AoI Minimization in Status Update Control with Energy Harvesting Sensors

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Abstract

Information freshness is crucial for time-critical IoT applications, e.g., environment monitoring and control systems. We consider an IoT-based status update system with multiple users, multiple energy harvesting sensors, and a wireless edge node. The users are interested in time-sensitive information about physical quantities, each measured by a sensor. Users send requests to the edge node where a cache contains the most recently received measurements from each sensor. To serve a request, the edge node either commands the sensor to send a status update or retrieves the aged measurement from the cache. We aim at finding the best action of the edge node to minimize the age of information of the served measurements. We model this problem as a Markov decision process and develop reinforcement learning (RL) algorithms: a model-based value iteration method and a model-free Q-learning method. We also propose a Q-learning method for the realistic case where the edge node is informed about the sensors’ battery levels only via the status updates. Furthermore, properties of an optimal policy are analytically characterized. Simulation results show that an optimal policy is a threshold-based policy and that the proposed RL methods significantly reduce the average cost as compared to several baseline methods.

Index terms – Internet of Things (IoT), age of information (AoI), energy harvesting, reinforcement learning (RL), value iteration, dynamic programming, Q-learning.

I. INTRODUCTION

Internet of Things (IoT) is an emerging technology to connect different devices and applications with minimal human intervention. IoT enables the users to effectively interact with the physical surrounding environment and empower context-aware applications like smart cities [1].

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A typical IoT network consists of multiple wireless sensors which measure physical phenomena and communicate the obtained measurements to a destination for further processing. Two inherent features of such networks are: 1) stringent energy limitations of battery-powered sensors which, however, may be counteracted by harvesting energy from environmental sources such as sun, heat, and RF ambient [2]–[4], and 2) transient nature of data, i.e., the sensors’ measurements become outdated after a while. This calls for the design of IoT sensing techniques where the sensors sample and send a minimal number of measurements to conserve the energy while providing the end users highly fresh data, as required by time-sensitive applications.

The freshness of information can be quantified by the recently emerged metric, the age of information (AoI) [5]–[9]. Formally, AoI is defined as the time elapsed since the latest successfully received status update packet at the destination was generated at a source node. The works that address AoI in energy harvesting IoT networks and cache updating systems can be divided into two main classes: 1) the works that focus on analyzing the AoI in a specific scenario under their proposed status update control/scheduling policies [10]–[14], and 2) the works that focus on finding an optimal control/scheduling policy for a specific system model. For the latter class, there are two main approaches. The first approach involves finding an optimal policy by applying different tools from optimization theory [15]–[20]. Such approaches need exact information about the models and statistics of the environment, e.g., the energy harvesting probabilities of sensors. The second category includes designs relying on dynamic programming and learning methods [21]–[26]. In this paper, we focus on this category and find an optimal control policy that minimizes the AoI about the sensors’ measurements received by the users in an energy harvesting IoT network.

A particular interest has arisen in designing AoI-aware IoT networks [10], [11]. In [10], a threshold-based age-dependent random access algorithm has been proposed for massive IoT networks, in which an IoT device transmits a status update when its age is greater than a predefined threshold. In [11], the authors presented a stochastic geometry analysis for the average AoI metric for a cellular-based IoT network wherein the IoT devices can communicate in a device-to-device fashion and also send status updates to the base stations.

AoI has also been investigated in cache updating systems [15]–[17]. In [15], the authors introduced a popularity-weighted AoI metric for updating dynamic content in a local cache, where the content is subjected to version updates. The authors in [16] considered a system
consisting of a library of time-varying files, a server that at all times observes the current version of all files, and a cache that stores the current versions of all files but afterwards has to update these files from the server. The aim of this work was to design an optimization based update policy that minimizes the average AoI of all files with respect to a given popularity distribution. The authors in [17] considered a cache updating system with a source, a single cache and a user, and found an analytical expression for the average freshness of the files at the user under their proposed threshold policy.

The works [12]–[14] focused on analyzing the AoI in energy harvesting IoT networks. The authors in [12] considered a known energy harvesting model and proposed a threshold adaptation algorithm to maximize the hit rate in an IoT sensing network. In [13], the authors analyzed the average AoI in a cache enabled status updating system with an energy harvesting sensor that monitors a random process. In [14], the author derived a closed-form expression for the average AoI in a wireless powered sensor network.

Age-optimal policies for status update packet transmissions in energy harvesting networks have been derived in [18]–[20] by using different methods from optimization theory. In [18], age-optimal transmission policies for energy harvesting two-hop networks have been investigated. In [19], the authors explored the benefits of erasure status feedback for online timely updating for an energy harvesting sensor with unit-sized battery. In [20], the authors derived an optimal update policy for an energy harvesting source that sends status updates to a network interface queue for delivery to a monitoring system.

Several works have tackled a problem of designing an AoI-optimal status update system by using dynamic programming and learning based methods [21]–[26]. In this line of works, the authors modeled the problem as a Markov decision process (MDP), and found an optimal policy using model-based reinforcement learning (RL) methods based on dynamic programming, e.g., value iteration algorithm, and/or model-free RL methods, e.g., Q-learning. A comprehensive survey of RL based methods for autonomous IoT networks was presented in [27]. The authors in [21] used deep RL to solve a cache replacement problem with a limited cache size and transient data in an IoT network. In [22], the authors studied average AoI minimization in cognitive radio energy harvesting communications. In [23], deep RL was used to minimize AoI in a real-time multi-node monitoring system, in which the sensors are powered through wireless energy transfer by the destination. In [24], a real-time IoT monitoring system, in which the IoT devices sample
a physical random process and send status updates to a destination, has been considered. The authors derived optimal sampling and updating policies that enable the IoT devices to minimize the average AoI at the destination. In [25], the authors studied the problem of an optimal device scheduling and status update sampling policy that minimizes the average AoI for a real-time IoT monitoring system with nonuniform sizes of status update packets under noisy channels. Minimizing AoI in a wireless ad hoc network via deep RL has been investigated in [26].

