop, uninitialized ports and data format conversions. Other example is math operation set as division and floating-point operations which could cause critical operation issues. To avoid such issues, the MCU pins requisite to be configured with correct function to moderate the energy waste. To avoid software delay loop, a timer is required in interval mode configuration to enable the MCU to enter the sleep mode during the interval time. This help the MCU to not run at maximum power during the interval time. Division and floating-point operations require large computational efforts which consume a lot of the processing time and big part of the memory. To avoid that, the math operations can be configured at fixed point [21]. The design of the FracBot nodes incorporates advanced energy strategies to optimize the energy consumption based on the energy availability. It also employs very low energy profile to balance between the hardware and the software/firmware in all components operation. Furthermore, using ULP tools and energy tracer permit the development of efficient codes [21].

C. *FracBots Performance Evaluation*

After thorough studies have been theoretically conducted, little work has been devoted to evaluate a sensor node (FracBot) in underground-like environments to validate the theoretical results. Toward this end, we design and implement an experimental testbed simulating a reservoir environment that comprises of numerous media such as air, sand, water, and stone with few FracBot nodes as demonstrated in Figure 12. One of the crucial outcomes is that the performance of the FracBot is influenced by sand and stone media. They reduce the energy transfer, and eventually harm MI signal propagation. Hence, the evaluation of hardware enables the designers to apprehend the challenges, enhance the electronic desgin and minimize essential assets to reduce the hardware size.

1) *FracBot Propagation Evaluation:*

The FracBot MI propagation is evaluated at the operating frequency of 13.56 MHz. The investigations are done according to the received power measured using a signal analyzer. We also examine the MI field produced by the transceiver with and without modulation. In addition, we examine magnetic induction signal propagations in the air. We measure and study the effect of the antenna alignment on the received power. Figure 13 shows the schematic of the experimental arrangement and the real setup in the laboratory. In this scenario, MI interaction is measured at distances between 0 and 25 cm and angles of 0, 30º, 60º and 90º, respectively.

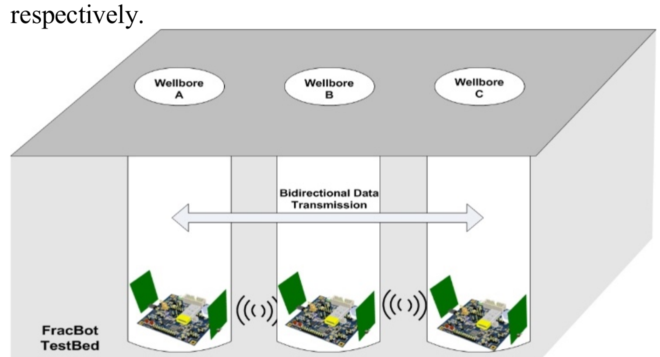

Figure 12. A model of physical testbed in hydraulic fracture.

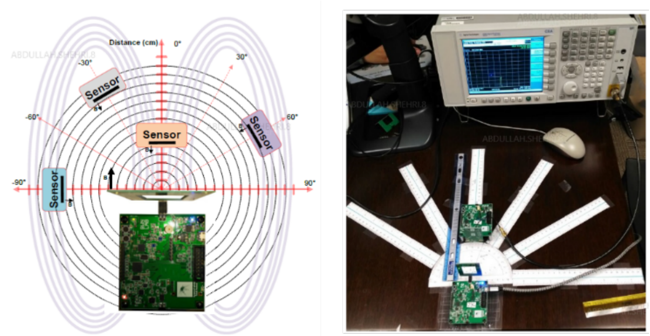

Figure 13. FracBot experimental setup.

2) Angular Analysis: The direction and the alignment of the transceiver and the receiver of the FracBots is one of the complications in MI-based communication. In the angular study, we perform measurements at 0, 30º, 60º and 90º angles. The results of distances between 6 and 25 cm, compared to those under 6 cm reveal minor variants. Figure 14 displays the power analyses of the angular variations. At distances of 6 cm and beyond, the angle between antennas (the transceiver and the receiver) affects the received power slightly, less than - 2 dBm.

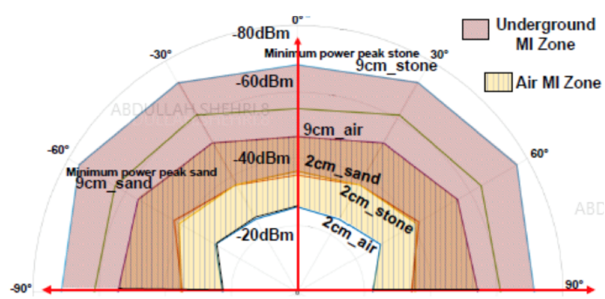

Figure 14. Angular plots of received power (air, sand/stone).

