Project Summary (Omid)

1 Motivation and Significance

For near two centuries, *petroleum* has been exploited as the main natural source for many indispensable industrial products such as gasoline, diesel, oil, gas, asphalt, and plastic. As petroleum resources become more scarce, companies need to extract oil and gas (O&G) from adverse locations, such as remote offshore reservoirs. Meanwhile, operating at remote sites is very costly and constrained with limited crew and equipment resources. In addition, petroleum extraction is a fault-intolerant process that requires ultra-high reliability. As seen repeatedly in the past [**?**], a single operational mistake during petroleum extraction process can result in death or drastic economical and environmental impact [**?**]. With that in mind, achieving efficient and safe petroleum extraction – especially when coupled with the location constraints of remote reservoirs – is a challenging task for O&G industries.

In this regard, both industry [**?**] and academia [?] have collectively emphasized the need for *smart oil fields* that can meet the following requirements of petroleum extraction process. *First*, O&G production requires constant decision-making during the extraction process to manage ??. Achieving this real-time process is even more challenging when the management team remotely controls the site operation. *Second*, real-time monitoring of the site – including rigs' structure, wells, distribution lines, etc – is needed to avoid any oil or gas leakage, identify corrosions in the infrastructure, and predicting potential future incidents to maximize production efficiency and minimize negative environmental impacts. *Third*, large number of sensors will generate an unmanageable amount of data that cannot be transferred to a remote server for processing. *Fourth*, due to several uncertainties in O&G extraction process – stemming from stochastic gas pressure in the reservoir and leakage of hazardous gases such as H2S – many risks are involved, especially in presence of on-site human workers.

To address these challenges, there is a need for an advanced *cyber* system that can meet specific communications and computational requirements of the *physical* system, i.e., oil extraction system in remote oil fields. In particular, the cyber system must enable: 1) Seamless wireless communications with high data rate and low latency among sensors, cameras, robots, and user equipment (UE); and 2) Fast and reliable task processing for real-time monitoring and decision making. In this regard, fast and reliable *wireless communications* and *edge computing* are the main pillars of *self-organizing* remote smart oil fields.

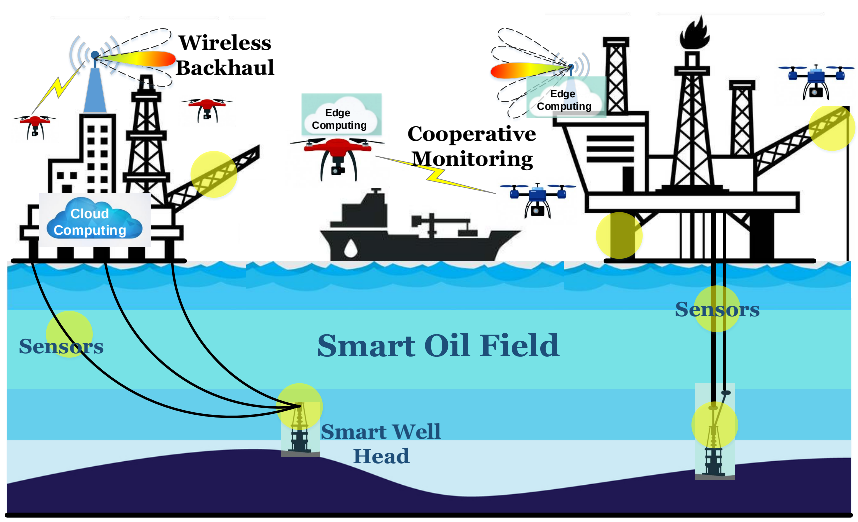

Figure 1: Smart oil field as a cyber physical system.

Despite recent technological advancements, to date, no comprehensive solution exists that can support bandwidth and computationally intensive operations expected in smart oil fields. Most of the existing communications protocols rely on connectivity to a nearby cellular base station that will not exist in remote sites. Moreover, satellite communications do not support enough capacity for a fast wireless connection between control centers and remote oil fields. In addition, conventional ad-hoc communication schemes in sensor networks only support few devices within limited range [?]. Regarding the computational task managements, prior art relies on sending information of oil fields periodically to off-site clouds for processing. However, these schemes will not be efficient for remote operations, if possible at all. That is because, it is infeasible to send large volume of data in real-time and receive control commands for online operations.

2 Research Description

2.1 Intellectual Merit

To address aforementioned challenges and realize the concept of smart oil fields, we envision an advanced cyber physical system (CPS), shown in Fig. 2, that fully integrates novel solutions from *wireless communications* and *edge computing* to optimize petroleum extraction process at offshore remote oil fields. To achieve fast wireless connections with small transmission latencies, we consider communications at high-frequency millimeter wave (mmWave) bands, due to the following key features: 1) MmWave frequencies offer large bandwidth – compared with sub-6 GHz frequencies – that can yield very high data rates; and 2) Highly directional links are feasible at mmWave frequencies, allowing to deploy large number of mmWave access points (APs) on a dense oil rig platform. Additionally, we focus on enabling AP-controlled unmanned aerial vehicles (UAVs) to carry out intensive operations – such as oil spill inspection – to save cost of operation and prevent hazards during oil extraction process. Meanwhile, we propose new methods to reap the full benefits of edge computing capabilities of advanced user equipments (UEs), robots, and UAVs in smart oil fields. The proposed CPS framework is composed of three interrelated thrusts that yield following innovations:

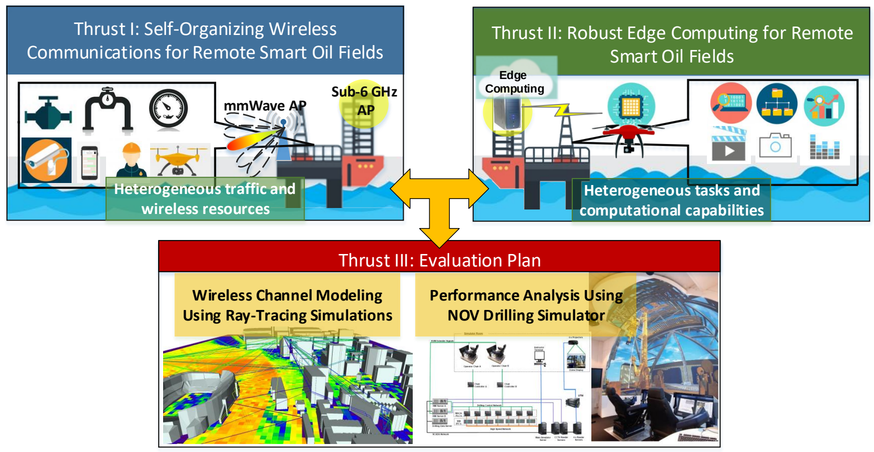

Figure 2: Proposed CPS framework.