We consider an IoT-based status update system consisting of multiple users, multiple energy harvesting IoT sensors, and a wireless edge node. The users are interested in time-sensitive information about physical quantities, each of which is measured by a sensor. The users send their requests to the edge node, which acts as a gateway between the users and the sensors. The edge node has a cache storage which stores the most recently received measurements of each physical quantity. To serve a user’s request, the edge node can either command the corresponding sensor to sample and send a fresh measurement in the form of status update packet, or use the available aged data in the cache. The former leads to serving a user with fresh measurement, yet at the cost of increased energy consumption at the sensor. The latter prevents the activation of the sensors for every request so that the sensors can utilize the sleep mode to save a considerable amount of energy [12], but the data forwarded to the users becomes stale. This results in an inherent trade-off between the AoI about the physical quantities at the users and the energy consumption of the sensors.

The main objective of this paper is to find the best action of the edge node at each time slot, which is called an optimal policy, to minimize a cost function that penalizes information staleness of the data served to the users; herein, the information staleness/freshness is quantified by the AoI. We model the problem as an MDP and propose three RL based algorithms to obtain an optimal policy. Namely, we first derive the state transition probabilities of the MDP and devise a model-based value iteration algorithm relying on dynamic programming. Then, we develop a model-free Q-learning algorithm which does not require the knowledge of the state transition probabilities. Furthermore, as a practical consideration, we propose a Q-learning method for a realistic scenario where the edge node is informed about the sensors’ battery levels only via the status update packets. Consequently, the edge node does not know the exact battery level of each sensor at each time slot, but only the battery level from each sensor’s last update. Moreover, structural properties of an optimal policy are analytically characterized. Simulation
results show that the proposed RL algorithms – including the Q-learning method with partial battery knowledge – significantly reduce the average cost compared to several baseline methods.

A. Contributions

To summarize, the main contributions of our paper are as follows:

- We consider an IoT based status update system with multiple users, multiple energy harvesting IoT sensors, and an edge node under probabilistic models for the energy harvesting and wireless communications from sensors to the edge node.
- We formulate a problem of finding an optimal policy to serve the users’ requests so as to minimize the AoI about the physical processes at the users under energy limitations at the sensors and unreliable reception of the status updates.
- We model the considered problem as an MDP and provide necessary definitions for the search and evaluation of an optimal policy via learning.
- We derive the state transition probabilities of the MDP and propose a model-based value iteration algorithm to find an optimal policy.
- We propose a model-free Q-learning method to search for an optimal policy, which does not require the knowledge of the state transition probabilities.
- As a practical consideration, we propose a Q-learning method for the realistic scenario where the edge node is informed about the sensors’ battery levels only via the status updates.
- We derive structural properties of an optimal policy analytically and show that an optimal policy has a threshold-based structure with respect to the AoI in a specific scenario.
- Extensive numerical experiments are conducted to show that an optimal policy is a threshold-based policy and that the proposed RL algorithms significantly reduce the average cost as compared to several baseline policies.
- The proposed Q-learning algorithm relying on the inexact battery knowledge is demonstrated to be a viable solution in practice.

The most related works to this paper are [13], [18], [19], [21], [24]–[26], with the following differences to our work. The work [13] is different in that it did not aim to find an optimal policy but rather analyzed the average AoI in a cache-enabled status updating system with an energy harvesting sensor. While we use learning based methods, the works [18], [19] are based on different methods from optimization theory. Different from these line of works, we also
propose a model-free RL approach, i.e., Q-learning, in which prior knowledge about statistics of
the environment, e.g., the energy harvesting probability and transmit success probability of the
link between the sensors and the edge node, are not needed. The works [21], [24]–[26] did not
consider energy limitations at the source nodes, whereas we consider energy harvesting source
nodes – sensors – in which the sensors rely only on the energy harvested from the environment.
Preliminary results of this paper appear in [28].

B. Organization

The paper is organized as follows. Section II presents the system model and problem definition.
A Markov decision process and definition of optimal policies are presented in Section III. Our
proposed three RL-based status update control algorithms are developed in Section IV. Structural
properties of an optimal policy are analytically characterized in Section V. Simulation results
are presented in Section VI. Concluding remarks are drawn in Section VII.

II. System Model and Problem Formulation

A. Network Model

We consider an IoT sensing network consisting of multiple users (data consumers), a wireless
edge node, and a set $\mathcal{K} = \{1, \ldots, K\}$ of $K$ energy harvesting sensors (data producers), as
depicted in Fig. 1. Users are interested in time-sensitive information about physical quantities
(e.g., temperature or humidity) which are independently measured by the $K$ sensors; formally,
sensor $k \in \mathcal{K}$ measures a physical quantity $f_k$. We assume that there is no direct link between
the users and the sensors, and the edge node acts as a gateway between them. Thus, the users’
requests for the values of $f_k$, $k \in \mathcal{K}$, are served (only) via the edge node.

The system operates in a slotted time fashion, i.e., time is divided into slots labeled with
discrete indices $t \in \mathbb{N}$. At the beginning of slot $t$, users request for the values of physical
quantities $f_k$ from the edge node. Formally, let $r_k(t) \in \{0, 1\}$, $t = 1, 2, \ldots$, denote the random
process of requesting the value of $f_k$ at the beginning of slot $t$; $r_k(t) = 1$ if the value of $f_k$ is
requested and $r_k(t) = 0$ otherwise. Note that at each time slot, there can be multiple requests
arriving at the edge node.

The edge node is equipped with a cache storage that stores the most recently received
measurement of each physical quantity $f_k$. Upon receiving a request for the value of $f_k$ at slot
Fig. 1: An IoT sensing network consisting of multiple users (data consumers), one wireless edge node (i.e., the gateway), and a set of $K$ energy harvesting wireless IoT sensors (data producers). The procedure of serving a request by using fresh data is shown by green lines, and the blue lines show the procedure of serving a request by using the previous measurements already existing in the cache.

At slot $t$ (i.e., $r_k(t) = 1$), the edge node can either command sensor $k$ to perform a new measurement and send a status update\(^1\) or use the previous measurement from the local cache, to serve the request. Let $a_k(t) \in \{0, 1\}$ denote the command action of the edge node at slot $t$; $a_k(t) = 1$ if the edge node commands sensor $k$ to send a status update and $a_k(t) = 0$ otherwise.

We assume that all the requests that arrive at the beginning of slot $t$ are handled during the same slot $t$. This assumption is invoked by the following considerations. First, we assume that the edge node communicates the values to the users in an instantaneous and error-free fashion. Second, we assume that at each slot $t$, the edge node can command multiple sensors to send their values for $f_k$ during the same slot $t$ and that these command actions $a_k(t), k \in K$, are independent across $k$. This models the case when the sensors have independent communication channels to the edge node. At this stage, we note that while the communications between the edge node and the users are error-free, the transmissions from the sensors to the edge node are prone to errors; this channel model is detailed in Section II-C.

