Attack-Resistant, Energy-Adaptive Monitoring for Smart Farms: Uncertainty-Aware Deep Reinforcement Learning Approach

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***Abstract*—This work proposes an energy-adaptive monitoring system for a smart farm using solar sensors attached to cows. The proposed system aims to achieve a high monitoring quality in the smart farm under fluctuating energy and cyberattacks disrupting the operations of collecting sensed data from solar sensors, such as protocol non-compliance, false data injection, denial-of-service, and state manipulation. We adopt Subjective Logic, a belief model, to consider multidimensional uncertainty in sensed data. We employ Deep Reinforcement Learning (DRL) for agents on gateways to collect high-quality sensed data from the solar sensors. The DRL agents aim to collect high-quality sensed data with low uncertainty and high freshness under fluctuating energy levels in solar sensors. We analyze the performance of the proposed energy-adaptive smart farm system in accumulated reward, monitoring error rate, and system overload. We conduct a comparative performance analysis of the uncertainty-aware DRL algorithms against their counterparts in choosing the number of sensed data to be updated to collect high-quality sensed data to achieve high resilience against attacks. Our results prove that MAPPO, with the uncertainty maximization technique incorporated, performs the best, ensuring a high monitoring quality and a low system overload.**

***Index Terms*—Smart farm, energy-adaptive, deep reinforcement learning, solar sensors, uncertainty, cyberattacks.**

I. Introduction

According to the Food and Agriculture Organization (FAO) of the United Nations [12], the food production rate must increase by a factor of up to 70 percent to absorb the increase in population, estimated as more than 9 billion people by 2050 [33]. To support farms' productivity, flexibility, or availability, smart farm technologies have developed by leveraging sensors, Internet-of-Things (IoT), edge and cloud computing technologies. Smart farm research is applied to develop agricultural business practices [7], improve monitoring of animal welfare [36], and provide data sensing and environmental controls [36]. Smart farm research also investigated efficient data transmission considering CPU usage, signal strength, and battery operation time [18] for wireless sensor networks [28].

However, existing research lacks efforts to develop secure solutions for wireless sensor networks (WSNs) with energy constraints such as ones powered by solar energy harvesting. According to the World Health Organization (WHO), over half a million people died due to food contamination caused by bacteria, viruses, toxins, or chemicals [ref]. Cyber attacks on farms, transportation systems, and food processing industrial control systems to distort and disrupt the handling of correct data can worsen the problem. Any distortion in the data received from the livestock monitoring systems can lead to serious situations such as the spread of disease, possible pandemics, and the provision of wrong information to potential customers of the livestock [14].

In this work, we are interested in improving the accuracy of the livestock monitoring system in farms under the presence of cyber attacks that can forge, modify, or drop sensed data from sensors to gateways or edge devices, or inject false data. Most WSNs are unable to accurately record biometrics for cattle because battery-powered sensors attached to the collar of the cattle can last only a few days or weeks. Frequent replacing or recharging of batteries for sensor nodes is laborious for a farm with a large number of animals. To address this problem, we consider wireless solar sensor nodes attached to the livestock's ears, which are powered by solar energy harvesting. Due to the small size of the solar panel attached to a sensor node, the amount of solar energy harvested is low. Moreover, the harvested energy level fluctuates as the livestock and/or its ear moves, which can make sensing and transmission of the data unstable.

To address the problem, we consider sensor nodes adopting two communication protocols, LoRa (Long Range) [**?**] and BLE (Bluetooth Low Energy) [**?**]. The LoRa protocol aims for long-distance communication with a range of several km, but the data rate is only 27 $kbps$. Contrarily, the BLE protocol aims for a short distance with a line-of-sight distance of 100 m and a higher data rate of 2 $Mbps$. Furthermore, the BLE protocol drains considerably less power than the LoRa one. Fig. 1 shows the WSN system considered in this paper. A sensor node monitors the energy level of the associated battery.

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A sensor node with a high energy level transmits the sensed data with LoRa to LoRa gateways, and the gateways upload the data to the cloud server accessible to the user. A sensor node with a low energy level may not be able to send the data directly to a LoRa gateway due to insufficient energy. Instead, the sensor node seeks a nearby sensor node with a high energy level. If it finds one, the sensor node sends the data by BLE to the nearby sensor node with a high energy level, and the nearby sensor node transmits the received data to LoRa gateways.

Under this scenario, since there may be multiple sensor nodes with low energy requesting to transmit their sensed data to the sensor node with high energy, a decision on which sensed data to transmit to the gateways can significantly impact the accuracy of monitored data. Instead of continuously transmitting sensed data that are already received sufficiently and hence high quality (i.e., low uncertainty), a sensor node with high energy can select a sensor node with low energy whose data have high uncertainty, and transmit the data, resulting in increase of the data certainty. The process will significantly increase the certainty of the overall data monitored from all animals on the farm. To this end, we introduce an uncertainty-aware transmission policy based on the assessment by LoRa gateways. Specifically, a LoRa gateway can request sensor nodes to send sensed data of particular animals whose monitored data have trended high uncertainty (i.e., low certainty). In this work, we leverage deep reinforcement learning (DRL) to identify sensor nodes whose data need to be transmitted to improve the overall monitoring accuracy.

This work makes the following **key contributions**:

- We propose an energy-adaptive monitoring system for WSN-based smart farms with solar-powered sensor nodes attached to cattle. This is the first work that considers how WSN-based smart farms can maintain high monitoring quality under limited and fluctuating energy availability due to solar energy harvesting in the smart farm.
- We develop two algorithms based on *Deep Reinforcement Learning* (DRL) [11] and *Subjective Logic* [19] (SL) to identify an optimal set of sensed data of animals in a farm to maximize the overall monitoring quality of the cattle, while maintaining an acceptable energy level for the sensor nodes (i.e., not overcharging or energy depletion). More specifically, we develop uncertainty-aware DRL algorithms to minimize uncertainty in aggregated sensed data at the gateways, with the uncertainty being measured in two dimensions based on SL, i.e., *vacuity* due to a lack of evidence and *dissonance* due to conflicting evidence.
- We consider various types of cyberattack behaviors (i.e., non-compliance to the data request by a gateway, false data injection, and denial-of-service) to evaluate the robustness of the proposed uncertainty-aware DRL-based monitoring system for the smart farm.
- We validate the performance of the proposed uncertainty-aware DRL-based monitoring system using real datasets obtained from Virginia Tech's Smart Farm Innovation Network. Furthermore, we design a framework where healthy sensor nodes generate synthetic datasets similar to real datasets, and compromised sensor nodes are modeled as attackers following the attack model for testing the robustness of our uncertainty-aware DRL-based algorithms against adversarial attacks. We conduct a comparative performance analysis of two proposed uncertainty-aware DRL-based algorithms (deep Q-learning, DQN, and multi-agent proximal policy optimization, MAPPO) against two baseline models (greedy and random) in choosing the number of sensed data to be updated to collect high-quality sensed data to achieve high resilience against attacks.

A preliminary version of the paper is published in [42]. This paper substantially extends [42] with the following additional contributions:

- We devise a novel *monitoring error rate metric* that can evaluate the monitoring quality independent of monitoring data distributions. The developed monitoring error rate metric enables our proposed monitoring system to handle multi-dimensional heterogeneous data simultaneously.
- We provide mathematical proof that can justify how SL's uncertainty maximization technique contributes to reducing monitoring errors. From the theoretical analysis, we found that using the uncertainty maximization technique can lead to using more recent evidence, reflecting recent network dynamics more appropriately.
- We enhance our attack model by considering the fast gradient sign method (FGSM) [13] as a state manipulation attack. No prior work in the literature has considered FGSM in monitoring animals on a smart farm.
- We identify an optimal deployment setting of LoRa gateways on which DRL agents run to maximize the chances for solar sensors to deliver their sensed data within the gateway wireless radio range.
- We provide the asymptotic complexity analysis of our proposed uncertainty-aware DRL-based algorithms. This analysis reveals a critical tradeoff between robustness/effectiveness vs. efficiency.
- We add extensive sensitivity analyses to investigate the effect of key designs and environmental factors on performance, including the attack severity, the initial sensor node energy level, the number of solar sensors, and the chance for sensor nodes to be exposed to the sun.