1) *Comprehensive Performance Analysis of the Wireless Network:* Important QoS metrics and requirements such as reliability, latency, and data rate are analyzed for wireless services in smart oil fields. In particular, new utility functions are designed, based on stochastic utility theory, to account for QoS uncertainties that stem from wireless channel quality randomness, amount of data generated during the drilling process, and mobility of users on the oil rigs.
2) *Wireless Resource Management:* A novel resource allocation approach is proposed, based on the *matching theory*, to enable fast wireless connectivity for large number of UEs that are densely deployed in oil rigs. The proposed scheme ensures distributed resource management, fast convergence, and fairness in optimizing QoS for broad range of applications in smart oil fields.
3) *Autonomous Oil Spill Inspection:* A novel route-planning algorithm is proposed to enable autonomous oil spill inspection by a swarm of UAVs. The developed method builds on *graph theory* to assign the optimal subset of inspection points across the oil field to each UAV, while accounting for the limited energy and communications constraints of each UAV.
4)
5)
6) *Evaluation of Proposed Methods with ab Advanced Drilling Simulator:*

These innovations will advance the O&G extraction process in remote oil fields from various dimensions. In particular, proposed integrated communication-computing framework will enable *self-organizing* O&G operation that can extract and manage substantial data (via a fast wireless network), process the data locally (using robust edge computing), and exploit the results to make necessary decisions instantly, predict hazards, and minimize time and cost of drilling process. Moreover, the proposed CPS will provide *automation* by reaping the benefits of UAVs and robots to carry out extensive tasks, such as oil spill inspection. This is particularly important in remote oil fields to minimize the number of human workers, reduce the risk while operating in adverse locations, and cut the operational costs.

The proposed solutions can be applied to both onshore and offshore oil fields. Nonetheless, we primarily focus on offshore oil fields, since extraction of O&G from bottom of ocean is generally more challenging that onshore operations. Furthermore, we note that proposed methods can be extended to advance other CPSs such as Internet-of-Things (IoT) networks or smart farms [?]. For example, our proposed routing and computing protocols for UAVs can be used to enable data collection from large number of low-power sensors in IoT networks, or autonomously inspect large farm lands for signs of pest attacks and spray pesticide locally over vulnerable regions.

2.2 Thrust I: Self-Organizing Wireless Communications For Remote Smart Oil Fields

Motivation and Basic Problem. Realizing the vision of smart oil fields is contingent upon seamless and reliable communications among workers, management teams, UEs, sensors, actuators, and robots. Despite submarine sensors and equipments – especially those utilized inside the oil wells – are mostly connected with a fiber to the oil rig for data communications, fiber connection cannot be accommodated for all equipments on the oil rig due to space limitations and mobility of devices. Meanwhile, wireless communications can provide following opportunities for oil extraction process: 1) Allowing workers to move flexibly without having cables connected to their UEs; 2) Enabling fast and cost-effective network deployment, especially for offshore operations with minimum environmental impact; 3) Facilitating oil extraction in adverse locations where extreme temperatures or humidity damage cables; 4) Enabling remote sensing, for example in oil spill inspection process.

Nonetheless, several challenges must be addressed to enable wireless communications in remote offshore fields. First, the network must support broad range of wireless services – varying from short packet control signals to real-time video streaming – with heterogeneous QoS requirements. Second, distribution of users is highly nonuniform since most of them are densely located inside oil rigs. Moreover, number of wireless devices can be very large, since most of tasks are managed by robots rather than human workers. Consequently, interference and resource management is very challenging. In addition, devices must operate with low power, especially those that are not easy to reach. Furthermore, given that there is no high capacity backhaul connectivity to the core network (Internet), wireless resource and mobility management cannot be managed centrally. Finally, the wireless network must support low-latency and ultra-reliable communications (URLLC) with high data rates, suitable for real-time decision making and operation during the oil extraction process.

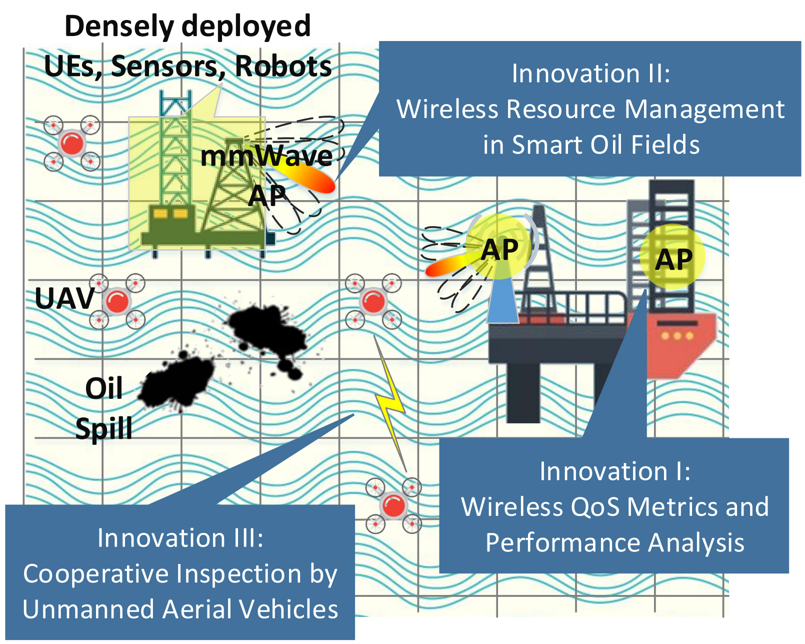

Figure 3: Overview of Thrust I innovations.