B. Energy Harvesting Sensors

We assume that the sensors rely on the energy harvested from the environment. Sensor $k$ stores the harvested energy into a battery of finite size $B_k$ (units of energy). Formally, let $b_k(t)$ denote the battery level of sensor $k$ at the beginning of slot $t$. Thus, $b_k(t) \in \{0, \ldots, B_k\}$.

\(^1\)In general, a status update packet contains the measured value of a monitored process and a time stamp representing the time when the sample was generated.
We consider a common assumption (see e.g., [18], [29]–[32]) that transmitting a status update from each sensor to the edge node consumes one unit of energy. Once sensor $k$ is commanded by the edge node to send a status update (i.e., $a_k(t) = 1$), sensor $k$ sends a status update if it has at least one unit of energy in its battery (i.e., $b_k(t) \geq 1$). Let random variable $d_k(t) \in \{0, 1\}$ denote the action of sensor $k$ at slot $t$; $d_k(t) = 1$ if sensor $k$ sends a status update to the edge node and $d_k(t) = 0$ otherwise. Accordingly, the relation between the action of sensor $k$ (i.e., $d_k(t)$) and the command action of the edge node (i.e., $a_k(t)$) can be expressed as

$$d_k(t) = a_k(t) \mathbf{1}_{\{b_k(t) \geq 1\}},$$

(1)

where $\mathbf{1}_{\{\cdot\}}$ is the indicator function. Note that quantity $d_k(t)$ in (1) characterizes also the energy consumption of sensor $k$ at slot $t$.

We model the energy arrivals at the sensors as independent Bernoulli processes with intensities $\lambda_k, k \in K$. Let $e_k(t) \in \{0, 1\}, t = 1, 2, \ldots$, denote the energy arrival process of sensor $k$. Thus, the probability that sensor $k$ harvests one unit of energy during one time slot is $\lambda_k$, i.e.,

$$\Pr\{e_k(t) = 1\} = \lambda_k, \; k \in K, \; t = 1, 2, \ldots$$

Finally, using the defined quantities $b_k(t)$, $d_k(t)$, and $e_k(t)$, the evolution of the battery level of sensor $k$ is expressed as

$$b_k(t + 1) = \min\{b_k(t) + e_k(t) - d_k(t), B_k\}.$$  

(2)

C. Communication Between the Edge Node and the Sensors

We consider an error-free binary/single-bit command link from the edge node to each sensor [19], [33], and an error-prone wireless communication link from each sensor to the edge node, as illustrated in Fig. 2. If a sensor sends a status update packet to the edge node, the transmission through the wireless link can be either successful or failed. Let $h_k(t) = 1$ denote the event that a status update from sensor $k$ has been successfully received by the edge node at slot $t$. Otherwise, $h_k(t) = 0$ which accounts for both the cases that either 1) sensor $k$ sends a status update but the transmission is failed, or 2) the sensor does not send a status update at all. Let $\xi_k$ be the conditional probability that given that sensor $k$ transmits a status update, it is successfully received by the edge node, i.e., $\Pr\{h_k(t) = 1 \mid d_k(t) = 1\} = \xi_k, \; k \in K, \; t = 1, 2, \ldots$. Thus, $\xi_k$ represents the transmit success probability of the link from sensor $k$ to the edge node.
D. Age of Information

Age of information (AoI) is a destination-centric metric that quantifies the freshness of information of a remotely observed random process [5]–[7]. Formally, let $\Delta_k(t)$ be the AoI about the physical quantity $f_k$ at the edge node at the beginning of slot $t$, i.e., the number of time slots elapsed since the generation of the most recently received status update packet from sensor $k$. Let $u_k(t)$ denote the most recent time slot in which the edge node received a status update packet from sensor $k$, i.e., $u_k(t) = \max \{t'| t' < t, h_k(t') = 1\}$; thus, the AoI about $f_k$ can be written as the random process $\Delta_k(t) = t - u_k(t)$. We make a common assumption (see e.g., [22]–[25]) that $\Delta_k(t)$ is upper-bounded by a finite value $\Delta_{k,\text{max}}$, i.e., $\Delta_k(t) \in \{1, 2, \ldots, \Delta_{k,\text{max}}\}$. This is reasonable, because after $\Delta_k(t)$ reaches a high value $\Delta_{k,\text{max}}$, the available measurement about physical process $f_k$ becomes excessively stale/expired, so further counting would be irrelevant.

At each time slot, the AoI either drops to one if the edge node receives a status update from the corresponding sensor, or increases by one otherwise. Accordingly, the evolution of $\Delta_k(t)$ can be written as

$$\Delta_k(t + 1) = \begin{cases} 1, & \text{if } h_k(t) = 1, \\ \min \{\Delta_k(t) + 1, \Delta_{k,\text{max}}\}, & \text{if } h_k(t) = 0, \end{cases}$$

(3)

which can be expressed compactly as $\Delta_k(t + 1) = \min \left\{ (1 - h_k(t)) \Delta_k(t) + 1, \Delta_{k,\text{max}} \right\}$.

E. Cost Function and Problem Formulation

We consider a cost function that penalizes the information staleness of the requested measurements received by the users. We define the per-sensor immediate cost at slot $t$ as

$$c_k(t) = r_k(t) \beta_k \Delta_k(t + 1),$$

(4)
where $\beta_k \geq 0$ is a pre-defined weight parameter accounting for the importance of the freshness of physical quantity $f_k$, and $\Delta_k(t+1)$ is the AoI defined in (3). Note that when the value of $f_k$ is not requested at slot $t$, i.e., $r_k(t) = 0$, the immediate cost becomes $c_k(t) = 0$, as desired. Moreover, since the requests for the value of physical quantities come at the beginning of slot $t$ and the edge node sends values to the users at the end of the same slot, $\Delta_k(t+1)$ is the effective AoI about $f_k$ seen by the users.