The rest of this paper is structured as follows. Section II provides a brief overview of the related work. Section IV describes the network model, node model, and attack model considered in this work. Section V provides a detailed description of our proposed uncertainty-aware DRL-based algorithms for animal monitoring. Section VI explains an experiment setup including datasets, parameterization of key design parameters, performance metrics, and baseline schemes considered for comparative performance analysis. Section VII demonstrates the key experimental results and their overall trends along with the physical interpretations of the observed results. Section VIII concludes the paper and suggests future work directions.

II. Related Work

In this section, we provide a brief overview of related work in DRL-based optimization of WSNs, energy-adaptive smart environments, and uncertainty-aware smart environments.

A. DRL-based Optimization of WSNs

Algorithms to achieve energy-aware WSNs have been proposed in various WSN applications, including routing [21, 22], resource management [31], power control [3, 4, 27], and system/hybrid design [44, 41, 37]. A cluster-based routing protocol was proposed based on a Q-learning approach called *QL-Cluster* [21]. The QL-Cluster was designed to identify the best routes between individual nodes and remote healthcare stations to efficiently monitor a patient's health. Qi et al. [31] proposed an adaptive energy management strategy for a solar-powered WSN with hybrid storage, consisting of both supercapacitors and batteries, based on avoiding high current charging/discharging of the batteries and making full use of the supercapacitors.

Chen et al. [5] proposed a sleep scheduling algorithm for rechargeable sensors based on a DRL algorithm. The authors developed a precedence operator-based group formation algorithm to ensure the desired area coverage and a Q-leaning-based active node selection algorithm to maximize the network lifetime while achieving an acceptable coverage. Chen et al. [3, 4] leveraged DRL with Q-learning to control power for communications between an in-body sensor and the Wireless Body Area Network (WBAN) coordinator to build jamming attack-resistant what (???) for healthcare applications. Their research aimed to develop a WBAN coordinator that chooses the sensor to transmit the data in the next time slot and decides the transmitting power of these sensors, which is then sent to the sensor. The WBAN coordinator uses Q-learning to achieve an optimal power control strategy.

Based on Q-learning and the application of transfer learning for learning the Q-learning parameters (to avoid random exploration at the start of the learning process), Chen et al. [3] achieved an optimal power control strategy that can help the WBAN coordinator to choose the sensor for transmitting the data along with the transmitting power for these sensors. Similarly, to address the issues of transmission reliability, energy efficiency, and Quality of Service (QoS) in WBANs, Chen et al. [4] proposed a sensor access control scheme based on DRL for the WBAN coordinator to choose the access time and transmit power of the sensor based on the sensor's state, including signal-to-interference plus noise ratio, transmission priority, battery level, and transmission delay (or signal latency). Furthermore, to accelerate the learning process and address the high dimensionality problem due to the increasing number of sensors, a convolutional neural network (CNN) is used to estimate the Q-values according to an approximate Q-function.

Since transfer learning often raises privacy concerns in a small feature space application, Zhuo et al. [44] proposed a novel federated DRL framework, called *FedRL*, to build models of high quality for agents while also preserving their privacy. The FedRL framework aims to learn a private Q-network policy for each agent by sharing limited information, which is the output of the Q-network, amongst the agents. Similarly, distributed DRL approaches of wireless distributed systems take much more time to converge than centralized DRL counterparts. Tehrani et al. [37] proposed a Federated Learning (FL) approach to DRL, referred to as *Federated DRL (F-DRL)*. In the F-DRL, the centralized DRL model is trained by sharing the model weights of the DRL agents at the base station in an FL fashion.

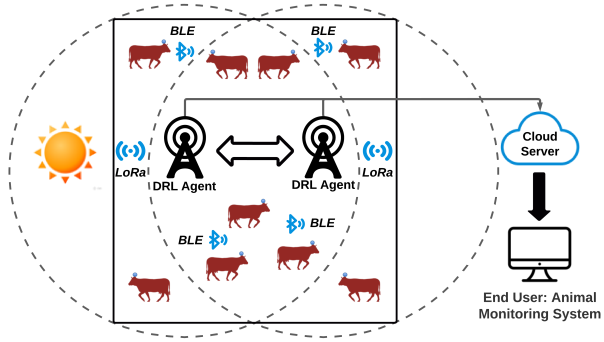


Fig. 1: Wireless Solar Sensor Node-based Smart Farm Network.

Yang et al. [41] conducted a comparative performance analysis for common DRL algorithms, including Deep Deterministic Policy Gradient (DDPG), Neural Episodic Control (NEC), and Variance Based Control (VBC), for the application of wireless network optimization. Through experiments on data gathered from a large cellular network, the authors showed the potential of DDPG and VBC. However, they found the limited action space of NEC because of the large Q-value table for this particular application. Naderializadeh et al. [27] used a multi-agent deep RL approach to tackle the problem of distributed user scheduling and downlink power control in multi-cell wireless networks. Compared against several decentralized and centralized baseline counterparts, the authors showed that the proposed algorithm outperforms two decentralized approaches, while performing comparably to the centralized scheduling algorithms. Moreover, the agents are trained for a specific environment. However, the approach is scalable only to different network configurations.

As discussed above, DRL has been applied to develop energy-efficient WSNs where privacy concerns are considered in applying deep neural networks (DNNs). However, no prior work has been done for energy-adaptive smart farms with solar sensors, which is tackled in this work. Specifically, we develop uncertainty-aware DRL algorithms to maximize uncertainty-aware monitoring quality with sensors having limited and fluctuating energy harvesting.

B. Energy-Adaptive Smart Environments

Igder et al. [17] introduced an energy-adaptive Fog Server that can handle all requests at the same time under low-energy conditions with a limited number of requests. Popa et al. [29] proposed an intelligent platform and DNN-based models to achieve energy-efficient smart environments. The authors applied two techniques, namely, energy load forecasting and non-intrusive load monitoring, for learning while reducing energy consumption. The former technique is used to predict patterns of energy consumption in a smart home environment and identify unusual energy usage, while the latter one to identify the appliance causing the anomaly to provide energy-saving tips.

Modarresi and Symons [26] proposed a multidimensional framework with an instance of a high-level smart home network. They argued that the diversity of services affects routing levels while providing routing services for both high and low energy consumption. Venkatesh et al. [40] proposed a system using ultrasonic sensors with Naïve Bayes model for resilient activity tracking in a smart home. This approach enables the system to accurately identify the activities of residents, who were not observed in the training stage, without retraining the model. However, their evaluation does not include the evaluation of resilience under various cyberattacks.

The works above focused on learning and predicting energy usage to minimize energy consumption. On the other hand, our work focuses on learning and deriving energy adaption strategies for LoRa gateways to obtain sensed data from solar sensors with limited and fluctuating energy, to maximize uncertainty-aware monitoring quality.

C. Uncertainty-Aware Smart Environments

Due to the dynamic nature of the multi-sensor smart environments, uncertainty and ambiguity can introduce significant impact on the data prediction and monitoring of these smart environments. Zhang et al. [43] proposed learning the inhabitant's activity patterns in a smart home environment to learn under uncertainty caused by sensor malfunctions. Alemdar et al. [1] proposed an uncertainty sampling-based active learning method that considers three different measures of uncertainty to select the most informative data points for activity recognition in smart homes. Several research works [2, 8, 9, 10, 15, 23] have been conducted on uncertainty in context-aware systems where the environment is well-defined. Various approaches have been proposed to model uncertainty, including semantic web [23], game theory [8], vector space model [30], asymptotic equipartition property (AEP) [34], signal processing and information-theoretic techniques [39], and Moore finite state machine (FSM) [32]. Machado et al. [23] proposed a contextual reference model based on the semantic web to deal with uncertainty in a smart environment. Almeida and de Ipiña [2] developed an ontology for context-aware systems in smart environments to consider both ambiguity and uncertainty. To improve the accuracy of probabilistic inference systems for multi-sensor data-fusion, De Paola et al. [9] suggested the context information be included to prevent the increase of uncertainty and pointed out that the right mix of context information is fundamentally important. Rocher et al. [32] proposed a framework for estimating behavior drift in smart-X systems at runtime. They leveraged Moore finite state machine (FSM) model combined with the control theory and validated their approach based on a real dataset to ensure effectiveness and efficiency.

Unlike the above cited works, we consider multiple types of uncertainty and the uncertainty maximization technique in Subjective Logic (SL) [20] for monitoring data updates based on new evidence, thus maximizing monitoring quality while minimizing energy consumption.