To date, limited work exists from academia and industry to design a wireless communication networks for remote smart oil fields [?]. Particularly, prior art cannot address the key challenges of remote operations, due to the following reasons: *First*, the works in [**?**] relay on satellite communications between the oil rigs and onshore management centers. However, satellite communication is not suitable for real-time decision making during oil extraction process, as delay can be substantially large. *Second*, the works in [**?**] assume existence of a macro cell BS at a nearby onshore location that provides wireless support for oil rigs. Nonetheless, remote reservoirs such as those in [?] can be very far away from the shore. *Third*, most of existing networks [**?**] operate at sub-6 GHz frequency bands with limited capacity that cannot manage large data rates and URLLC requirements of smart oil fields. *Fourth*, ad-hoc communications protocol with random channel access cannot satisfy the ultra-reliability requirements in smart oil fields with dense number of wireless devices. *Fifth*, existing works do not provide theoretical foundations for performance analysis and wireless resource management in smart oil rigs.

Solution Approach and Novelty. To address these challenges, our *goal* is developing a new wireless networking paradigm that 1) Supports URLLC along with high data rates by enabling joint mmWave and sub-6 GHz communications (multi-RAT); 2) Enables scalable and efficient distributed resource management by small BSs (SBSs) and wireless devices (Self-organizing); 3) Reaps the full benefits of robots and UAVs to carry out extensive tasks, such as oil spill inspection (Autonomous). To this end, we propose a novel framework that employs analytical tools from stochastic utility theory, matching theory, and graph theory, that yields several innovations as shown in Fig. 3.

In Task I.A, we aim to understand how different network metrics – such as density of devices and sensors, type of devices and tasks, number of BSs – impact wireless QoS. We build our approach using *stochastic utility theory* [?], a mathematical framework to find suitable utilities for problems that involve repeated decision-making under uncertainties. Particularly, in smart oil fields, decision-making must be done continuously by devices and BSs to manage resource, i.e., to allocate transmission power, processing, and spectral resources to many bandwidth-intensive applications. Meanwhile, such decision-making involves uncertainties, due to the stochastic location of devices, wireless channel quality, weather condition (that may impact link budget, especially at mmWave frequencies), and uncertainties in type of computational tasks (as we elaborate in Thrust III).

In Task I.B, we develop a wireless resource management framework to optimize QoS (derived as utility functions in Task I.A) for users (UEs, sensors, actuators, UAVs) across the oil field. That is, given a set of BSs located on an oil rig, we aim to find an assignment between users and BSs that satisfies QoS requirements for each user. To find a tractable solution for this combinatorial assignment problem, we develop a novel framework based on the concept of *firms-workers matching problems* [?] and find a self-organizing solution for allocating users (workers) to BSs (firms). A unique feature of our proposed approach is ... *The uplink traffic in smart oil fields mainly includes data generated by sensors, videos recorded by surveillance cameras, and location information of users. Moreover, downlink transmissions manage control signals for actuators on the rig, routing information for UAVs, and video streaming to UEs for real-time monitoring of drilling process and other inspection points**

Next, we develop a framework to enable automated oil spill inspection in smart oil field by a set of cooperative UAVs. That is, UAVs visit a set of inspection points, take photos or record videos from the area, and send the data to a BS. The objective is to find optimal trajectory of each UAV across inspection points to minimize the inspection time across the oil field, while considering limited number, power, and transmission range of UAVs. To tackle this challenging problem, we exploit *graph theory* and propose a novel algorithm that builds on the concept of minimum spanning tree (MST) [?]. In fact, we model the oil field inspection area as a weighted graph (weights are determined by utility functions designed in Task I.A) with inspection points as vertices of graph.

Preliminary Results. The PIs Semiari and Salehi have a substantial research background in wireless communications [?] and oil extraction process [?], respectively. In [?], we have proposed several resource management schemes based on matching theory [?]. In [?], we have developed a resource management scheme in wireless networks with both mmWave and sub-6 GHz RATs. As shown in Fig. **??**, the proposed integrated mmWave-sub 6 GHz scheme can substantially improve the reliability of communications for delay intolerant applications. Recently, we have ... Regarding oil extraction process, we ...

Task I.A - Quality-of-Service Metrics and Performance Analysis. The *goal* of this task is identifying QoS requirements – latency, data rate, reliability – for wireless communications, as functions of smart oil fields parameters. To this end, for each agent j – such as a UAV, user equipment (UE), small BS, actuator, or sensor – in the network, we design a multi-attribute *utility function*, $U_j(s_j) = f(q_{1j}(\boldsymbol{a}, s_j), q_{2j}(\boldsymbol{a}, s_j), \cdots q_{mj}(\boldsymbol{a}, s_j))$, that captures m relevant QoS metrics $q_{ij}, i = 1, 2, \cdots m$, for agent j. Here, the attribute vector $\boldsymbol{a}$ constitutes all variables that can affect QoS metrics within the utility function. For example, attribute vector for a UAV may include the remaining battery life, UAV distance to a serving BS, computational power, among others. Moreover, s_j represents an *action* chosen by agent j from all possible actions in $\mathcal{S}$. From previous example, action set for a UAV may include inspecting a new area or returning to the oil rig. In this regard, utility function $f\colon \mathcal{S} \to \mathbb{R}$ is a mapping from action set $\mathcal{S}$ to real numbers. Designing such multi-attribute utility functions provides the following opportunities: 1) It enables distributed network management by defining unique utility functions for different agents in the network. This flexibility is critical in smart oil fields where heterogeneous type of devices are expected; and 2) It allows to maintain tradeoffs between different QoS metrics such as instantaneous data rate (as a short-tem QoS metric) versus reliability (as a long-term QoS metric).