The objective of our work is as follows. We aim to find the best action of the edge node at each time slot, i.e., $a_k(t)$, $t = 1, 2, \ldots, k \in \mathcal{K}$, called an optimal policy, that minimizes the long-term average cost, defined as

$$\bar{C} = \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \sum_{k=1}^{K} c_k(t).$$

(5)

In order to shed light on the search for such an optimal policy, we next present several points regarding the problem structure. First, recall from Section II-A that in order to serve the requests for the value of $f_k$ at slot $t$ (i.e., $r_k(t) = 1$), the edge node can either command sensor $k$ to send a status update, i.e., $a_k(t) = 1$, or use the available data in the cache, i.e., $a_k(t) = 0$. The former action (i.e., $a_k(t) = 1$), depending on the battery of sensor $k$ and the situation of the communication link between sensor $k$ and the edge, may lead to having a fresh measurement (i.e., the AoI drops to one $\Delta_k(t+1) = 1$, minimizing the immediate cost $c_k(t)$ in (4)), yet at the cost of consuming one unit of energy from the battery of sensor $k$. On the other hand, the latter action (i.e., $a_k(t) = 0$) provides energy saving at the cost of serving the requests by stale data. This introduces an inherent trade-off between (myopically) minimizing the immediate cost or saving energy for the possible future requests to minimize the cost in a long run.

Second, it is easy to verify that if there are no requests for the value of $f_k$ at slot $t$ (i.e., $r_k(t) = 0$), the optimal action $a_k(t)$ that minimizes the long-term average cost (5) is $a_k(t) = 0$. In this case, the immediate cost (4) becomes zero (i.e., $c_k(t) = 0$), and furthermore, the command action $a_k(t) = 0$ implies $d_k(t) = 0$ as per (1), leading to energy saving for sensor $k$. Therefore, the search for an optimal policy boils down to finding the optimal actions $a_k(t)$ for the cases with $r_k(t) = 1$.

Remark 1. As described in Section II-A, the command action of the edge node for a given sensor does not affect the decisions for the others, i.e., the actions $a_k(t)$ at any slot $t$ are independent across sensors $k \in \mathcal{K}$. Thus, the problem of finding the optimal actions $a_k(t)$, $k \in \mathcal{K}$, that
minimize (5) is separable across sensors $k \in K$.

Based on Remark 1, we express the cost in (5) equivalently as

$$\bar{C} = \sum_{k=1}^{K} \bar{C}_k,$$

(6)

where $\bar{C}_k$ is the long-term average cost associated with sensor $k$, i.e., the per-sensor long-term average cost, defined as

$$\bar{C}_k = \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} c_k(t), \quad k = 1, \ldots, K.$$  

(7)

Thus, minimizing the system-wise cost in (5) reduces to minimizing the $K$ per-sensor long-term average costs in (7). This will be a key factor in developing our reinforcement learning (RL) algorithms in Section IV. Prior to this, in Section III we model the considered problem as a Markov decision process (MDP) and give definitions of optimal policies, which are needed in our algorithm development.

III. MARKOV DECISION PROCESS AND OPTIMAL POLICIES

As discussed in Section II-E, the problem of finding an optimal policy that minimizes the long-term cost in (5) is separable across the sensors. Thus, we present the derivation of such an optimal policy for a particular sensor $k$ but, clearly, the derivations are valid for any sensor $k \in K$; the edge node runs in parallel one policy for each sensor in the network. First, we model the problem as an MDP. Then, we give a formal definition of an optimal policy, followed by introducing the key quantities needed to evaluate and search for such an optimal policy. All these serve as preliminaries for the development of our RL-based algorithms in Section IV.

A. MDP Modeling

The MDP model associated with sensor $k$ is defined by the tuple

$$\{S_k, A_k, \mathcal{P}_k(s_k(t+1)|s_k(t), a_k(t)), c_k(s_k(t), a_k(t)), \gamma\},$$

where

- $S_k$ is the state set. Let $s_k(t) \in S_k$ denote the state at slot $t$, which is defined as $s_k(t) = \{b_k(t), \Delta_k(t)\}$, where 1) $b_k(t)$ is the battery level of sensor $k$ given by (2), i.e., $b_k(t) \in \{1, 2, \ldots, B_k\}$, and 2) $\Delta_k(t)$ is the AoI about the physical quantity $f_k$ in the local cache, i.e., $\Delta_k(t) \in \{1, 2, \ldots, \Delta_{k, \text{max}}\}$.
- $A_k = \{0, 1\}$ is the action set. The action selected by the edge node at slot $t$ is denoted by $a_k(t) \in A_k$ (see Section II-A).
• $P_k(s_k(t+1)|s_k(t), a_k(t))$ is the state transition probability that maps a state-action pair at slot $t$ onto a distribution of states at slot $t+1$.

• $c_k(s_k(t), a_k(t))$ is the immediate cost function, i.e., the cost of taking action $a_k(t)$ in state $s_k(t)$, which is also denoted simply by $c_k(t)$, and is calculated using (4).

• $\gamma \in [0, 1]$ is a discount factor used to weight the immediate cost relative to the future costs.

B. Optimal Policy

In an MDP environment, the immediate and long-term costs that the agent – the edge node in our model – expects to receive depends on what actions the edge node takes at each time slot, which are selected based on a policy. Intuitively, a policy $\pi_k$ defines the edge node’s action selection in any given state. Generally, policies can be stochastic or deterministic [34, Sect. 1.3]. A stochastic policy $\pi_k = \pi_k(a|s) : S_k \times A_k \rightarrow [0, 1]$ is defined as a mapping from state $s \in S_k$ to a probability of choosing each possible action $a \in A_k$. A deterministic policy is a special case of the stochastic policy where in each state $s \in S_k$, $\pi_k(a|s) = 1$ for some $a \in A_k$.

The discounted long-term accumulated cost is defined as

$$C_k(t) = \sum_{\tau=0}^{\infty} \gamma^\tau c_k(t + \tau),$$  

(8)

where $c_k(\cdot)$ is the immediate cost calculated using (4). Our goal is to find an optimal policy $\pi_k^*$ that minimizes the expected long-term cost in (8), defined as

$$\pi_k^* = \arg \min_{\pi_k} \mathbb{E}_{\pi_k} [C_k(t) \mid \pi_k],$$  

(9)

where $\mathbb{E}_{\pi_k}[\cdot]$ denotes the expected value of $C_k(t)$ given that the edge node follows policy $\pi_k$.

Herein, we use the same notation $\pi_k$ for both stochastic and deterministic policies.

Having defined an optimal policy, we now present essential definitions as a means to search for such an optimal policy. These serve as a basis for our algorithms developed in Section IV.