III. Problem Statement

In this work, we aim to minimize the monitoring error rate (i.e., a gap between the sensed data aggregated from sensors and the ground truth; see Eq. (14)) and system overload (i.e., a mean fraction of the failed requests of all requests sent from low-energy sensors; see Eq. (15)) in a sensor network by identifying an *optimal policy*. An updated policy $\mathcal{P}_T = \{p_1, p_2, \ldots, p_T\}$ contains monitoring actions p_i, where $i \in [1, T]$, $p_i \in \mathcal{P}_T$ and $\mathcal{P}_T$ is a set of monitoring actions available to the sensor in every monitoring step. Given a dynamic sensor network $\mathcal{G}_T = \{g_1, \ldots, g_i, \ldots, g_T\}$, the objective function is defined by:

$$\begin{aligned} &\arg\max_{\mathcal{P}_T} \sum_{i=1}^{T} f(g_i(p_1, p_2, \ldots, p_i)), \\ &s.t. \quad \forall i \in [1, T], p_i \in \mathcal{P}_T, \end{aligned} \tag{1}$$

where $f(g)$ is based on the evaluation function $f : g \mapsto -\mathcal{ME}(g) - \mathcal{OL}(g)$, aiming to minimize the monitoring error rate $\mathcal{ME}$ and system overload $\mathcal{OL}$, that is detailed in Section VI. Determining an optimal update policy to achieve multiple objectives is non-trivial given the complexity involved in solving a multi-objective optimization problem [6]. This is discussed in detail based on the experimental results discussed in Section VII.

IV. System Model

This section discusses the network, node, and attack models.

A. Network Model

Our target WSN consists of solar sensors attached to the cattle and continuously measure the bio-metric information and transmit the sensed data to the LoRa gateway, which then aggregates and transmits the clustered data to the cloud. Given the relatively low cost of transmitting data over long ranges (LoRa) via the standard IP protocol for IoT devices, the LoRa gateways act as the optimal intermediary between the sensor nodes and the cloud server. In the given smart farm network (see Fig. 1), using BLE (Bluetooth Low Energy) each low-battery sensors (LBS) can relay the sensed data to one of high-battery sensors (HBS). The high-battery sensor can then send the received data along with its own data to the LoRa gateway via LoRa. We assume that each sensor has a Microchip SAM R34/35 micro-controller with an embedded LoRa radio which dissipates 170 mW during transmission, while the micro-controller itself dissipates only 8 mW in active mode. For example, a Texas Instruments CC2640R2F micro-controller with an embedded BLE radio [38] dissipates only 11 mW during transmission. Therefore, sending a single bit of data dissipates about 1,100 times lesser energy for the Texas Instruments CC2640R2F micro-controller when compared with the LoRa radio of the SAM R34/35 micro-controller. We assume that the initial battery level of each deployed sensor is 5 kWs which is equivalent to a full charge. Outdoor solar has a power density of about 10 mW/cm^2 whereas indoor light has a power density of 0.1 mW/cm^2 [24]. For a solar panel of 5 cm, the maximum harvestable power for indoor light is about

2 mW and outdoor light is about 200 mW. Fig. 1 describes the considered network model in this work, describing a smart farm environment with solar sensors attached to the cattle.

With the main objective of minimizing the monitoring error rate and the system overload, a DRL agent is deployed at every LoRa gateway to shortlist, select and prioritize which animal's sensed data is required, at regular intervals. The process of identifying the important data, by the DRL agent is described in Section V. To energy saving energy, we assume that there is no encryption when the sensors communicate with each other via BLE and hence, malicious entities can intercept the data in transmission and modify/forge data. Additionally, an attacker can imitate a sensor by using its authentication key with the gateway and sending false data for the sensor itself as well as for other low-battery sensors. We assume that the communication between the LoRa gateway and the cloud server is secure and encrypted based on traditional secret cryptography. As shown in Fig. 1, multiple LoRa gateways, while each running a DRL agent, can collaborate with each other in sharing collected sensed data received from sensors.

B. Node Model

Sensor nodes in a given smart environment are assumed solar-powered and deployed as implants and can transmit data on request. Depending upon the animal's movement and the varying weather condition from day to day, the battery levels of the sensor may fluctuate throughout the day. Therefore, it is essential to utilize the energy wisely for high availability, consistency, and sustenance. Each sensor node i is characterized by $\mathrm{sn}_t^i = [\mathrm{temp}_t^i, \mathrm{hb}_t^i, \mathrm{ma}_t^i, \mathrm{bl}_t^i]$, where temp_t^i refers to sensor node i's temperature at time t in Celsius, hb_t^i is the number of i's heartbeat at time t, ma_t^i is i's speed at time t and bl_t^i is i's battery life at time t scaled in $[0, 100]$ in percent. Most of the sensor's energy will be used to transmit the sensed data to the LoRa gateway. In contrast, considerably less battery power will be used for communication between the sensor and other nearby sensors via BLE as it consumes roughly 1,100 times less (see Section IV-A).

Utilizing the data reported by the sensors to the LoRa gateway, each DRL agent will try to maximize the monitoring quality by selecting what data is needed with priority to accurately estimate the well-being of all the animals on the farm. To this end, the sensor nodes in the WSN is categorized into high battery-level sensors (HBS) and low battery-level sensors (LBS) based on the recommended battery level T_M. Since we are only interested in transmissions from LBS to HBS, we model the sensor network as a directed bipartite graph. Section V describes the actions performed by the DRL agent running on every LoRa gateway. The end-user will get the efficient monitoring results of the smart farm from the cloud server, which aggregates data on individual animals from various LoRa gateways. This work aims to evaluate how the DRL agent on LoRa gateways can enhance the quality of animal monitoring in the presence of cyberattacks and fluctuating sensor energy levels.

C. Attack Model

This work considers the following attack behaviors:

- *Non-compliance to the protocol*: A sensor node can be compromised and exhibit non-compliant behavior to the request by the DRL agents on LoRa gateways. For example, when an animal A's sensed data is requested by a DRL agent, the attacker can either not send A's data or send another sensor's data to the LoRa gateway. We model this with the attacker's non-compliance probability, P_{NCA}.
- *False data injection*: An attacker (e.g., a compromised sensor) can transmit forged/modified data or inject false data to gateways. In addition, man-in-the-middle attackers (MIMAs) can intercept data being transmitted in the middle and replace it with forged/modified data. The attackers can inject false data during the training phase (i.e., poisonous attacks) or the testing phase (i.e., evasion attacks). We call the compromised sensors *internal attackers* while calling the external attackers intercepting sensed data for forgery/modification or injecting false data *external attackers*. These attacks are modeled by the forging/modifying data attacks an internal or external attacker can launch, P_{IDA} and P_{EDA}, respectively.
- *Denial-of-Service (DoS)*: A compromised high-battery sensor can send a request to nearby sensors requesting them to send its fake sensed data. As it is a type of internal attacks, we also model this DoS attack probability by P_{IDA}. This can make other sensors' energy levels drained quickly but wasted in sending false data. To avoid an infinite loop, we assume the attacker will request sending its fake sensed data to legitimate sensors.
- *Fast Gradient Sign Method (FGSM)*: This state manipulation attack model is firstly proposed in [13] to generate adversarial examples in image classification tasks. To apply it in the context of DRL-based algorithm execution, we generalize DRL settings by considering actions as class labels. To make a fair comparison, we use the original loss function of each DRL algorithm to compute the gradients. Since we have multiple DRL agents in our smart farm system, we assume the attack will happen in both local agent states and global agent observations. We define the perturbation strength as P_{FGS}.

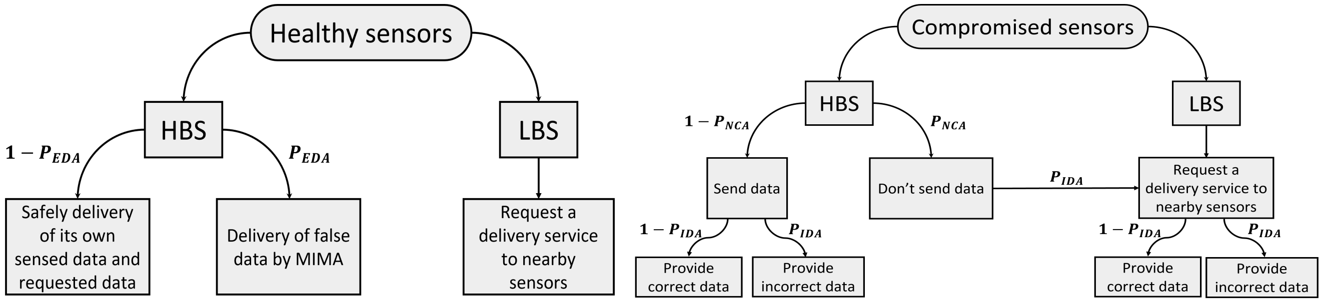
We summarize the above four types of attacks in Fig. 2.