In this regard, first, we find mathematical expressions for new QoS metrics, such as communications reliability in smart oil fields, as a function of network parameters. As shown in Fig. **??**, we consider advanced features such as multi-connectivity of devices with multiple mmWave BSs. As such, reliability can be considered as a binary variable which is equal to one, if wireless connection with at least one mmWave BS is feasible, otherwise, it is zero. While QoS metrics can be derived based on the location of oil rigs, devices, etc., designing multi-attribute utility function f highly depends on the operation scenario. For example, considering an inspection UAV, $f(q_{1j}, q_{2j}) = q_{1j}^{\alpha} q_{2j}^{1-\alpha}$ where α is a constant parameter controlled by the UAV or a BS. Moreover, q_{1j} and q_{2j} represent, respectively, power consumption and latency. Using this utility, a UAV can decide to process recorded video locally (which consumes power) or transfer the file to a BS for processing (which increases latency).

Next, we find statistical distribution of QoS metrics. To this end, we first build a model for wireless channel over the mmWave and sub-6 GHz bands in offshore oil fields. As we explain in Section ??, channel modeling can be done via ray-tracing simulations. Based on the derived model, we find probability density function (PDF) of the data rate via theoretical Shannon capacity bound (that relates data rate with wireless channel gain via a logarithmic function). Furthermore, we follow delay analysis by defining an end-to-end (E2E) latency for an arbitrary task k as $\tau(k) = \tau_u(k) + \tau_d(k) + \tau_p(k)$ where $\tau_u(k)$, $\tau_d(k)$, and $\tau_p(k)$ represent, respectively, the uplink delay (over-the-air latency for transmission from device to BS), downlink delay (over-the-air latency for transmission from BS to device), and processing latency for edge computing of task k. The PDF of $\tau_u(k)$ and $\tau_d(k)$ can be found by considering that transmission latency is inversely proportional to data rate. For processing latency, we follow analysis proposed in Thrust III. Using these distributions and derived multi-attribute utility functions, we find mathematical expressions for joint distribution of QoS metrics, $P(q_{1j}, q_{2j}, \cdots, q_{mj})$, and accordingly, calculate the expected value of utility function $\mathbb{E}[U_j(s_j)]$ for an arbitrary agent j that takes actions s_j. These utility functions will be used in Tasks II.B and II.C – as reward functions – to optimize wireless resource management.

Task I.B - Wireless Resource Management in Smart Oil Fields. Using utilities designed in task I.A as objective functions, our *goal* here is to assign users to BSs across multiple oil rigs, while meeting the QoS requirements of each user. That is, we aim to find an efficient association of users (UEs, UAVs, and sensors) in a set $\mathcal{J}$ to BSs in a set $\mathcal{B}$. This combinatorial assignment problem is NP and thus, there is a need to find an efficient solution with manageable complexity. To solve the resource management problem, we develop a novel approach based on the concept of firms-workers matching [?], as shown in Fig. **??**. In particular, we define the resource management problem as a matching $\mu : \mathcal{J} \to \mathcal{B}$, that 1) for any user $j \in \mathcal{J}$, its associated BS $\mu(j) \in \mathcal{B}$; 2) for any BS $b \in \mathcal{B}$, its associated subset of users $\mu(b) \subseteq \mathcal{J}$; and 3) $\mu(j) = b$, if and only if $j \in \mu(b)$. Each user j aims to match to a BS b that can maximize its utility (derived in the previous task), i.e.,

$\mathrm{argmax}_b\, U_j(b)$. Accordingly, each user builds a *preference list* over the set $\mathcal{B}$ that ranks BSs in descending order of U_j. In addition, each BS aims to match with a subset of users $\mathcal{C}^b \subseteq \mathcal{J}$ for whom it can maximize the sum-utility $\sum_{j\in\mathcal{C}^b} U_b(j)$. As such, each BS b builds a *preference profile* over all possible subsets $\mathcal{C}^b$ that ranks them in a descending order of sum-utility.

Within this framework, we find a distributed, self-organizing algorithm that takes into account the preference list of users and preference profile of BSs to match users with BSs. In particular, we aim to find an *equilibrium matching* μ^* that for any BS b and a subset of users $\mathcal{C}$ not matched to b by μ^*, it is guaranteed that users in $\mathcal{C}$ and the BS b cannot improve their utilities by making a matching pair $(b, \mathcal{C})$. The notion of equilibrium matching ensures fairness in resource management for satisfying QoS across users. To find μ^*, we first show that the classic matching approaches, such as deferred acceptance algorithm [**?**], cannot guarantee an equilibrium. Thus, we develop a new scheme that jointly solves resource management for uplink and downlink transmissions. Building on utility functions from Tasks I.A, we first find the preference list/profiles for the uplink communications and propose an algorithm to find an equilibrium matching μ_u^* for the uplink. Then, depending on the uplink resource management, users and BSs will update their QoS requirements and build their preferences for downlink communications. We use the developed algorithm to find an equilibrium matching μ_d^*. Here, we note that a user might be associated to different BSs or RATs in the uplink and downlink. For example, large data from a survilliance camera can by managed over the mmWave RAT, while control signals to change direction of camera are handled over the μW RAT. For the proposed resource management framework, we analytically find conditions for guaranteeing the existence of an equilibrium matching pair (μ_u^*, μ_d^*), optimality of our solution, and the complexity of our algorithm with respect to the number of users and BSs.

Task I.C - Cooperative Inspection by Unmanned Aerial Vehicles. A key challenge in O&G extraction from remote offshore reservoirs is to perform periodic inspection for potential oil spills. Past incidents have shown that oil spills typically cover sparse, but large areas that may not be close to the location of oil rigs [?]. Hence, oil spill inspection requires periodic scanning of a large geographical area which is costly, especially at remote fields with limited human workers. In this regard, we propose a framework to assign a UAV swarm for oil spill inspection operation. The *goal* here is to find an algorithm that finds optimal trajectories for a set of UAVs to minimize average inspection time across the smart oil field, while considering power and communication constraints of each UAV.