C. State-Value and Action-Value Functions

In order to evaluate policies and search for an optimal policy $\pi_k^*$, we define the state-value and action-value functions. The state-value function specifies how beneficial it is for the edge node to be in a particular state under a policy $\pi_k$. Formally, the state-value function of state $s \in S_k$ under a policy $\pi_k$, denoted by $v_{\pi_k}(s)$, is the expected long-term cost when starting in state $s$ and following the policy $\pi_k$ thereafter, and it can be written as

$$v_{\pi_k}(s) = \mathbb{E}_{\pi_k} [C_k(t) \mid s_k(t) = s], \forall s \in S_k.$$  

(10)
The action-value function specifies how beneficial it is for the edge node to perform a particular action in a state under a policy \( \pi_k \). Formally, the action-value function, denoted by \( q_{\pi_k}(s, a) \), is the expected long-term cost for taking an action \( a \in A_k \) in state \( s \in S_k \) and thereafter following the policy \( \pi_k \), and it can be written as

\[
q_{\pi_k}(s, a) = \mathbb{E}_{\pi_k}[C_k(t) | s_k(t) = s, a_k(t) = a], \quad \forall s \in S_k, a \in A_k.
\] (11)

Value functions define a partial ordering over policies. More precisely, a policy \( \pi_k \) is defined to be better than or equal to a policy \( \pi'_k \) (i.e., \( \pi_k \geq \pi'_k \)) if and only if \( v_{\pi_k}(s) \leq v_{\pi'_k}(s) \) for all \( s \in S_k \) [34, Sect. 3.6]. Therefore, an optimal policy \( \pi^*_k \), which is better than or equal to all other policies, minimizes the state-value function for all states. Although there may be more than one optimal policy, they all achieve the same state-value function, called the optimal state-value function, denoted by \( v^*_k(s) \), and it is expressed as

\[
v^*_k(s) = \min_{\pi_k} v_{\pi_k}(s), \quad \forall s \in S_k.
\] (12)

Note that optimal policies also share the same action-value function, called the optimal action-value function. More precisely, the optimal action-value function for state \( s \in S_k \) and action \( a \in A_k \), denoted by \( q^*_k(s, a) \), and it is defined as

\[
q^*_k(s, a) = \min_{\pi_k} q_{\pi_k}(s, a), \quad \forall s \in S_k, a \in A_k.
\] (13)

The optimal action-value function \( q^*_k(s, a) \) represents the minimum expected long-term cost that the edge node is going to get if it is in state \( s \), takes action \( a \), and follows an optimal policy \( \pi^*_k \) from there onwards. Accordingly, an optimal deterministic policy \( \pi^*_k \) can be obtained by choosing the action \( a \) that minimizes \( q^*_k(s, a) \) in each state \( s \), which can expressed as

\[
\pi^*_k(a|s) = \begin{cases} 
1, & \text{if } a = \arg \min_{a \in A_k} q^*_k(s, a), \quad \forall s \in S_k, \\
0, & \text{otherwise}
\end{cases}
\] (14)

According to (14), the knowledge of the optimal action-value function \( q^*_k(s, a) \) suffices to find an optimal policy \( \pi^*_k \). Also, an optimal policy \( \pi^*_k \) can be found via the optimal state-value function \( v^*_k(s) \), provided that the state transition probabilities are known. In this case, we first find optimal action-value function \( q^*_k(s, a) \), given that \( v^*_k(s) \) is available for all the states, and then find an optimal policy using (14). More precisely, under an optimal policy \( \pi^*_k \), for any state \( s \in S_k \) and its possible successor states \( s' \in S_k \), the relationship between the optimal state-value
and action-value functions can be derived as
\[
q^*_k(s, a) = \mathbb{E}_{\pi^*_k}[\sum_{\tau=0}^{\infty} \gamma^\tau c_k(t+\tau)|s_k(t) = s, a_k(t) = a]
\]
\[
= \mathbb{E}_{\pi^*_k}[c_k(t) + \gamma C_k(t+1)|s_k(t) = s, a_k(t) = a]
\]
\[
= \mathbb{E}_{\pi^*_k}[c_k(t) + \gamma v^*_k(s_k(t+1))|s_k(t) = s, a_k(t) = a]
\]
\[
= \sum_{s' \in S_k} P_k(s'|s, a)[c_k(s, a) + \gamma v^*_k(s')], \quad \forall s \in S_k, \forall a \in A_k.
\]

(15)

In summary, one can find an optimal policy if either 1) the optimal action-value function \(q^*_k(s, a)\) is available, or 2) the optimal state-value function \(v^*_k(s)\) and state transition probabilities \(P_k(s'|s, a)\) are available. We next discuss how to find \(v^*_k(s)\) and \(q^*_k(s, a)\).

A fundamental property of the optimal state-value and action-value functions is that they satisfy particular recursive relationships, called \textit{Bellman optimality equations}, which can be used to find the optimal state-value and action-value functions \([34, \text{Sect. 3.5}]\). Formally, under an optimal policy \(\pi^*_k\), the recursive relationship between the optimal state-value function of state \(s\), \(v^*_k(s)\), and the optimal state-value function of its possible successor state \(s'\), \(v^*_k(s')\), is given by

\[
v^*_k(s) = \min_{a \in A_k} q^*_k(s, a) = \min_{a \in A_k} \sum_{s' \in S_k} P_k(s'|s, a)[c_k(s, a) + \gamma v^*_k(s')], \quad \forall s \in S_k.
\]

(16)

The recursive equation in (16) is called the Bellman optimality equation for optimal state-value function \(v^*_k(s)\). It expresses the fact that the value of a state under an optimal policy must equal the expected long-term cost for the best action for that state.

Assuming the availability of the state transition probabilities \(P_k(s'|s, a)\), the Bellman optimality equation in (16) can be used to estimate the optimal state-value function recursively; this is the basis for our proposed value iteration algorithm developed in Section IV-A. Similar to (16), the Bellman optimality equation for the optimal action-value function \(q^*_k(s, a)\) is expressed as

\[
q^*_k(s, a) = \sum_{s' \in S_k} P_k(s'|s, a)[c_k(s, a) + \gamma \min_{a' \in A_k} q^*_k(s', a')], \quad \forall s \in S_k, a \in A_k.
\]

(17)

The Bellman optimality equation in (17) is the basis for our proposed Q-learning algorithms devised in Section IV-B and Section IV-C.