The angular study shows that the MI field radiated at 13.56 MHz is omni-directional. It enabls the Base station to assess the location of each sensor and produce a fracture map, when this characteristic is incorporated with the received signal strength indicator (RSSI) measurement. The FracBot MCU needs 50 ms to complete all reading tasks and then stock them in the NFC transponder. This task consumes 33µW of the energy available in the storage system. Based on the angular analysis, the node can function constantly by harvesting energy of the MI field if the receiver is positioned at 23 cm or nearer to the succeeding FracBot node. As an outcome, the received power in the area of 6-25 cm is approximately -50 dBm that delivers adequate energy to the node each hour and allows it to transmit information in a 50 ms time frame. After 25 cm, the received power is less than -50 dBm, that is not enough to power the node each hour. As a result, the node require to collect the necessitated energy and transmit information within a time frame of 50 ms every 2 hours at minimum. It is worth to mention that the FracBot can operate in an intermittent status if the MI signal strength is lower than -50 dBm.

3) FracBot Underground Testbed: To measure the FracBot nodes performance, we design and develop a testbed similar to underground environment comprising of a plastic container containing water, sand, and stone, demonstrated in Figure 15. The system involves several underground settings, comprising dry soil, wet soil, stone and dry soil with stone. The testbed setting permits to position the FracBots at different depths until 14 cm with a adjustable distance between the nodes. This flexibility enable changes of the experimental setup to easily evaluate the FracBot nodes performance. Using the spectrum analyzer, we measure the MI circuits characteristics such as MI propagation and antenna tuning.

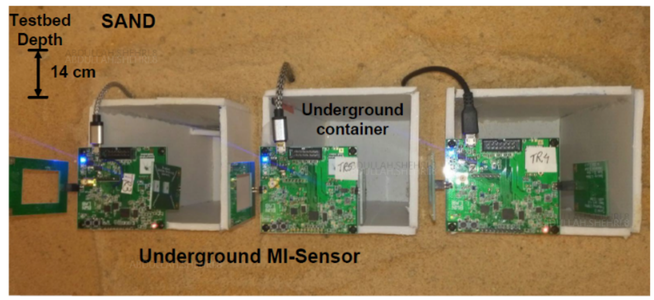

Figure 15. Underground testbed of the FracBot.

To assess the transmission link, we wirelessly link the NFC tag of first FracBot to the transceiver of second FracBot. The FracBots conduct one communication task every 3 minutes and one temperature reading per minute in the laboratory. For experimental purposes, the data transmission of long interval can be simulated by the adjustable interval time in a short time. The nodes utilize NFC technique, but as they are intended to operate in air, a consistent reference test and data analysis in air is essential. The node is examined to transmit in air and with a sand obstacle.

Table 1 displays the experimental performance for OOK and ASK modulations with data rates of 26 and 1.6 kbit/s. In an underground environment, the modulation OOK at data rate of 1.6kbit/s, compared with that at 26 kbit/s, lowers the transmission error. However, in stone, ASK modulation does not work for both rates due to high attention. On the other hand, OOK modulation works but at a higher transmission error than that in sand for both rates. Former study in underground field claims 10 MHz as an optimum frequency with data rate of 1 kbit/s [15]. To estimate the transmission link among FracBots, the nodes are located at 5 cm distant from each other, as shown in Figure 15 because of the restriction posed by the sensitivity of the off-the-shelf transponder chip limited to -50 dBm. At 5 cm, the signal strength is -50 dBm. Beyond 5 cm, the signal quality will degrade as well as the communication becomes impossible.

Table 1. Experimental performance of the ASK and OOK modulation.