V. DRL-based, Uncertainty-Aware Animal Monitoring

In this section, we provide a detailed description of our proposed uncertainty-aware DRL-based algorithms for smart farm animal monitoring

A. Uncertainty-Aware Animal Monitoring

First, based on received data from sensors in the past, a gateway can estimate uncertainty in each animal's condition, such as heart rate, average temperature, minimum/maximum temperature, average activity, battery level of a sensor worn by the animal, and timestamp. Recall that each LBS will send its sensed data to a HBS within 100 meters. Hence, we distinguish direct sensed data from indirect sensed data in terms of whether a sensor sent its own sensed data or another sensor's sensed data. If the sensor with high energy



(a) Outsider attacks by false data injection

(b) Insider attacks by false data injection, DoS, or non-compliance

Fig. 2: Attack scenarios by both outsider and insider attackers. Recall that P_{EDA} is the probability of an external attacker performing false data injection attacks, P_{NCA} is the probability of an internal attacker performing non-compliance attacks, and P_{IDA} is the probability of an inside attacker performing false data injection attacks or DoS attacks.

transmitted other sensor's sensed data, it is treated as indirect sensed data. Otherwise, it is direct sensed data. The gateway periodically reports its collected data from sensors to the cloud server. Since the given network has multiple gateways, the corresponding multiple DRL agents will share information about sensed data and estimate each animal's conditions (see Table I) and associated confidence level on each observation item. A database on the gateway keeps recording all animals' condition data where sensed data by sensor i (i.e., ID) for an animal are stored.

Each observation item's condition (e.g., average temperature) will be reported as one of the K classes of the range, e.g., for the temperature reading, $K = 5$ meaning that there are 5 classes of ranges: 35 or below, 36-37, 38-39, 40-41, 42 or above. The end user can then easily determine if the temperature is normal based on the cloud server's received data. Since the gateway will periodically report average conditions for all animals to the cloud, it will aggregate sensed data from sensor nodes and measure their average with the probability of a condition being with K classes and multiple types of uncertainty values. To utilize the concept of uncertainty, we will apply SL [20] to compute an opinion on each animal's condition in a given attribute (e.g., temperature, heartbeats, activity, or battery level).

1) SL-based Formulation of a Multinomial Opinion: SL can explicitly express uncertainty caused by a lack of evidence, called *vacuity* in its opinion representation. In addition, SL can consider base rates as prior probabilities in a Bayesian way to formulate a second-order opinion and corresponding uncertainty estimates, where a second-order opinion is represented by Dirichlet distribution. We will use a Dirichlet probability density function (PDF) to model the distribution of class probabilities and corresponding uncertainty masses. In SL, a multinomial opinion in a given proposition x (e.g., an animal condition in our smart farm context, such as a temperature or heartbeats) is represented by $\omega_X = (\boldsymbol{b}_X, u_X, \boldsymbol{a}_X)$ where a random variable $X \in \mathbb{X}$ (a subject domain) and $K = |\mathbb{X}| > 2$ and the additivity requirement of ω_X is given as $\sum_{x \in \mathbb{X}} \boldsymbol{b}_X(x) + u_X = 1$. To be specific, each parameter indicates,

- $\boldsymbol{b}_X$: *belief mass distribution* over $\mathbb{X}$;
- u_X: *uncertainty mass* representing *vacuity of evidence*;
- $\boldsymbol{a}_X$: *base rate distribution* over $\mathbb{X}$.

The projected probability distribution of multinomial opinions is given by:

$$\boldsymbol{P}_X(x) = \boldsymbol{b}_X(x) + \boldsymbol{a}_X(x) \cdot u_X, \quad \forall x \in \mathbb{X} \tag{2}$$

The base rate for belief $\boldsymbol{b}_X(x_i)$, which is $\boldsymbol{a}_X(x_i)$, means the prior preference over the x_i belief (e.g., a class). If no preference is given, we consider the base rate equally for each belief mass, i.e., $\boldsymbol{a}_X(x_i) = 1/K$ for any x_i.

Given the amount of evidence supporting belief x_i is $\boldsymbol{r}(x_i)$, the observed evidence in the Dirichlet PDF can be mapped to the multinomial opinions as:

$$\boldsymbol{b}_X(x) = \frac{\boldsymbol{r}(x)}{W + \sum_{x_i \in \mathbb{X}} \boldsymbol{r}(x_i)}, \; u_X = \frac{W}{W + \sum_{x_i \in \mathbb{X}} \boldsymbol{r}(x_i)}, \tag{3}$$

where W refers to the amount of uncertain evidence. Commonly, W is set to the number of belief masses (i.e., $W = K$).

2) Estimation of Multiple Types of Uncertainty: SL categorizes uncertainty into two primary sources [20]: (1) basic belief uncertainty derived from single belief masses, and (2) intra-belief uncertainty based on the relationships between different belief masses. These two sources of uncertainty can categorize the two uncertainty types, *vacuity* and *dissonance*, respectively, that correspond to vacuous beliefs and contradicting beliefs. In particular, the vacuity of an opinion ω_X is captured by uncertainty mass u_X while dissonance of an opinion, $\boldsymbol{b}_X^{\mathrm{Diss}}$, is formulated by [19]:

$$\boldsymbol{b}_X^{\mathrm{Diss}} = \sum_{x_i \in \mathbb{X}} \left(\frac{\boldsymbol{b}_X(x_i) \sum\limits_{x_j \in \mathbb{X} \setminus x_i} \boldsymbol{b}_X(x_j) \mathrm{Bal}(x_j, x_i)}{\sum\limits_{x_j \in \mathbb{X} \setminus x_i} \boldsymbol{b}_X(x_j)} \right), \tag{4}$$

where the relative mass balance between a pair of belief masses $\boldsymbol{b}_X(x_j)$ and $\boldsymbol{b}_X(x_i)$ is expressed by:

$$\mathrm{Bal}(x_j, x_i) = 1 - \frac{|\boldsymbol{b}_X(x_j) - \boldsymbol{b}_X(x_i)|}{\boldsymbol{b}_X(x_j) + \boldsymbol{b}_X(x_i)}. \tag{5}$$

The dissonance estimation is useful to measure the *inconclusiveness* of an opinion even under a large amount of evidence that almost equally supports each singleton belief.

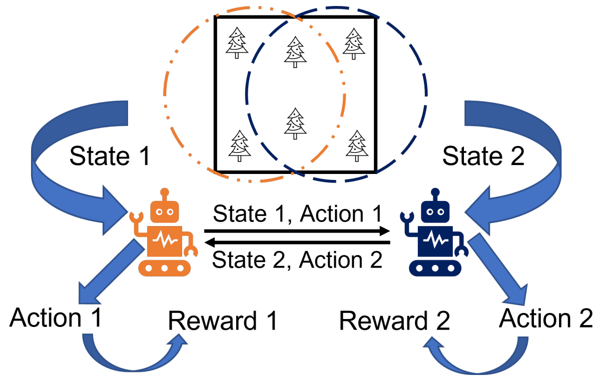


Fig. 3: The proposed Multi-Agent Deep Reinforcement Learning (MADRL) framework.

In this work, we regard each reported data from sensor nodes to a gateway as evidence. For instance, in a temperature report, if 38 C is reported, b_2 (i.e., b_1 = lower than normal, b_2 = normal, b_3 = higher than normal) should be updated based on Eq. (3). When the uncertainty mass becomes zero, an opinion will not be updated anymore, which makes new evidence cannot be properly utilized in the latest opinion. To avoid this, we will deploy the *uncertainty maximization* technique [20] to reduce the impact of conflicting evidence while transforming the amount of conflicting evidence into the vacuity of an opinion.