IV. REINFORCEMENT LEARNING BASED STATUS UPDATE CONTROL ALGORITHMS

In this section, we develop three RL-based status update control algorithms for the considered IoT network. The algorithms fall into two main categories: model-free RL and model-based RL. For the MDP model described in Section III-A we first develop a model-based value iteration algorithm relying on dynamic programming in Section IV-A and then in Section IV-B we
propose a model-free Q-learning algorithm. As a practical consideration in Section [IV-C] we redefine the presented state definition of the MDP and propose a Q-learning method for the scenario where the edge node is informed of the sensors’ battery levels only via the status update packets. As a key advantage, the proposed algorithms are simple with low complexity of implementation, which is an important point in practice.

A. Value Iteration Algorithm

Value Iteration is a model-based RL method that finds the optimal state-value function $v^*_k(s)$, and consequently, an optimal policy $\pi^*_k$ by turning the Bellman optimality equation (16) into an iterative update procedure [34, Section 4.4].

1) Derivation of the State Transition Probabilities: In order to apply (16), the value iteration requires the knowledge of the state transition probabilities of the MDP (see Section III-A). These are derived in the following. In the considered system model, for a given action $a_k(t)$, the state transition probabilities are functions of both energy harvesting rate $\lambda_k$ and transmit success probability $\xi_k$, which were defined in Section II-B and II-C, respectively. The probability of transition from state $s_k(t)$ to state $s_k(t+1)$ under action $a_k(t)$ is given by

$$P_k(s_k(t+1)\mid s_k(t) = \{b_k(t) < B_k, \Delta_k(t)\}, a_k(t) = 0) =$$

$$\begin{cases}
\lambda_k, & s_k(t+1) = \begin{cases} b_k(t + 1) = b_k(t) + 1, \\
\Delta_k(t + 1) = \min\{\Delta_k(t) + 1, \Delta_k, \max\} \end{cases}; \\
1 - \lambda_k, & s_k(t + 1) = \begin{cases} b_k(t + 1) = b_k(t), \\
\Delta_k(t + 1) = \min\{\Delta_k(t) + 1, \Delta_k, \max\} \end{cases}; \\
0, & \text{otherwise.}
\end{cases}$$ (18a)

$$P_k(s_k(t+1)\mid s_k(t) = \{b_k(t) = B_k, \Delta_k(t)\}, a_k(t) = 0) =$$

$$\begin{cases}
1, & s_k(t + 1) = \begin{cases} b_k(t + 1) = B_k, \\
\Delta_k(t + 1) = \min\{\Delta_k(t) + 1, \Delta_k, \max\} \end{cases}; \\
0, & \text{otherwise.}
\end{cases}$$ (18b)

$$P_k(s_k(t+1)\mid s_k(t) = \{b_k(t) = 0, \Delta_k(t)\}, a_k(t) = 1) =$$

$$\begin{cases}
\lambda_k, & s_k(t + 1) = \begin{cases} b_k(t + 1) = 1, \\
\Delta_k(t + 1) = \min\{\Delta_k(t) + 1, \Delta_k, \max\} \end{cases}; \\
1 - \lambda_k, & s_k(t + 1) = \begin{cases} b_k(t + 1) = 0, \\
\Delta_k(t + 1) = \min\{\Delta_k(t) + 1, \Delta_k, \max\} \end{cases}; \\
0, & \text{otherwise.}
\end{cases}$$ (18c)
\[ P_k(s_k(t+1)|s_k(t) = \{b_k(t) > 0, \Delta_k(t)\}, a_k(t) = 1) = \]

\[
\begin{align*}
&\lambda_k \xi_k, & s_k(t+1) = \left\{ \begin{array}{l}
  b_k(t+1) = b_k(t), \\
  \Delta_k(t+1) = 1
\end{array} \right\}; \\
&\lambda_k (1 - \xi_k), & s_k(t+1) = \left\{ \begin{array}{l}
  b_k(t+1) = b_k(t), \\
  \Delta_k(t+1) = \min\{\Delta_k(t) + 1, \Delta_k, \max\}
\end{array} \right\}; \\
&(1 - \lambda_k) \xi_k, & s_k(t+1) = \left\{ \begin{array}{l}
  b_k(t+1) = b_k(t) - 1, \\
  \Delta_k(t+1) = 1
\end{array} \right\}; \\
&(1 - \lambda_k)(1 - \xi_k), & s_k(t+1) = \left\{ \begin{array}{l}
  b_k(t+1) = b_k(t) - 1, \\
  \Delta_k(t+1) = \min\{\Delta_k(t) + 1, \Delta_k, \max\}
\end{array} \right\}; \\
&0 & \text{otherwise.}
\end{align*}
\]

In brief, the first three expressions \((18a)-(18c)\) correspond to cases where sensor \(k\) does not send a status update, whereas in \((18d)\) sensor \(k\) sends a status update. These cases are detailed in the following.

The first case \((18a)\) corresponds to the situation in which the edge node does not command sensor \(k\) (i.e., \(a_k(t) = 0\)), and thus, the sensor does not send a status update. The second case is similar in that \(a_k(t) = 0\), but differently from \((18a)\), the battery of sensor \(k\) is full and thus, there is no room left for possible harvested energy units. In the third case \((18c)\), sensor \(k\) is commanded to send a status update, but since its battery is empty (i.e., \(b_k(t) = 0\)), no update takes place. Since there is no update in all three cases \((18a)-(18c)\), the AoI about the physical quantity \(f_k\) in the local cache increases by one. Moreover, in cases \((18a)\) and \((18c)\), a possible harvested energy unit increases the battery state of sensor \(k\) by one. The fourth case \((18d)\) stands for the case in which the edge node commands sensor \(k\) to send a status update and sensor \(k\) has at least one unit of energy in its battery. In this case, sensor \(k\) sends the status update, consuming one unit of energy. Here, four possible events can occur, depending on the success of the transmission attempt and the energy arrivals. Namely, the transmitted status update is prone to a transmission failure, reaching the edge node with probability \(\xi_k\). Also, sensor \(k\) has a chance to harvest one unit of energy which occurs with probability \(\lambda_k\).

2) Algorithm Summary: Having defined the state transition probabilities above, we now employ the Bellman optimality equation \((16)\) and set up an iterative update procedure, the value iteration algorithm, to find an optimal policy \(\pi_k^*\). The proposed value iteration algorithm is presented in Algorithm 1. Next, we detail the algorithm steps.