Environment	Modulation	Date rate (kbit/s)	Error (%)
Air	ASK	26	2
Air	OOK	26	1

Sand	ASK	26	70
Sand	OOK	26	78
Sand	ASK	1.6	40
Sand	OOK	1.6	32
Stone	OOK	26	87
Stone	OOK	1.6	58

VI. REAL-TIME INTELLIGENT SENSOR SELECTION

In order to efficiently and long-term deploy subsurface sensors, it is crucial to optimize the sensor capability to sense as well as extend the lifetime of each sensor as long as possible. An essential part of optimizing the sensor capability to sense in the reservoir formation is to optimally select the best number of sensors. There are several trade-offs that have to be taken into account such as the battery utilization of sensors as well as need to have multiple close sensors being in operation during the same time. Specifically, one aims to reduce the number of sensors being in operation at the same time, while maintaining sufficient sensing reach. The resulting problem can then be transformed into a sensor selection problem. The sensor selection problem is mathematically defined as given a set of sensors $S = \{S_1, \ldots, S_n\}$, then we need to select the best subset with k sensors that satisfy one or multiple missions. The challenge that arises from this problem is in most instances NP-complete, which implies that there is no polynomial-time algorithm for solving the problem. This represents a major challenge for real-time data interpretation and the optimization of the sensors as in order to be able to have a recommendation available within an acceptable timeframe, an approximate solution is only feasible [22]. We will demonstrate a novel intelligent sensor selection framework for the optimization of sensor selection in real-time for flow and fracture monitoring. The objective of the framework is to maximize longevity of the operations while maintaining measurement accuracy and flow detection ability.

A. *Method*

We have developed an innovative real-time sensor utilization optimization framework that incorporates a deep learning driven optimization framework connected to a subsurface fracture network model. This forms then a crucial part of the sensor selection optimization problem that aims to optimize in real-time to minimize the number of sensors required in order to maintain sufficient data quality. This challenge is equivalent to maximize the longevity of the sensors deployed while maintaining sufficient reservoir coverage in order to limit the uncertainty in the multi-data interpretation.

The framework incorporates a deep learning approach for the sensor measurements combined with a fast iterative solver for real-time optimization of the sensor selection. The framework is outlined in Figure 16.

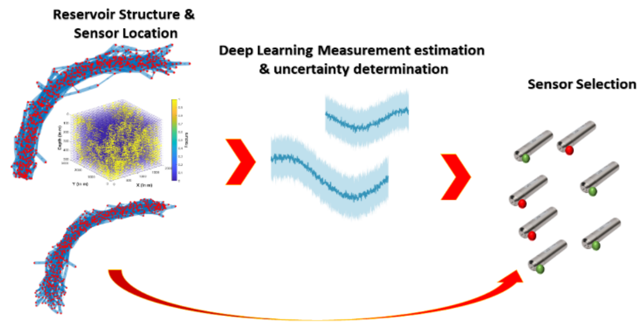

Figure 16. Framework representation with the fracture network structure and the uncertainty estimates.

First, a fracture-flow reservoir model is established using a connectivity and sensing data quality determination approach. The assumption is that the flow between injecting and producing wells is primarily within the fractures with only limited flow in the matrix structures. This is in line with conventional assumptions when utilizing discrete fracture network models, as well as observations on fractured carbonate reservoir rocks, where the flow is primarily in the fractures. The network flow model is then integrated into a deep learning framework for the sensor data estimation and the uncertainty in the estimates. The deep learning framework utilizes a feedforward network structure for determining from the sensor derived flow measurement data based on multiple potential scenarios in terms of the reservoir formation condition. The estimations relate to whether the sensors are close to the matrix or in the fracture, and what the water saturation in the vicinity of the sensor is. The main objective of the deep learning framework is to have a data-driven approach to the estimation of the fracture and water saturation in the vicinity of the sensor based on pressure and temperature measurements. The sensor selection problem is then posed as an integer optimization problem as outlined below:

$$\begin{aligned} &\min f' z \\ &s.t.\ C_z > 0 \\ &U_z \leq b_u, \forall_i \in N \end{aligned} \tag{9}$$

The integer optimization problem is solved in real-time where the vector f is the cost function dependent power consumption over time of the sensors. For each update time step, the cost function is updated from the previous, implying that if the sensor i is operational, then f_i is gradually increasing, while for the inactive sensors, f_i may remain constant or is reduced in case the sensors can be recharged. The constraint $Cz > 0$ ensures that there is for each reservoir area at least one sensor that covers this area. The matrix C is the connectivity matrix between the sensors and the area, implying that $C_{ij} = 1$ if the j-th sensor covers the i-th area. This ensures that each area is covered, and that the sensor can connect and transfer data between each other. Data transmission is a crucial

The constraint $Uz \leq b_u$ implies that the data sensing reliability for each node is maintained, implying that the sensing uncertainty must be below a threshold value. The matrix or vector U is the sensing reliability matrix, and b_u is the reliability threshold. The last constraint is a binary constraint, indicating whether the sensor is active ($z_i = 1$) or inactive ($z_i = 0$). For solving the integer optimization problem, we utilized a fast and efficient branch and bound method, via utilizing a feedback approach incorporating the solutions of previous optimizations. The framework is easily scalable to larger flow network models, allowing in near real-time to optimize the selection of sensors and maintain longevity of the sensor deployments.