Given opinion $\omega_X = (\boldsymbol{b}_X, u_X, \boldsymbol{a}_X)$ where $\boldsymbol{P}_X = \boldsymbol{b}_X + \boldsymbol{a}_X \cdot u_X$ for a domain $\mathbb{X}$, the corresponding vacuity-maximized opinion is denoted by $\ddot{\omega}_X = (\ddot{\boldsymbol{b}}_X, \ddot{u}_X, \boldsymbol{a}_X)$ where $\ddot{u}_X$ and $\ddot{\boldsymbol{b}}_X$ are computed by:

$$\ddot{u}_X = \min_i \left[\frac{\boldsymbol{P}_X(x_i)}{\boldsymbol{a}_X(x_i)}\right], \tag{6}$$
$$\ddot{\boldsymbol{b}}_X(x_i) = \boldsymbol{P}_X(x_i) - \boldsymbol{a}_X(x_i)\cdot \ddot{u}, \quad \text{for } x_i \in \mathbb{X}.$$

We use a threshold ρ to trigger the vacuity maximization. That is, Eq. (6) above can be triggered only when $u_X < \rho$ where ρ is sufficiently low (e.g., 0.05). The purpose of updating ω_X to $\ddot{\omega}_X$ is to allow the opinion to be further updated by receiving new evidence or being combined with other opinions which is possible only when $u_X > 0$.

In a given category X, the animal condition is estimated as an opinion, ω_X, where the corresponding uncertainty types, vacuity and dissonance are estimated, respectively, at the gateways that aggregate sensed data and transmit the average condition value in a given category along with the belief masses and uncertainty masses associated with ω_X.

B. DRL-based Monitoring Update

This section describes how DRL agent's states, actions, and immediate reward are formulated in this work.

1) State Space ($\mathcal{S}_t$): We assume a partially observable environment where each DRL agent can only access information in the dataset of the local gateway it is running on. We formulate the state space of each agent i at time t indicating the total number of local reports for the duration of t, $\{\ell_1^i, \ell_2^i, \ldots, \ell_{t-1}^i, \ell_t^i\}$, where $\ell_{t^*}^i$ refers to the number of local reports in $[t^*-1, t^*]$. To be specific, assume $t \in [0, T]$, the overall state space is given by $\mathcal{S}_t = \{s_t^1, \ldots, s_t^i, \ldots, s_t^m\}$, where m is the number of DRL agents (i.e., LoRa gateways) and s_t^i is the state space for agent i at time t, which is given by $s_t^i = \{\ell_1^i, \ell_2^i, \ldots, \ell_t^i, 0, \ldots, 0\}$.

2) Action Space ($\mathcal{A}_t$): For each DRL agent, it will choose k animals whose data is more helpful in improving monitoring quality and reducing system overload. Note that a certain amount of redundant information is desired since there is a possible situation that sensors fail to transmit data due to limitations of their energy level or topology. Based on the agent i's local gateway dataset, the utility of animal j is given by:

$$\text{utility}_{ij} = (1-\text{vac}_t^{ij}) + (1-\text{diss}_t^{ij}) + \text{fr}_t^{ij} + f(\text{bl}_t^{ij}), \tag{7}$$

where vac_t^{ij}, diss_t^{ij}, and fr_t^{ij} are vacuity, dissonance, and degree of freshness of animal j's sensed data at time t by DRL agent i. To calculate vacuity and dissonance, we use each evidence (i.e., a report of animal conditions from the sensor node) to hold a categorical class (i.e., below normal range, normal range, above normal range). We initialize the opinion for a given animal with one evidence (i.e., $\mathbf{r}(x_l) = 1$) for each class l and $K = 3$. fr_t^{ij} is formulated by $\text{fr}_t^{ij} = e^{-\phi \mathbb{T}(t)}$, where $\mathbb{T}(t)$ is the time elapsed from the last update and ϕ is a constant to normalize the freshness. $f(x)$ is defined by $f(x) = -(x - T_M)^2$ where x is set to bl_t^{ij}, the battery life of sensor j at time t by DRL agent i. By scaling $\text{vac}_t^{ij}, \text{diss}_t^{ij}, \text{bl}_t^{ij}$, and fr_t^{ij} in $[0,1]$, we set each component of utility_{ij} to $[0,1]$ as a real number. Here T_M denotes the recommended level that the battery of a sensor node should be maintained. A list of animal IDs will be calculated based on Eq. (7) in ascending order, so each agent will request data for the top k animals. The action space has three actions selecting the first k animal IDs such that $k \in \{0, \lfloor \frac{nl}{2} \rfloor, nl\}$, where nl is how many LBS nodes are in the current environment. In this way, the size of action space is not dependent on nl (i.e., 3), which is able to reduce the computation load raised by infinite action spaces and make this monitoring system possible for applying to larger-scale sensor networks as a generalization. For a lower k, it may impact the monitoring quality. At the same time, a higher k will obtain a larger amount of unnecessary data transmission and result in a system overload. Therefore, the DRL agent aims to identify the best action, which is the optimal k for this setting.

3) Immediate Reward (r_t): This is formulated by $r_t^i = f(g_t^i(k_1^i, k_2^i, \ldots, k_t^i), g_t)$ based on $f(g_t^i, g_t) = -\mathcal{ME}(g_t^i) - \mathcal{OL}(g_t)$ given in Eq. (1), where g_t^i and k_t^i are the local sensor network and action with respect to gateway i at time step t.

In this work, we consider a cooperative framework where multiple DRL agents share their states and actions to obtain the global observation of the whole farm area, i.e. the system overload. Fig. 3 provides an overview of the proposed Multi-Agent Deep Reinforcement Learning (MADRL) framework.

C. Data Aggregation at LoRa Gateways

For each sensor node, it will send its sensed data to LoRa gateways or a high-energy sensor close to it, as the information shown in Table I. After receiving the reports from all sensor nodes capable of transmitting their data, a LoRa gateway will compute an opinion based on the received data. The opinion is composed of belief and uncertainty in terms of vacuity and dissonance masses. We define the opinion as a *monitoring opinion* (MO) below, of the measured temperature, heartbeats, and activity in the period of monitoring time Δ. Δ is computed based on the time interval of the current time and the last reported time. When the amount of sensed data becomes large enough, the MO may not be updated further because vacuity approaches closely to zero, which an opinion cannot be updated from new sensed data based on Eq. (3). To update the MO properly from received new evidence, we will deploy the vacuity (uncertainty) maximization technique in Eq. (6). We use a threshold ρ (i.e., $0 < \rho < 1$) to determine when to update the MO based on Eq. (6). That is, if $u_X < \rho$, this evidence will update an opinion based on Eq. (6). To evaluate the system monitoring error based on Eq. (14), we also introduce a system database to collect the latest monitoring opinions for each animal among all gateways.

D. Mathematical Proof of Effectiveness Using Uncertainty Maximization

In this section, we formally prove the effectiveness of the *uncertainty maximization* technique [20] by mathematical proof. We observe that uncertainty mass and the monitoring error rate can be viewed as functions of evidence. Based on Eq. (3), the uncertainty (*vacuity*) drops when the amount of received evidence increases. Furthermore, given Eq. (4), *dissonance* solely depends on the distribution of belief masses without vacuity being involved. Thus, the dissonance can be viewed as a constant when there is enough evidence from the same distribution.

The uncertainty (vacuity) maximization in Eq. (6) reinitializes the vacuity by transforming previous evidence from the belief masses to the uncertainty mass. Given the following [20],

$$j = \arg\min_i \Big[\frac{\boldsymbol{P}_X(x_i)}{\boldsymbol{a}_X(x_i)}\Big], \tag{8}$$

where $\boldsymbol{P}_X(x_i)$ is the projected probability of having x_i and $\boldsymbol{a}_X(x_i)$ is the base rate (i.e., prior belief) that supports a belief mass x_i. Then, we have the updated belief masses and the uncertainty (vacuity) mass given by:

$$\ddot{\boldsymbol{b}}_X(x_k) = \frac{\boldsymbol{r}(x_k) - \boldsymbol{r}(x_j)}{W + \sum_{x_i \in \mathbb{X}} \boldsymbol{r}(x_i)}, \ddot{u}_X = \frac{W + K\boldsymbol{r}(x_j)}{W + \sum_{x_i \in \mathbb{X}} \boldsymbol{r}(x_i)}, \tag{9}$$

where W is the amount of non-informed evidence (i.e., uncertain evidence), K is the number of belief masses (e.g., classes), and $\boldsymbol{r}(x)$ is the amount of evidence supporting belief mass x. Since the amount of non-informed evidence, W, increases to $W + K\boldsymbol{r}(x_j)$, we replace W with $W + K\boldsymbol{r}(x_j)$ in the denominators of both $\ddot{\boldsymbol{b}}_X(x_k)$ and $\ddot{u}_X$ as

$$\ddot{\boldsymbol{b}}_X(x_k) = \frac{\boldsymbol{r}(x_k) - \boldsymbol{r}(x_j)}{(W + K\boldsymbol{r}(x_j)) + \sum_{x_i \in \mathbb{X}}(\boldsymbol{r}(x_i) - \boldsymbol{r}(x_j))}, \tag{10}$$

$$\ddot{u}_X = \frac{W + K\boldsymbol{r}(x_j)}{(W + K\boldsymbol{r}(x_j)) + \sum_{x_i \in \mathbb{X}}(\boldsymbol{r}(x_i) - \boldsymbol{r}(x_j))}. \tag{11}$$

TABLE I: EVD Dataset Description

Metric	Description
serial	A unique animal identifier
HR	Heart Rate of the animal
average-temperature	Average body temperature in Celsius
min-temperature	Minimum temperature in Celsius
max-temperature	Maximum temperature in Celsius
average-activity	Average activity recorded by the number of steps taken
battery-level	Residual battery life
timestamp	Date and time of transmission

The above implies that the updated vacuity only considers partial history evidence, indicating more recent evidence than past evidence.