The algorithm consists of four main stages: 1) start with an arbitrary initial approximation for the optimal state-value function, e.g., \(v_k^*(s) = 0, \forall s \in S_k\), 2) in each iteration, update the
Algorithm 1 Value iteration algorithm for estimating the optimal state-value function

1: Initialize $v_k^*(s) = 0$, $k \in K$, $\forall s \in S_k$, and determine a small threshold $\theta > 0$.
2: for $k = 1, \ldots, K$ do
   3:   repeat \{Update $v_k^*(s)$\}
   4:   \hspace{1em} $\delta = 0$ \{For stopping criterion\}
   5:   \hspace{2em} for $s \in S_k$ do
   6:   \hspace{3em} $\nu = v_k^*(s)$
   7:   \hspace{3em} $v_k^*(s) = \min_{a \in A_k} \sum_{s' \in S_k} P_k(s'|s,a) \left[ c_k(s,a) + \gamma v_k^*(s') \right]$
   8:   \hspace{3em} $\delta = \max \{ \delta, |\nu - v_k^*(s)| \}$ \{Maximum deviation between the iterations\}
   9:   \hspace{2em} end for
10:  \hspace{1em} until $\delta < \theta$
11: end for
12: for $k = 1, \ldots, K$ do
13:   \hspace{1em} for $s \in S_k$ do
14:   \hspace{2em} Output a deterministic policy $\pi_k^*(a|s)$ such that
15:   \hspace{3em} $\pi_k^*(a|s) = \begin{cases} 1, & \text{if } a = \arg\min_{a \in A_k} \sum_{s' \in S_k} P_k(s'|s,a) \left[ c_k(s,a) + \gamma v_k^*(s') \right] \\ 0, & \text{otherwise} \end{cases}$
16: end for

estimated value for $v_k^*(s)$, $\forall s \in S_k$, 3) stop when the maximum difference in $v_k^*(s)$ between two consecutive iterations is below a pre-defined threshold $\theta$, and 4) determine an optimal deterministic policy $\pi_k^*(a|s)$ by using (15) and (14).

In the value iteration algorithm, it is assumed that the state transition probabilities are known in advance. According to (18), in order to calculate the state transition probabilities $P_k(s'|s,a)$, the probabilistic model of the environment, i.e., the energy harvesting probability $\lambda_k$ and the transmit success probability $\xi_k$ are assumed to be known, which are not always available in practice. For the case in which the state transition probabilities are unknown, we use a model-free RL algorithm to find an optimal policy. This is carried out in the next subsections.

B. Q-learning Algorithm

Q-learning is an online model-free RL algorithm that estimates/learns the optimal action-value functions by experience and finds an optimal policy iteratively. The main difference to the value iteration algorithm in Section IV-A is that Q-learning does not require the knowledge of the state transition probabilities $P_k(s'|s,a)$.

In the Q-learning method, the estimated action-value function for sensor $k$, denoted as $Q_k(s,a)$, $s \in S_k$, $a \in A_k$, directly approximates the optimal action-value function $q_k^*(s,a)$ in (13) [34].
The convergence $Q_k \rightarrow q_k^*$ requires that all state-action pairs continue to be updated. To satisfy this condition, a typical approach is to use the "exploration-exploitation" technique in the action selection. The $\epsilon$-greedy algorithm is one such method that trade-offs exploration and exploitation [34, Sect. 6.5]. Intuitively, exploration is finding more information about the environment, while exploitation is exploiting known information to minimize the long-term cost.

Our proposed Q-learning algorithm is presented in Algorithm 2. To allow exploration-exploitation, the edge node takes either a random or greedy action at slot $t$; the probability of taking a random action is denoted by $\epsilon(t)$, and thus, the probability of exploiting the greedy action $a_k(t) = \arg \min_{a \in A_k} Q_k(s_k(t), a)$ is $1 - \epsilon(t)$. Generally, during initial iterations, it is better to set $\epsilon(t)$ high in order to learn the underlying dynamics, i.e., to allow more exploration. On the other hand, in stationary settings and once enough observations are made, small values of $\epsilon(t)$ become preferable to increase tendency to exploitation.

As it is shown on line 23 in Algorithm 2, at each slot/iteration, the value for the Q-function of the current state is updated based on the action taken and the resulting next state, where $\alpha(t)$ represents the learning rate at slot $t$.

C. Q-Learning Algorithm with Partial Battery Knowledge

In Section III-A, we modeled the state of the MDP as $s_k(t) = \{b_k(t), \Delta_k(t)\}$. Consequently, both the proposed value iteration algorithm in Section IV-A and the Q-learning algorithm in Section IV-B rely on the assumption that the edge node knows the exact battery levels of the sensors at each time slot. This requires extra coordination between the edge node and the sensors at each time slot, which may not always be feasible. In this section, we consider a realistic environment where the edge node is informed about the battery levels of the sensors only via the status update packets. Consequently, the edge node has only partial knowledge about the battery levels at each time slot.

Since we consider a case where the edge node is informed about the battery levels of the sensors only via the status update packets, we need to modify the state definition of the MDP accordingly. A status update packet generated at the beginning of slot $t$ consists of the value of physical quantity $f_k$, the battery level of sensor $k$ (i.e., $b_k(t)$), and the timestamp $t$ when the sample was generated. Let $\tilde{b}_k(t)$ denote the knowledge about the battery level of sensor $k$ at the edge node at time slot $t$. Formally, $\tilde{b}_k(t) = b_k(u_k(t))$, where $u_k(t)$ represents the most
Algorithm 2 Online status update control algorithm via Q-learning