To this end, we propose a new framework that models the inspection area of smart oil field as a weighted, undirected graph $G(\mathcal{V}, \mathcal{E})$. As shown in Fig. **??**, the entire area is decomposed by a grid into small areas that can be covered by one UAV at a time (to take a picture or record video of ocean surface). In our model, the center of each grid point is a vertex within the set $\mathcal{V}$. In addition, the time required for a UAV to traverse from vertex i to a neighboring vertex j is the weight $w(i, j)$ of the edge $(i, j) \in \mathcal{E}$. Finally, we consider that each rig is equipped with a swarm of K UAVs. Using this model, we formulate the oil spill inspection as an optimization problem that aims to minimize $\sum_{v_j\in\mathcal{V}} \tau(v_j)$, where $\tau(v_j)$ is the time that takes for an inspection node v_j to be visited by one UAV. This problem can be shown analogous to the *K-traveling repairmen problem* [?], while here, we consider a budget – maximum available power – for each UAV to visit inspection points. Another main difference between this problem and K-traveling repairmen problem is the constraint on communication distance between the UAV and oil rig. Unfortunately, our problem is NP and thus, finding optimal solution for large inspection areas – as expected in smart oil fields – is inviable. With this in mind, we will propose an α-approximation algorithm that partitions graph G into K non-overlapping trees (all with the oil rig location as their root). To this end, we build on the concept of minimum spanning tree (MST), subject to a certain tolerable latency constraint. The algorithm incrementally increases the tolerable latency such that the union of K MSTs covers all inspection points. Then, we assign each distinct tree to one of K UAVs. To ensure the feasibility of our solution with regard to power and communication constraints of UAVs, we will allow cooperation among UAVs to swap vertices of their MSTs. Trajectory of each UAV will be determined by choosing an Euler tour over its assigned tree. The outcome of this task sheds light on enabling autonomous inspection of smart oil fields and provides a guideline for operators to determine parameters such as the average inspection time, coverage area, or required number of UAVs.

2.3 Thrust II: Robust Edge Computing for Remote Smart Oil Fields

Basic Problem. A typical smart offshore oil field collects around 0.75 Terabytes of raw data weekly from various sensors during the extraction process []. In a remote offshore oil fields and for super majors, it can collect up to two Terabytes of data in a single day of extraction []. Most of the collected data in an smart oil field, particularly those related to emergency applications, must be processed in a real-time and present the processing results to remote decision makers []. Processing such volume of data requires high-end communication and computation facilities [] that are available in onshore datacenters. However, establishing a low-latency communication to onshore datacenters in a reliable manner is not possible for offshore smart oil fields [].

Specifically, the main challenges of a remote smart oil field is: **Real-time processing of resource-intensive emergency applications in the presence of low and unreliable connectivity to onshore data-centers.** In this project, our focus is particularly on emergency application (e.g., those to detect and manage oil spill []). Early detection of such disasters can save human lives, minimizes environmental impacts, and reduces the cost of disaster recovery []. However, these applications are time-sensitive and resource-intensive [], hence, require a low-latency and ultra-reliable connectivity to high-end computational resources and to remote monitoring centers.

As mentioned in Thrust I, transferring acquired sensor data to processing servers in remote oil fields is currently achieved through satellites []. However, satellite communication incurs a substantial delay [**?**]. In addition, a large portion of the sensed data are either redundant (i.e., do not provide new information) or noisy []. Therefore, even the satellite bandwidth and the server processing capabilities are not used efficiently. These characteristics in the remote smart oil fields are counterproductive for real-time processing, monitoring, and decision making of emergency operations [].

Provided the difficulties in achieving a real-time response required for disaster management applications in remote smart oil fields, enabling smartness for remote oil fields remains as an open challenge. However, edge computing systems, if deployed cleverly, has the potential to obviate the difficulties of remote oil fields and enable them to take advantage of smart oil field services particularly for disaster management applications.

The basic problem in deploying an edge computing system in a remote oil field is the limited computational power of edge and unreliable connection to the back-end datacenters []. These issues hinder processing of resource-intensive and real-time applications needed in smart oil fields. Accordingly, the **goal** of this thrust is *to efficiently manage limited computational resources and unreliable connection in the edge resources of a remote oil field*. Efficiency here refers to solutions that are aware of the connectivity, limited computational capacity, and resource intensiveness of emergency management applications in remote oil fields.

The more specific problem of resource provisioning for real-time disaster management applications in edge computing with low-connectivity to the back-end datacenters has not been explored in the context of remote smart oil fields or and there is a limited research on these issues in other contexts. Efforts towards smart oil fields have been predominantly on analyzing the big data extracted from oil wells [**?**] or applying machine learning methods to reduce exploration or drilling costs [**?**] or warning systems for early prediction of disasters [**?**]. These solutions are all reliant on onshore datacenters [**?**] which is not viable for remote and offshore oil fields []. In other domains, a common solution for low connectivity and allocation of resource-intensive applications is based on federation of edge systems [] which is not always an option in remote smart oil fields.

Solution Approach and Novelty. In edge computing, as we move from the edge resources to the main onshore datacenters, although processing power increases, the system exhibits less real-time properties, due to increase in latency (delay).

Our approach to tackle the problems of smart oil fields in remote areas is to use an edge computing system in the oil field that is aware of: (A) the QoS demands of emergency and other applications types in smart oil fields; (B) performance characteristics of the computational resource and their limited availability in the edge environment; (C) low and unreliable connectivity to the onshore datacenters. Such an edge computing environment will fulfill the goals of an smart oil field in the following ways:

- Real-time and low-latency processing of latency-sensitive emergency applications.
- Efficient use of limited computational resources to minimize reliance on onshore resources.
- Efficient use of the low-connectivity communication to onshore network and use back-end servers for high-end and off-line (i.e., delay intolerant) processing.