As shown in Eq. (14), the monitoring error rate is closely related to the amount of evidence. Assume that at each time step $t \in [0, T]$, the information of n_t animal is being updated and each animal j's information is updated m_j times in total. Hence, we have the expected monitoring error rate given by,

$$\begin{aligned} E(\mathcal{ME}) &= \frac{E(\sum_{t \in T}\sum_{x \in X} \mathrm{me}_t^x)}{NT|X|} \\ &= \frac{\sum_{t \in T}\sum_{x \in X} E(\sum_{j=1}^{n} D(\mathrm{eo}_t^x(j), \mathrm{gt}_t^x(j)))}{NT|X|} \\ &= \frac{\sum_{x \in X, t \in T} E(\sum_{j=1}^{n_t} 0 + \sum_{j=n_t+1}^{n} 1)}{NT|X|} \\ &= \frac{\sum_{x \in X}\sum_{t \in T}(N - n_t)}{NT|X|} \\ &= 1 - \frac{\sum_{x \in X}\sum_{j=1}^{n} m_j}{NT|X|}. \end{aligned} \tag{12}$$

Here T is the total monitoring time, N is the number of solar sensors attached to cows, me_t^x is the overall monitoring error rate of all N cows' conditions of attribute x at time t, $\mathrm{eo}_t^x(j)$ and $\mathrm{gt}_t^x(j)$ is the estimated and ground truth observation of cow j's condition in x attribute at time t, respectively. The above derivation proves that $E(\mathcal{ME})$ is only dependent upon n_t and it increases when n_t decreases. In addition, each animal j's monitoring error rate is only related to the amount of corresponding evidence, m_j. Therefore, we prove that the order of any pair of sensors remains invariant under the partial order relations of vacuity and monitoring error rate.

VI. Experimental Setup

This section describes the datasets, parameterization, DRL schemes, and performance metrics used for the experiments conducted in this work.

A. Datasets

At Virginia Tech, we have a collection of interconnected data collection and analysis hubs called the *SmartFarm Innovation Network* (TM), which is designed to facilitate the testing and demonstration of emerging technologies throughout the state. From the smart farm, we obtained sample datasets collected from four different sensors, namely, EmbediVet Implantable Temperature Device (EVD), Halter Sensor, Heart Rate Sensor, and Implantable Temperature Sensor. The dataset from the EVD consists of 8 components as described in Table I. We consider 6 components out of them, except a serial number and timestamp, as the sensed data to represent the physical conditions of animals. The temperature and the heart rate sensor provide us with temperature in Celsius and heart rate in beats per minute (bpm), respectively. The Halter sensor could identify each animal's geolocation and assess its motion and posture to report its activity level. Since the existing dataset obtained from Virginia Tech's smart farm does not include any data compromised by attackers, we designed a framework where each sensor could generate synthetic datasets similar to real datasets and some compromised sensors are modeled as attackers following the attack model described in Section IV-C.

B. Parameterization

We consider 20 cows within a 40 acres ($\sim$ 160K square meters) square farm area (A) with 402 meters in length (a). We consider two gateways with the same circular coverage. We further assume that these gateways could cover the farm area and each of them is covered by the other. In general, for a given number of m gateways with the same radius r, we aim to find the minimum radius r_m such that the farm area is fully covered by the total gateway coverage and each gateway is covered by other gateways to enable mutual communications. To this end, we solve the following optimization problem to identify the minimum radius r_m:

$$r_m = \min_r \{r : \exists P_i = (x_i, y_i) \in \mathbb{R}^2\}, \tag{13}$$
$$\text{where } 1 \leq i \leq m, \ \ s.t. \ \forall P = (x, y) \in [-a/2, a/2]^2,$$
$$(\min_i d(P, P_i) \leq r) \wedge \forall (i, j) \in [1, m]^2, \ \ \mathrm{d}(P_i, P_j) \leq r,$$

where a is the length of farm side, P_i is the center of gateway, and $\mathrm{d}(\cdot,\cdot)$ is the Euclidean distance function. We only consider the case when $m = 2$, where gateways locate in $(-\frac{a}{4}, 0)$ and $(\frac{a}{4}, 0)$ respectively with the same radius $\frac{\sqrt{5}a}{4}$. Fig. 1 shows how two gateways are optimally deployed with the corresponding wireless radio ranges used in our smart farm network environment.

To model the availability of solar energy based on the sun's movement in a day, we define a charging probability distribution $P(x, y, t)$ over the farm area as the probability of being charged if a sensor is located at (x, y) at time t. For simplicity, we assume that $P(x, y, t)$ has a quadratic form at time t and is represented by $P(x, y, t) = \max\{0, -\frac{1}{6}(t - t_{xy})^2 + 1\}$, where t_{xy} is a function of location (x, y) based on the farm's direction. We consider a square farm with its center at the origin and x axis towards the west. Thus, t_{xy} is formulated as $t_{xy} = \frac{t_0}{a} \times (x - \frac{a}{2}) + 12$, where t_0 is a hyper-parameter. In general, to model different weather conditions, we can use a weight α to discount the charging probability as $\alpha P(x, y, t)$ with $0 \leq \alpha \leq 1$.

Each cow's attributes are collected by an attached solar-powered sensor. We adopt normal distributions $\mathcal{N}(38,\ 1^2)$ and $\mathcal{N}(1.5,\ 0.1^2)$ to describe a cow's temperature and velocity respectively. The cow's heartbeat is modeled as two uniform distributions: $\mathcal{U}(60, 84)$ when it moves or $\mathcal{U}(48, 60)$ when it does not move. We use P_i^{mv} for cow i's moving probability.

For an opinion about a cow's attributes, we will simply categorize based on three beliefs, i.e., lower than normal, normal, and higher than normal. The normal ranges of a cow's temperature, heart rate, and moving activity are given $[37.8, 39.2]$ Celsius, $[48, 84]$ number of beats per min., and $[1, 2]$ meters per sec., respectively. We consider the number of uncertain evidence to be three where each belief mass has the same base rate (i.e., 1/3) [20].

We consider 24 consecutive hours as the total monitoring session. For every $T_a = 60$ sec, each gateway would take an action to identify an optimal monitoring strategy. We assume 5 HBS with a full initial battery level and 15 LBS with random initial battery levels below T_M. All LBS could only broadcast their own data to HBS via BLE. Each sensor can broadcast at most two sets of sensed data to each LoRa gateway within the wireless range per $T_u = 30$ sec. In this way, each HBS can send its own data and another set of data requested by the LBS. The monitoring system would derive the consolidated priority list of update lists from gateways. Then the system would leverage the Hopcroft–Karp algorithm [16] to solve the maximum matching problem in bipartite sensor networks. In this way, the system could ensure the maximum number of transmissions being executed.

As for energy consumption, message transmissions need 170 mW per sec and the sleep mode costs 2 mW per sec. We assume a sensor is only activated for message transmissions. A sensor can be charged by the outdoor solar with 200 mW per sec. In this way, a sensor can be charged 200 mW $\times$ 6 h = 4.32 kWs under 6 hours of the sun.