B. *Results*

We examined the framework on a complex fracture network structure in 2D in order to outline the performance of the framework. The 2D model is a graph-based model consisting of 500 nodes and 1000 different network structure realizations. We have displayed in Figure 17 two examples of the different network realizations and connection between the fracture network nodes. The realizations illustrate the considerable difference between the connectedness of the fracture network which reflects the general challenge of monitoring and determining the fracture network structure and connectedness between the fractures. We then utilized a deep learning approach to estimate the uncertainty of the data based on the network structure. The data set was divided 75/15/15 into a training, validation and test dataset, and a fully connected feedforward neural network structure was used.

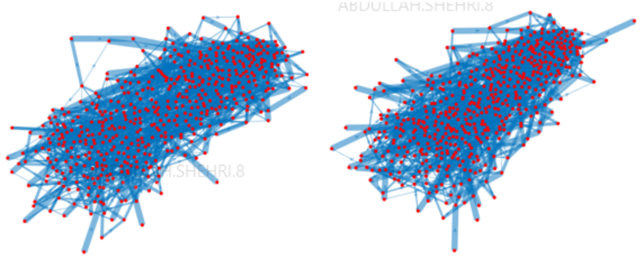

Figure 17 Different realizations of the fracture network structure.

For the optimization, we used a scaled conjugate gradient approach given the substantial size of the problem. The sensors record pressure and temperature data at each location, and for each of the sensors an interpreted uncertainty parameter is computed. The uncertainty parameter varies from 0 to 1.5, where a higher uncertainty parameter indicates stronger uncertainty in the measured data. The uncertainty measurement parameters are derived from multiple repeat measurements of the sensors that are then classified in terms of their accuracy and variation. The training, validation and testing results of the deep neural network are displayed in Figure 18. The estimation results are rather strong, outlining overall accurate estimation of the sensor data uncertainty, with the larger number of data points for lower uncertainties only marginally affecting the estimation quality for higher uncertainties.

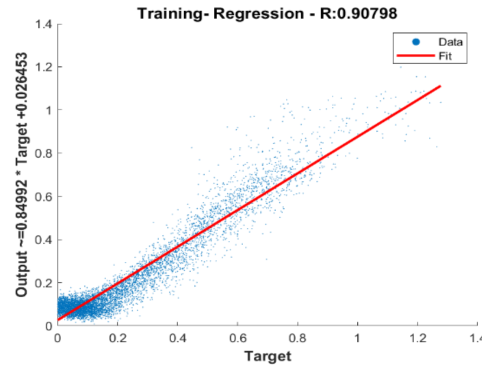

Figure 18 a. Comparison of the neural network estimation of the data uncertainty.

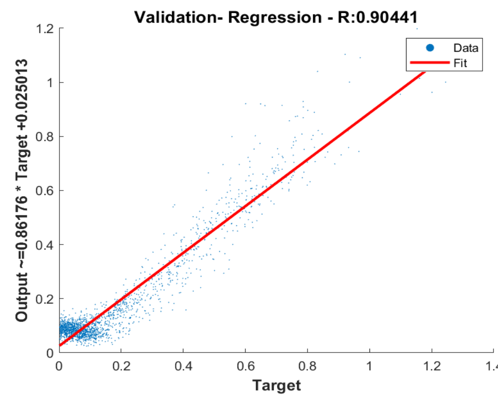

Figure 18 b. Comparison of the neural network estimation of the data uncertainty.

Figure 18 c. Comparison of the neural network estimation of the data uncertainty.

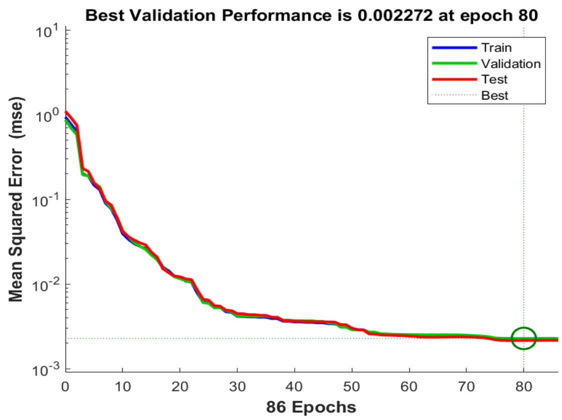

Figure 18 d. Comparison of the neural network estimation of the data uncertainty.