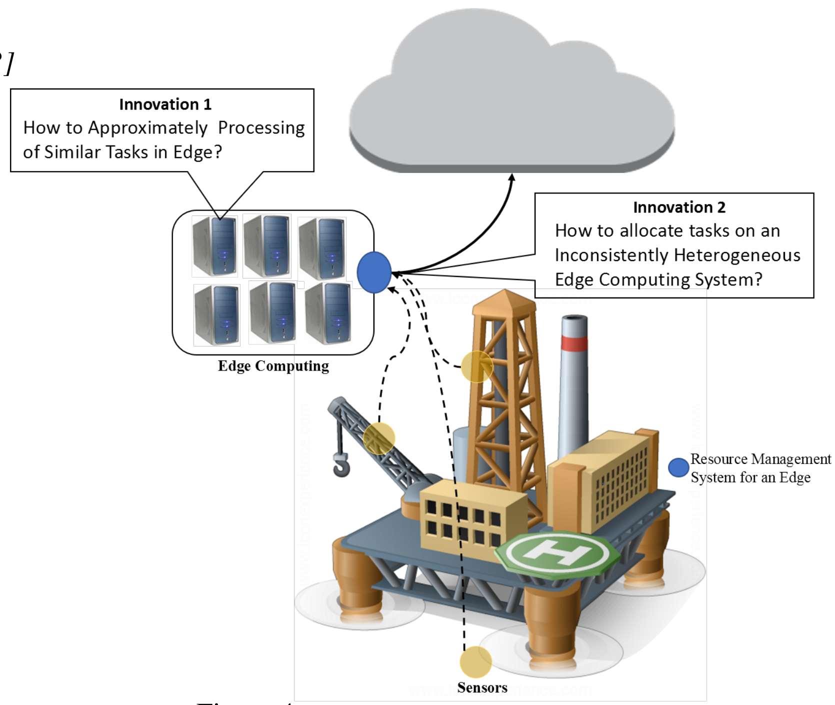

Figure 4: Overview of Thrust II innovations.

The tasks of Thrust II will be *implemented in the CloudSim [**?**] discrete simulator* which is widely used to model cloud and edge computing environments. The tasks will also be evaluated as explained in Thrust III of the proposal. The framework developed in this thrust will complement the communication model developed in Thrusts I. As an example, one of the goals in previous thrusts was to minimize the XXXXXXXXX latency (e.g., by optimizing XXXX). The research of Thrust II complements this goal by minimizing the computational delay via efficient allocation of computing tasks. For instance, in Task II.A, we leverage the XXXXXXXX Thrust I to XXXX. In Tasks II.B-C, we leverage the XXXXXXX in Thrust I to prevent and avoid oversubscription in the edge computing. Task II.C enhances stability in XXXXX aligned with one of the goals of Thrust I. To address the cyber challenges of a remote smart oil field as a physical system, we propose a novel framework that integrates ideas from scheduling, queuing theory, probability theory, wireless communication, and oil industry to develop a novel QoS-aware resource allocation scheme for emergency applications in edge computing of a remote oil field that is robust against oversubscription. Robustness implies maintaining the QoS requirements desired by emergency applications of an oil field. Efficient oversubscription handling enables execution of emergency management application in an edge computing environment with low-connectivity to onshore resources.

There are resource allocation methods for edge computing environments that consider unreliable network connectivity []. However, they neither consider the case of emergency management applications nor the heterogeneity of edge resources, while performing resource allocation [**?**, **?**, **?**].

Preliminary results. In [**?**], we developed a new approach for low-latency processing of video streams captured by embedded or crowd-sourced cameras in a smart city during a disaster. In particular, we considered an edge computing system that is oversubscribed during a natural disaster and proposed resource allocation methods to maintain video streaming real-time quality, in presence of oversubscription. Our proposed method is context-aware and approximately processes tasks with lower importance to mitigate oversubscription in favor of important streaming tasks that show events of interest to higher-level management and incident commanders. The resource allocator backfills low-priority tasks with higher priority ones, as long as they do not cause QoS violation (in terms of deadline) of lower priority tasks. Results of our study, shown in Fig. 5, indicate the impact of context-aware resource allocation on reducing QoS violation in the presence of oversubscription in an edge computing environment. The results also indicate that context-aware scheduling increases reliability and reduces latency for tasks. Other early works relevant to Thrust II include our results on fog and edge computing in [**?**, **?**, **?**, **?**].

Task II.A - Edge Computing for Coordinated Emergency Operations in Smart Remote Oil Fields. When a disaster occurs during the extraction or maintenance process in an smart oil field, many emergency activities across several entities within the field in a coordinated manner. In particular, in the event that an oil spill alert from a UAV (as discussed in Thrust II) is received by the edge computing platform, the following coordinated activities should take place urgently to manage the disaster and prevent spread of the oil spill:

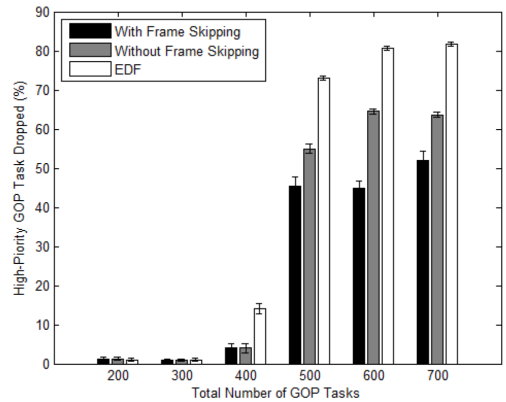

Figure 5: Impact of context-aware resource allocation in edge computing for real-time response to disaster management applications.

- More UAVs should be dispatched to the suspected area for a closer and more accurate inspection of the environment. Later, their captured data, in forms of images and videos, must be streamed and processed in the edge to find anomalies;
- Maintenance technicians must be alerted to physically inspect the suspected area.
- Data (e.g., pictures and videos) received from technician's hand-held devices must be processed with a high priority along with the data received from UAVs to accurately determine the scale and type of the oil spill.
- Simulation modeling applications should be executed to predict the spread of the oil spill.

However, such coordination applications urgently require plenty of computational resources to handle the emergency situation. The coordination applications need highly reliable computational resources with low-latency that are available on edge machines (as opposed to onshore datacenters). Accordingly, the challenge in this task is how the edge computing resource manager with limited hardware capabilities can allocate resources for coordinated emergency applications?