We set all attack probabilities to P_A. For inside attackers, we initially pick them among the total number of sensors at random. For outside attackers (i.e., MIMAs), we pick a set of nodes at random transmitting messages intercepted by MIMAs with $P_{EDA}(P_A)$. The attackers launch attacks based on Fig. 2. Finally, we consider FGSM as a state manipulation attack to disturb the DRL training phase. Table II summarizes the key design parameters, their meanings, and default values.

C. DRL Algorithms

We develop two uncertainty-aware DRL algorithms (MAQN and MAPPO) whose performance is compared against two baseline schemes (Greedy and Random), described as follows:

- **Multi-Agent Deep Q-Learning (MADQN)** [25]: DRL agents learn a state-value Q function to select the optimal actions. In a multi-agent scenario, we extend DQN to MADQN, where each DRL agent learns an independent local Q function. We consider two variants of MADQN using UM or not and name them MADQN-UM and MADQN-NUM, respectively.
- **Multi-Agent Proximal Policy Optimization (MAPPO)**: MAPPO extends the PPO [35] to a multi-agent environment to mitigate non-stationarity by adopting a global critic value function to guide each local actor value function. We consider two variants of MAPPO with and without using uncertainty maximization. We name them MAPPO-UM and MAPPO-NUM, respectively.

TABLE II: KEY DESIGN PARAMETERS, THEIR MEANINGS AND DEFAULT VALUES

Param.	Meaning	Value
m	The number of gateways	2
N	The number of sensors(cows)	20
T_M	A minimum battery level to transmit sensed data by a sensor	30%
LBS/HBS	Low/High battery level sensors	/
P_i^{mv}	Cow i's probability to move	$[0.3, 0.7]$
P_A	Probability for an attacker or a compromised node to perform a certain attack (e.g., P_{NCA}, P_{IDA}, P_{EDA}, P_{FGS})	0.1
A	Area of a given smart farm	40 acres
a	length of a given smart farm	402 m
ρ	Uncertainty maximization threshold	0.05
t_0	Hyper-parameter used in sun model	0.2
T_u	Time interval for a sensor to send sensed data	30 s
T_a	Time interval for a gateway to take an action to adjust k	60 s
T_L	Initial battery level for low battery level sensors	30%
α	The probability for a cow to be exposed to the sun depending on its position when the sun is available	1

- **Greedy Algorithm**: DRL agents make heuristic choices by enumerating all actions at each step and choosing the one with the optimal reward.
- **Random**: DRL agents randomly select an action, e.g., k animal IDs to receive their sensed data.

D. Metrics

We consider the following metrics to evaluate the performance of the four DRL schemes described in Section VI-C:

- **Accumulated reward** ($\mathcal{R}$): This metric represents the sum of the mean accumulated reward for all DRL agents through all simulation runs.
- **Monitoring error rate** ($\mathcal{ME}$): This metric is measured based on the mean difference between the latest data of each animal's condition from all gateways and the ground truth data of the corresponding animal's condition. We measure $\mathcal{ME}$ by:

$$\mathcal{ME} = \frac{\sum_{t\in T}\sum_{x\in X}\mathrm{me}_t^x}{NT|X|}, \quad \mathrm{me}_t^x = \sum_{j=1}^{n} D(\mathrm{eo}_t^x(j), \mathrm{gt}_t^x(j)), \tag{14}$$

$$s.t. \quad D(a,b) = \begin{cases} 1 & \text{if } a \neq b; \\ 0 & \text{if } a = b. \end{cases}$$

  Here T is the total monitoring time, N is the number of animals, me_t^x is the overall monitoring error rate of all N animals' conditions of attribute x at time t, $\mathrm{eo}_t^x(j)$ and $\mathrm{gt}_t^x(j)$ are the estimated and ground truth observation of animal j's condition in x attribute at time t, respectively.
- **Overload** ($\mathcal{OL}$): This metric evaluates the system overload by the mean fraction of the failed requests over all sent requests from LBS. In specific, we have

$$\mathcal{OL} = \frac{1}{T}\sum_{t\in T}\frac{rq_t^f}{rq_t}, \tag{15}$$

TABLE III: Asymptotic Complexity Analysis of the Considered Schemes

Scheme	Complexity
MADQN/MAPPO	$O(n_e \times t_{train})$
Greedy	$O(n_{action})$
Random	$O(1)$

where T is the total monitoring time, rq_t^f and rq_t are the numbers of failed requests and total requests at time t, respectively.

VII. EXPERIMENTAL RESULTS AND ANALYSIS

A. Algorithmic Complexity Analysis

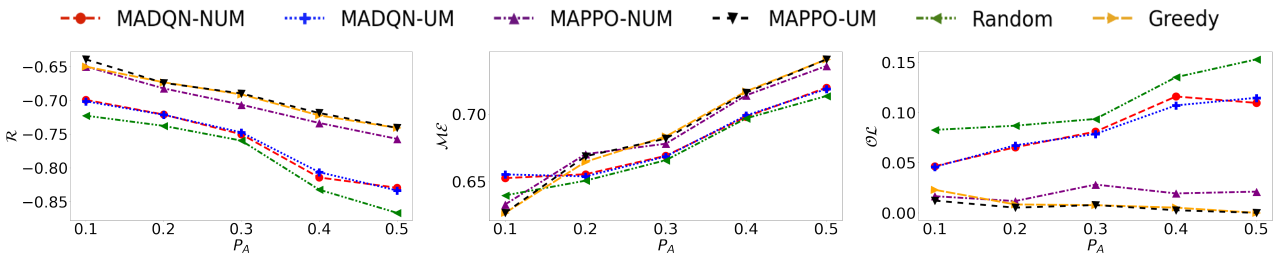
We first analyze the algorithmic complexity of the four DRL schemes described in Section VI-C. Table III shows the asymptotic complexities in Big-O notation for the four schemes discussed in Section VI-C. We notice that cost of MADQN/MAPPO only depends on the training episode n_e and training time per episode t_{train}. Greedy needs to enumerate the total action space and thus its complexity depends on the action space size n_{action}. When the action space is large enough, greedy can incur more cost than MADQN/MAPPO. Table III shows that the Random is the most efficient algorithm among all while showing the worst performance (to be discussed further in the next section).

B. Sensitivity Analyses

Below we conduct in-depth sensitivity analyses of the two baseline schemes (Greedy and Random) and the two uncertainty-aware DRL schemes (i.e., MADQN, MAPPO) with uncertainty maximization (i.e., MADQN-UM, MAPPO-UM) vs. without uncertainty maximization (i.e., MADQN-NUM, MAPPO-NUM) over a wide range of the attack probability, P_A, the initial low battery level T_L, the number of cows (sensors) N, and the chance for a cow to be exposed to the sun, α.

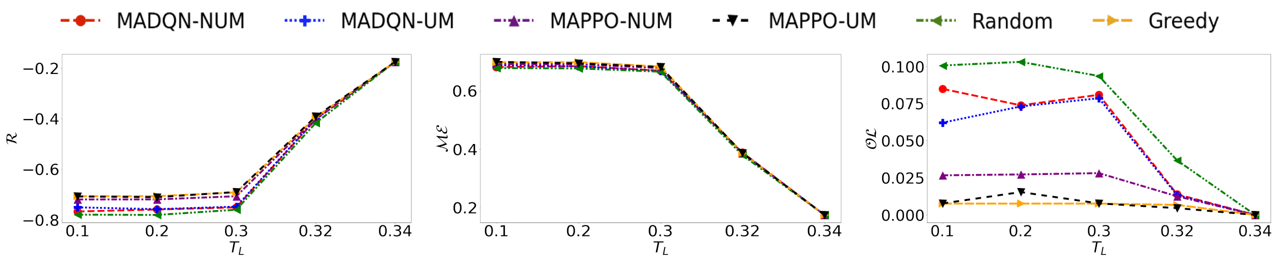
1) Effect of Varying the Attack Severity: Fig. 4 shows the effect of varying the attack probability, P_A, on the performance of the six schemes in terms of the three metrics in the network. We observe that increasing P_A decreases $\mathcal{R}$ while increasing $\mathcal{ME}$ and $\mathcal{OL}$. When P_A increases, the monitoring system gets severely compromised, thus the payoff per monitoring update would drop. MAPPO and Greedy can successfully identify this change in the payoff and achieve better performances than other schemes. The overall performance order with respect to the three metrics is: MAPPO-UM $\geq$ Greedy $\geq$ MAPPO-NUM $\geq$ MADQN-UM $\geq$ MADQN-NUM $\geq$ Random.