Utilizing the deep learning network model, we then solved the sensor selection problem in real-time under uncertainty. The uncertainty matrix U is updated in each simulation step to reflect the changing reservoir conditions as well as sensing parameters. The cost vector f for the sensors is increased in each step for the active sensor components, reflecting the power utilization of sensor and to penalize excessive usage of an individual sensor. In case the sensor is not anymore operational f_i (e.g., lack of power), then f_i was set to positive infinity. The timeframe for the sensor optimization was from April 1st, 2019 until January 11th, 2020, where the sensors were optimized every 15 days. The optimization results are displayed in Figure 19 outlining the active sensors in green and the inactive in black.

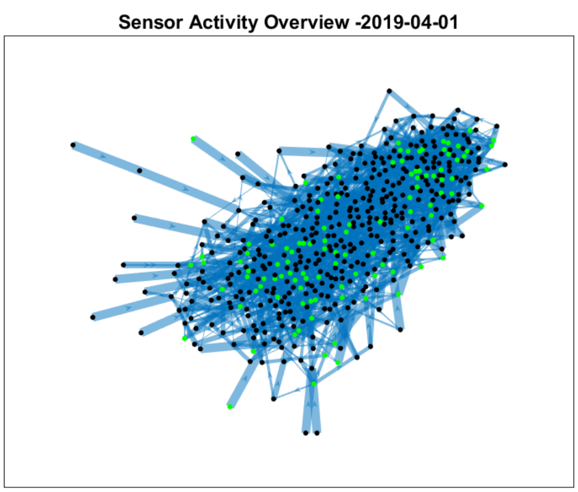

Figure 19 a. Overview of the selected sensors for different time steps.

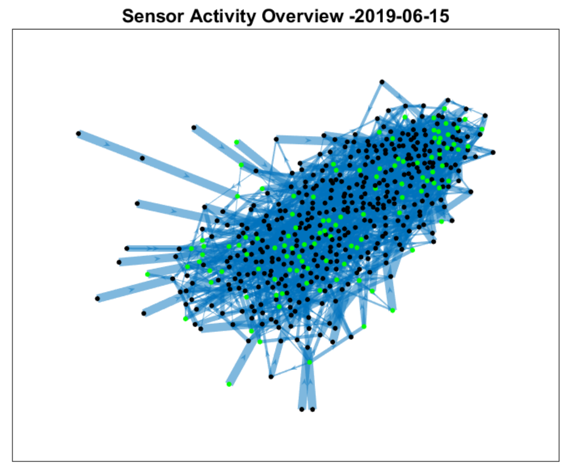

Figure 19 b. Overview of the selected sensors for different time steps.

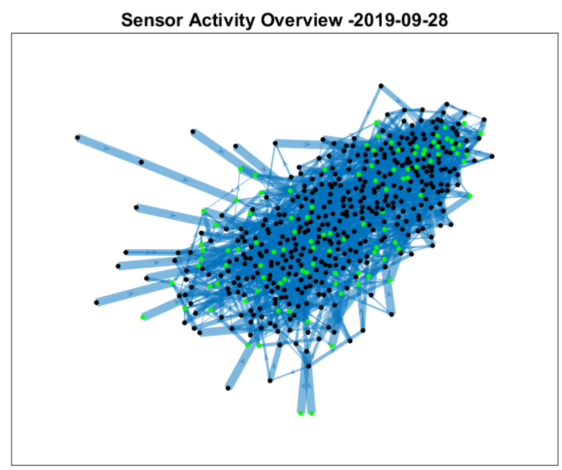

Figure 19 c. Overview of the selected sensors for different time steps.