In this project, we will handle the resource allocation challenge for emergency coordination application by assigning a higher priority to these applications. As such, they will have precedence to be allocated on the limited edge computing resources of the smart oil field. Because the edge computational resources are limited, to enforce the precedence of emergency tasks, the edge computing resource manager will preempt the allocated resources to the currently executing applications in the edge. The challenge in this part is to determine the number and type of resources required to be preempted with the minimum impact of the other executing tasks in the system. This can be also related to the nature of applications running on the edge resources. For instance, some of the applications are not latency sensitive or can tolerate intermittent connection to the mail cloud can be resumed (or pushes) to the main cloud whereas some other applications are critical and preempting their resources will cause malfunction in smart oil field operation.

Task II.B - Inconsistently Heterogeneous Edge Computing Systems in Smart Oil Field. The goal of this task is to enable real-time processing of captured data through UAVs and other sensors in an oil field.

The nature of processing in the edge computing environment of a smart oil field is limited to certain applications. Few examples of the application (task) types in a smart oil field are processing of the surveilled videos to detect oil spill anomalies []; processing of the temperature and pressure sensors in the well to determine drilling strategy []; and model the pipe and flow-lines to predict and monitor flow both in the well and at the surface []. (CONSULT WITH SAEED ABOUT BETTER INFORMATION ABOUT task types).

Each of these task type has requires different processing type. For instance, processing video surveillance videos require GPU and CPU intensive resources to perform anomaly detection analysis on it. Predict and monitor flow both in the well and at the surface can be efficiently carried out on FPGA chips, and some big data analytics application (SAEED like what?) [] need memory intensive computational resources. Therefore, our edge computing system will be in form of a heterogeneous computing (HC) system in which each machine is appropriate for a certain type of tasks. This form of a HC systems are known as inconsistently heterogeneous systems [] in which different task types have *affinities* with different machine types. That is, a task type has its best performance on a certain machine type while it can be still executed with a lower performance on other machine types.

The arrival rates of different task types to the edger are not regular, besides, as discussed in Task III.A emergency applications introduce bust arrivals sporadically. In these circumstances, optimal resource allocation of different task types on heterogeneous edge machines is challenging. The challenge becomes further complicated during an emergency operation, when the edge machines are oversubscribed. The goal of the edge resource allocation is to assign arriving tasks to machines so that they complete before their allowed latency (deadline).

Our approach to tackle this challenge is to assign tasks to machines so that the chance of meeting the task's deadline is maximized. For that purpose, we need the execution time information of tasks types on different machine types. As the task types, in the system, are known in advance, we can collect the historic execution information and understand the execution time distribution of each type of each machine type. We can collect these information in form a matrix called Estimated Time to Completion (ETC). The ETC matrix can be used to obtain the completion time distribution of an arriving task on different machines in the edge. From such distribution, the probability of meeting deadline for the arriving task can be obtained. In this research, we propose to drop tasks that have a low probability of meeting their deadline. However, the value of this deadline is not static and must be determined in a dynamic manner based on the intensity of the workload in the system.

Task II.C - Security of Smart Oil field in Presence of Intermittent Network Access. Oil fields in remote areas are generally less protected against physical malicious attacks from rival companies or countries []. Accordingly, the goal of this task is to enhance the security of smart oil fields in remote areas.

Multi-camera video surveillance through embedded cameras and UAVs are extensively used to secure smart oil fields. The surveilled video streams are streamed to a monitoring center to be processed. The video stream processing includes converting (i.e., transcoding) the video streams format based on multi-screen monitoring display devices and applying anomaly detection algorithms [] on the streamed videos. However, streaming videos requires a reliable and high bandwidth network connection to monitoring center, which is not available in a remote oil field.

To adapt with the intermittent network access of remote smart oil fields, in this task, we will utilize edge computing resources within the smart oil field to detect anomaly in the surveilled videos. Then, in the event an anomaly is detected by the edge, the streaming of it to the monitoring center and recording that on main cloud servers are achieved.

This approach can make a better use of low-bandwidth connection in remote and offshore oil fields and provide the monitoring and protection needed for the oil fields. However, the challenge is the limited resources exist in the edge to process these videos. We should note that processing video streaming tasks must be carried out within a deadline, otherwise the surveillance will of little use. To overcome this challenge, we propose to intelligently process useful parts of surveilled videos.

Our strategy to process useful video streams has two parts: *first,* aggregating processing of video contents covering the same area. For instance, a UAV may surveille an area that is already covered by an embedded camera. Processing such streaming tasks can be aggregated. In addition, in the events a suspected anomaly is detected, the surveilled videos of other cameras can be approximately processed in favor processing more accurately the suspected area. Frame skipping [] is a technique proven to be effective in approximately processing video streams.

2.4 Thrust III: Evaluation Plan

Motivation and Basic Problem. Despite substantial operational cost of drilling process in remote offshore areas, limited experimental works exist to evaluate and validate theoretical methods prior to applying them in real scenarios. The need for testing analytical methods is even more important in smart oil fields, since operations are mostly managed autonomously by a cyber system rather than operators. Therefore, our *goal* is to validate the developed wireless communications and computing schemes in Thrusts I and II. To this end, we propose a comprehensive evaluation plan, shown in Fig. 6, composed of two main components: 1) A state-of-the-art offshore drilling simulator to evaluate the performance of edge computing schemes in Thrust II; and 2) Ray tracing simulations by using Remcom's Wireless InSite Propagation Software [?] to model the wireless channel in offshore oil fields and measure the performance of wireless resource management schemes proposed in Thrust I.

Solution Approach and Novelty. Our evaluation plan mainly builds on the National Oilwell Varco (NOV) drilling simulator available at the University of Oklahoma (OU). The NOV drilling simulator is an industrial standard simulator that provides a unique experience for students to safely apply theoretical methods into real-life drilling and oil extraction scenarios. The core of our testbed is Drilling Hardware-In-The-Loop (HIL) Simulator (DHS), a rig-specific software to simulate both operator stations and equipment control systems. In fact, the DHS will enable us to program faulty and hazardous scenarios during the oil extraction process – by manipulating drilling machines and sensors – and measure the performance of our propose schemes in managing those critical situations. As shown in Fig. 6, the user interfaces are two CyberbaseTM Operator Stations that provide operators the same interface as in the Driller's Cabin. These stations are connected to a 3D animation display – visualizing a full-3D model of the drill floor and equipment – that enables operators to observe the simulated drilling operation in real time.