2) Effect of Varying the Initial Battery Levels (T_L): Fig. 5 shows the effect of varying the initial battery level assigned to low-battery level sensors (LBS), T_L, on the performance of the six schemes in terms of the three metrics in the network. We observe that increasing attack probability (T_L) increases the accumulated reward ($\mathcal{R}$) while decreasing the monitoring error rate ($\mathcal{ME}$) and the degree of overload ($\mathcal{OL}$). We also observe that when T_L increases, all three metrics converge to one point due to the decreased number of LBS. Monitoring policies only apply to LBS and thus negligible differences



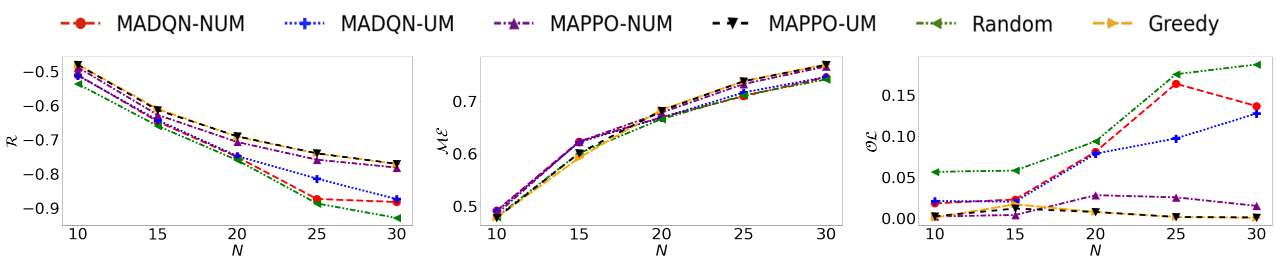
(a) Accumulated reward ($\mathcal{R}$) (b) Monitoring error rate ($\mathcal{ME}$) (c) Overload ($\mathcal{OL}$)

Fig. 4: Comparative performance with respect to varying attack probability (P_A).



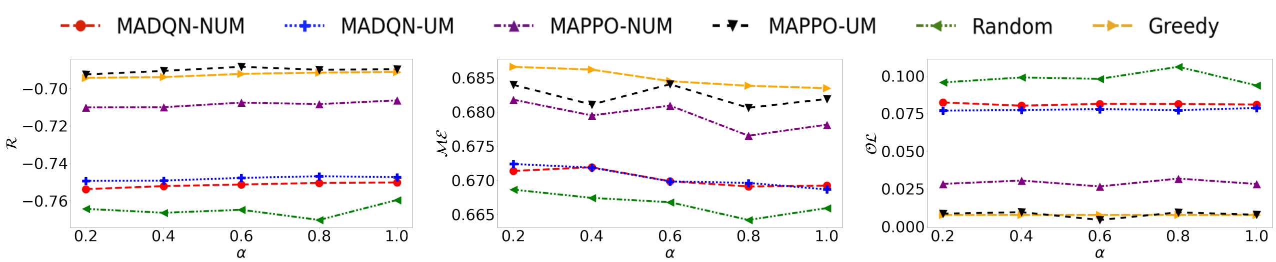
(a) Accumulated reward ($\mathcal{R}$) (b) Monitoring error rate ($\mathcal{ME}$) (c) Overload ($\mathcal{OL}$)

Fig. 5: Comparative performance with respect to varying the initial low battery level (T_L).



(a) Accumulated reward ($\mathcal{R}$) (b) Monitoring error rate ($\mathcal{ME}$) (c) Overload ($\mathcal{OL}$)

Fig. 6: Comparative performance with respect to varying the number of solar sensors (N) attached to cows.



(a) Accumulated reward ($\mathcal{R}$) (b) Monitoring error rate ($\mathcal{ME}$) (c) Overload ($\mathcal{OL}$)

Fig. 7: Comparative performance with respect to the different levels of sun exposure (α).

are observed under high T_L. Overall, our proposed MAPPO-based schemes can achieve a low monitoring error rate with the lowest overload.

3) Effect of Varying the Node Density (N): Fig. 6 shows the effect of varying the number of solar sensors, N, on the performance of the six schemes in terms of the three metrics in the network. We observe that increasing the number of sensor nodes (N) decreases the accumulated reward ($\mathcal{R}$) while introducing higher $\mathcal{ME}$ and $\mathcal{OL}$. When N increases, there are not enough HBS (high battery level sensors) to transmit data for LBS. Consequently, the update requests from LBS may mostly fail. Our proposed MAPPO-UM scheme achieves the lowest monitoring error rate when N is low and the lowest overload when N is high, revealing the tradeoff that a lower monitoring error rate can incur a higher system overload.

4) Effect of Varying the Degree of Sun Exposure (α): Fig. 7 shows the effect of α (the probability for a cow to be exposed to the sun for energy harvesting) on the performance of the six schemes. We observe that a higher α contributes to boosting $\mathcal{R}$ while reducing $\mathcal{ME}$. Moreover, $\mathcal{OL}$ is not sensitive to varying α because the energy harvesting speed exceeds the battery consumption speed. We also observe that $\mathcal{ME}$ is equally reduced for every monitoring policy. Thus, when α is high, small changes in monitoring policies lead to insensitive $\mathcal{OL}$ while decreasing $\mathcal{ME}$.

Summarizing above, MAPPO-UM performs the best among all schemes, the effect of which is especially pronounced when the system is under high-stress situations, such as high attack severity, low initial battery energy, low node density, and low sun exposure. The reason is that MAPPO-UM applies not only an actor-critic framework (from *Deep Reinforcement Learning* [11]) but also uncertainty maximization (from *Subjective Logic* [19]) to derive stable monitoring policy updates based on new evidence, thus maximizing monitoring quality in terms of $\mathcal{R}$ and $\mathcal{ME}$ while reducing energy consumption in terms of $\mathcal{OL}$. This allows LoRa gateways to obtain more accurate sensed data from solar sensors having limited and fluctuating energy and to maximize uncertainty-aware monitoring quality.

VIII. Conclusions & Future Research

Our work achieved the following. The proposed monitoring system for smart farms is the first that proposed technologies to support an energy-adaptive monitoring system properly operating even in the presence of various adversarial attacks, including false data injection, DoS, and state manipulation (i.e., poisoning datasets in deep learning models) attacks. Unlike existing works that mainly focused on energy-aware approaches, our work achieved energy-adaptiveness and data security under energy-fluctuating, adversarial, and dynamic IoT environments. In addition, we introduced uncertainty-aware data aggregation and update approaches to enhance the monitoring quality of the proposed smart farm system without the system being overloaded. We validated this approach via mathematical proof and extensive experiments using real datasets. We also considered multiple deep reinforcement learning agents to identify optimal settings to maximize the monitoring quality of smart farms with solar-powered sensors. This design allowed high sustainability and scalability. Moreover, collaborative learning results in high performance in monitoring quality and system overload.

From this study, we found the following **key findings**:

- The system overload does not always increase the monitoring error rate. Our proposed MAPPO-UM scheme can find monitoring policies that can minimize both the monitoring error rate and the system overload.
- The payoffs to monitoring updates are vastly different under different scenarios. This discrepancy can result in different optimal monitoring policies being identified and applied in different scenarios.
- Our proposed MAPPO-UM scheme is shown to have an acceptable time complexity for which the major complexity comes from the training time and the size of the action space. MAPPO-UM outperformed other counterparts with an 8% reduction in both the monitoring error rate and the system overload.
- Among all schemes considered, MAPPO-UM can best adapt to different scenarios and identify the best monitoring policies for minimizing the monitoring error rate and the system overload.
- Our proposed MAPPO-UM scheme also showed strong robustness, particularly under harsh environments as demonstrated via extensive sensitivity analyses.

We also plan to conduct the following **future research**:

- We will use more than two gateways to introduce more DRL agents for the proposed smart farm system to be applicable to larger-scale networks.
- We will leverage *transfer learning* algorithms to further improve the speed of learning convergence.
- We will identify an optimal energy level that can be used for low-energy solar sensors to request data transmission to nearby high-energy sensors.

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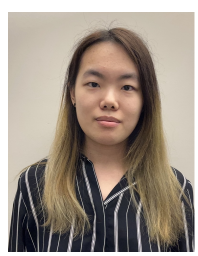

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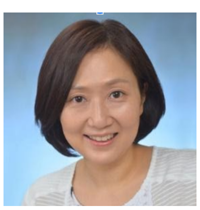

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