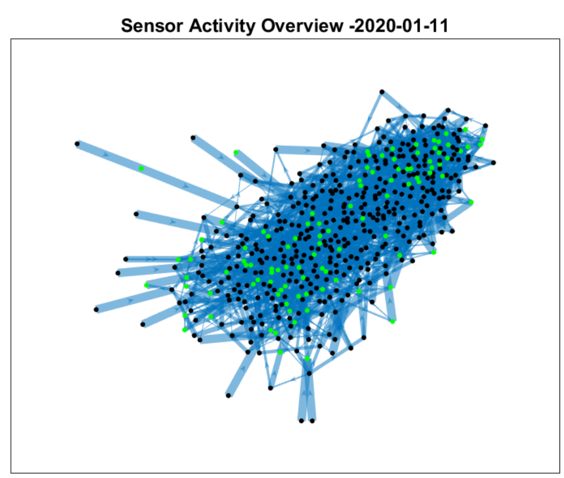

Figure 19 d. Overview of the selected sensors for different time steps.

As observed there are certain sensor clusters that are active for longer durations indicating that these sensors are placed in crucial fracture intersection points as well as exhibit a low degree of measurement uncertainty. This is confirmed via a sensor utilization analysis for the 500 sensors in Figure 20 and Figure 21. The indication is that most sensor are rarely active, or solely active for a short period of time, while there are a few sensors that are heavily utilized and operational for more than 250 days out of 285 days .

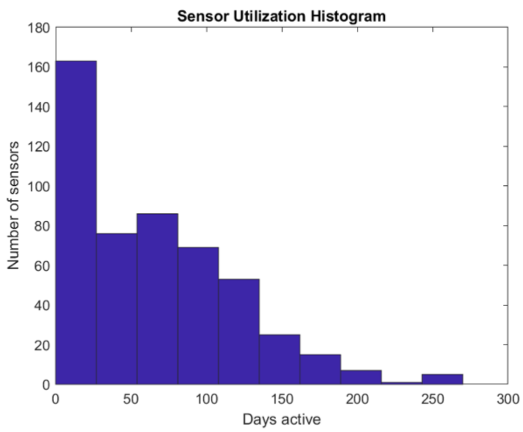

Figure 20. Sensor utilization histogram.

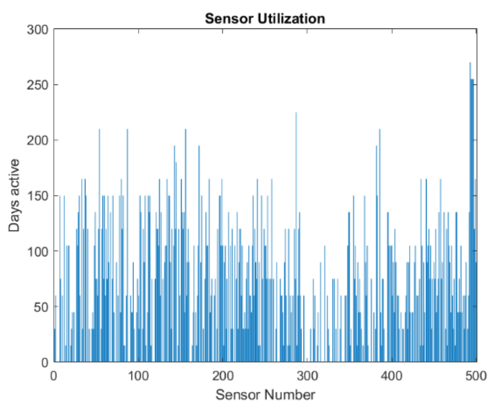

Figure 21. Sensor utilization in days.

VII. CONCLUSION

This paper proposed FracBots systems for monitoring oil and gas reservoirs, mapping hydraulic fractures and collect other wellbore parameters. We established a platform of the FractBots comprising of software and hardware solutions. We formulated and developed three key functions. We developed cross layer communication model for magnetic induction networks in altering underground environments to enable the communication in dynamically changing underground environments. We developed an innovative MI-based localization framework to capture the locations of the randomly deployed FracBot nodes by exploiting the exceptional properties of the MI-field. We developed an energy model framework for a linear FracBot network topology to estimates FracBot data transmission rates while respecting harvested energy constraints. We designed and developed novel prototypes of wireless FracBots for potential use as a platform for a new generation of WUSNs for monitoring hydraulic fractures and unconventional reservoirs, and measuring other wellbore parameters. We developed the hardware of the MI-based wireless FracBots for short-range communication using near-field communication (NFC) as a physical layer combined with an energy-harvesting capability and ultra-low power requirements. Finally, to examine the functionalities of FracBot nodes in air, sand, and stone media, a physical MI-based WUSN test bed was implemented. Experiments indicated that the constructed FracBots can form a transmission link and transfer data over ASK modulation using a data rate of 1.6 Kbit/s and a minimum receiver sensitivity of -70 dBm. The hardware development and the testbed analyses allow us to better understand the environment challenges, improve the electronic sensitivity and optimize the minimum resources that are necessary to miniaturize the FracBot hardware.

In addition, we presented a novel AI driven sensor selection framework for the optimal selection of subsurface pressure and temperature sensors in a fractured reservoir. The framework presents the ability to optimize the selection of sensors for subsurface sensing in real-time, thereby maximizing the overall coverage of the sensors for efficient waterfront tracking. The results outline the ability to efficiently and long term perform reservoir sensing if the sensors are optimally selected and utilized.

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