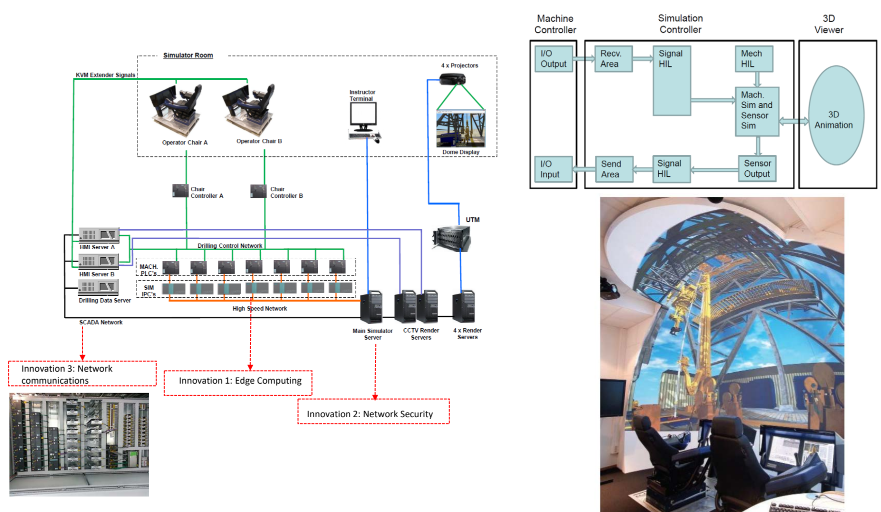

Figure 6: Evaluation Plan.

Figure 6?? shows a simplified block-diagram of the simulator, composed of a 3D animation unit, mechanical HIL, signal HIL, as well as send and receive areas to the machine control. Figure 6?? shows more details about the architecture of different servers, visualization units, drilling control, and high speed networks utilized in the drilling simulator. **many parts are not described**.**How do I connect top-left figure with the block-diagram (top-right figure)? **Which parts can be controlled by us to evaluate the computational schemes in Thrust II?**

Evaluation Metrics. **what are the performance metrics for edge computing?** What are the formats for data in/out of the NOV simulators? How do we connect this data with edge computing simulator?**

Task III.A - Verification of edge computing developed in thrust II. In this task, we will create two scenarios of a routine drilling operation in offshore rig. The developed scenarios will be based on creating a large volume of drilling data such as mechanical, pressure and operational reliability data. In the first scenario, participant will rely on the current simulator capability in order to make decision such as changing an operational parameter for further optimizing drilling speed or mitigating a specific risk such as equipment movement speed. In second scenario, we will use algorithms (Check with Mohsen if outcome is algorithm) developed in second thrust to optimize and process real time data collected while executing the scenario. The user in second scenario will have access to edge computing outcomes for decision making. We will then compare user performance in two scenarios for instance reliability on making a decision faster leading to higher drilling speed or less risk while conducting a sensitive operation. Further faults can be implemented in the scenario by creating an emergency situation such as a near imminent kick and compare user performance from one test to another.

•*Preliminary results:* if any

Task III.B - Verification of network security protocols developed in thrust II. One of the main challenges in smart oilfield development is security of data. This is of critical importance especially in remote operations where advanced infrastructure is not available. With access to main server on drilling simulator, we will create a testbed scenario, where an intruder tries to penetrate the simulator network and halt the operation (Check with Mohsen /Omid if intruding is correct terminology). The scenario will require two participants, in which first participant acts as typical driller on a rig performing a drilling operation while second participant tries to intrude into the network and either steal data from network or halt a specific piece of simulator resembling part of rig. Using this testbed scenario, we can verify protocol outcomes from second thrust for improving network security in remote oil and gas operations.

Task III.C -Wireless channel modeling and performance analysis of proposed schemes in Thrust I. As mentioned in Task I.A, there is a need for modeling the wireless communication channel at offshore sites. In this regard, we utilize the Remcom's Wireless InSite software that provides efficient and accurate predictions of radio wave propagation and communication channel characteristics in almost any environment. In fact, our *goal* is to 1) develop accurate empirical mmWave channel models for SBS-to-UE and SBS-to-UAV links at offshore sites; and 2) measure the performance of proposed schemes in Tasks I.B-C, in terms of data rate, transmission latencies, and oil spill inspection delay.

In particular, we consider ray-tracing simulations at both 28 GHz and 73 GHz mmWave frequency bands. The path loss at these bands is relatively smaller, enabling to reach communications range of several hundred meters. To achieve an accurate model for offshore communications, we first employ a 3D model of offshore rigs (using a 3D digital content creation tool, readily available in *.dae* formats [?]) and import this model to the ray-tracing simulator. Next, we set simulation parameters – such as site temperature, humidity, barometric pressure, materials for ocean surface and rig's structure, and antenna height for SBSs and UEs at the oil rig – according to average environmental variables in offshore sites. Moreover, we specify transceivers' antenna array specifications, such as beamwidth for both azimuth and elevation beams. Using the developed model, we the power delay profiles (PDPs) at different locations on the oil rig (for UEs) and ocean (for UAVs) at both frequency bands. Using the measured PDPs, we derive path loss models by finding the best linear fit with the measured data. Analogously, we build a model for communications at a sub-6 GHz frequency band. The path loss models enable us to calculate the received signal power at different locations and frequency bands. Furthermore, the developed model will be used to calculate data rate and transmissions latency of each mmWave link in Tasks I.B-C.

3 Broader Impacts (1 page Omid)

4 Project Management and Collaboration Plan (1.5 pages Omid)

Subsections for "Team composition", "Industry collaboration", "Project timeline" and "collaboration activities".

5 Results from Prior NSF Support (Omid, 0.1 page)