1: Initialize $Q_k(s, a) = 0$, $\forall s \in S_k, a \in A_k, k \in K$
2: for each slot $t = 1, 2, 3, \ldots$ do
3:     for $k = 1, \ldots, K$ do
4:         if $r_k(t) = 0$ then
5:             $a_k(t) = 0$
6:         else
7:             $a_k(t)$ is chosen according to the following probability
8:                 $a_k(t) = \begin{cases} 
                  \arg \min_{a \in A_k} Q(s_k(t), a), \text{ w.p. } 1 - \epsilon(t) \\
                  \text{a random action } a \in A_k, \text{ w.p. } \epsilon(t)
                 \end{cases}$
9:             if $a_k(t) = 1$ then
10:                Command sensor $k$ to send a status update packet
11:                $d_k(t) = 1$
12:         else
13:                $d_k(t) = 0$
14:             end if
15:         else
16:             $d_k(t) = 0$
17:         end if
18:     end if
19:     Update AoI according to (3) and calculate $c_k(t)$
20: end for
21: Wait for the next requests and compute $s_k(t + 1), \forall k \in K$
22: for $k = 1, \ldots, K$ do
23:     Update the Q-table
24:     $Q_k(s_k(t), a_k(t)) \leftarrow (1 - \alpha(t))Q_k(s_k(t), a_k(t)) + \alpha(t)(c_k(t) + \gamma \min_{a \in A_k} Q_k(s_k(t+1), a))$
25: end for

recent time slot in which the edge node received a status update packet from sensor $k$, i.e., $u_k(t) = \max\{t'|t' < t, h_k(t') = 1\}$ (see Section II-D). In other words, at time slot $t$, $\tilde{b}_k(t)$ describes what the battery level of sensor $k$ was at the beginning of the most recent time slot at which the edge node received a status update from sensor $k$. To conclude, the edge node does not know the exact battery level of the sensors at each time slot, but it only has the partial/outdated knowledge based on each sensor’s last update.

Based on the discussions above, we modify the state definition of the MDP defined in Section III-A as $s_k(t) = \{\tilde{b}_k(t), \Delta_k(t)\}$. Thus, as compared to the setting with exact battery knowledge, the state contains $\tilde{b}_k(t)$ instead of $b_k(t)$. However, with this state definition, it is impossible to calculate the state transition probabilities and use the value iteration algorithm. In particular, the
underlying decision process is non-Markovian (i.e., not an MDP), caused by the uncertainty that exists in the wireless channel. For better clarification, consider state \( s_k(t) = \{ \tilde{b}_k(t), \Delta_k(t) \} \) and action \( a_k(t) = 0 \); the next state is \( s_k(t+1) = \{ \tilde{b}_k(t), \min\{\Delta_k(t) + 1, \Delta_{k,\text{max}}\} \} \) with probability one. However, given \( s_k(t) \) and \( a_k(t) = 1 \), it is impossible to calculate the state transition probabilities without knowing the actions taken by the edge node during the last \( \Delta_k(t) - 1 \) slots, i.e., \( a_k(t-\Delta_k(t)), \ldots, a_k(t-1) \). This is because the energy consumed by the sensor is unknown during these \( \Delta_k(t) - 1 \) slots (in which, by definition, no update has been received); at each such slot, three indistinguishable cases might have happened: 1) the edge node commanded the sensor, but the transmission was failed, or 2) the edge node commanded the sensor and it could not send a status update because its battery was empty, or 3) the edge node did not command the sensor. While the first case consumes one unit of energy from the battery of the sensor, the second and third cases do not. This means that in order to model the underlying decision process as an MDP and be able to calculate the state transition probabilities, the exact actions taken by the edge node during the last \( \Delta_k(t) - 1 \) slots must be included in the state definition. More precisely, at slot \( t \), the state would be defined as \( s_k(t) = \{ \tilde{b}_k(t), \Delta_k(t), a_k(t-\Delta_k(t)), \ldots, a_k(t-1) \} \). This, however, makes the state space grow exponentially in terms of \( \Delta_k(t) \).

Despite the aforementioned non-Markovity property of the decision process, we apply the Q-learning presented in Algorithm 2 for the partial battery knowledge case with state definition \( s_k(t) = \{ \tilde{b}_k(t), \Delta_k(t) \} \). Recall that the Q-learning algorithm does not need any prior knowledge about the state transition probabilities. We will assess the performance of this Q-learning method via simulations in Section VI, and show that it achieves considerable performance gains compared to several baseline methods.

V. STRUCTURAL PROPERTIES OF AN OPTIMAL POLICY

In this section, we analyze the properties of an optimal policy defined in (9). We first prove that the optimal state-value function has monotonic properties. Then, we exploit this monotonicity to prove that an optimal policy has a threshold-based structure with respect to the AoI for the case where the link from sensor \( k \) to the edge node is perfect, i.e., \( \xi_k = 1 \). Threshold-based structures are also numerically illustrated in Section VI-B.

Next, we present two propositions, which are used to prove properties of an optimal policy expressed in Theorem 1.
Proposition 1. The optimal state-value function $v^*_k(s)$ is (i) non-decreasing with respect to the AoI, and (ii) non-increasing with respect to the battery level.

The proof is presented in Appendix A.

Proposition 2. For the case where the link from sensor $k$ to the edge node is perfect, i.e., $\xi_k = 1$, the difference between the optimal action-value functions for different actions, denoted by $\delta q^*_k(s) = q^*_k(s, 1) - q^*_k(s, 0)$, is non-increasing with respect to the AoI.

The proof is presented in Appendix B.

Theorem 1. For the case where the link from sensor $k$ to the edge node is perfect, i.e., $\xi_k = 1$, an optimal policy has a threshold-based structure with respect to the AoI.

Proof. Proving that an optimal policy has a threshold-based structure with respect to the AoI is equivalent to showing that if the optimal action in state $s = \{b, \Delta\}$ is $a^*_k(s) = 1$, then for all the states $s = \{b, \Delta\}$, in which $\Delta \geq \Delta$, the optimal action is $a^*_k(s) = 1$ as well. According to Proposition 2, $q^*_k(s, 1) - q^*_k(s, 0) \leq q^*_k(s, 1) - q^*_k(s, 0)$. The optimal action in state $s$ is $a^*_k(s) = 1$, thus $q^*_k(s, 1) - q^*_k(s, 0) \leq 0$. Accordingly, $q^*_k(s, 1) - q^*_k(s, 0) \leq 0$, which shows that the optimal action for state $s$ is $a^*_k(s) = 1$.

VI. SIMULATION RESULTS

In this section, simulation results are presented to demonstrate the performance of the proposed value iteration algorithm summarized in Algorithm 1 and the proposed Q-learning algorithms – Q-learning with exact and partial battery knowledge – obtained by Algorithm 2.

A. Simulation Setup

The simulation scenario consists of $K = 3$ energy harvesting sensors, i.e., $\mathcal{K} = \{1, 2, 3\}$. Each sensor $k \in \mathcal{K}$ has a battery of finite capacity $B_k = 15$ units of energy. At each time slot, the probability that the value of $f_k$ is requested (i.e., $r_k(t) = 1$) is denoted by $p_k$, i.e., $\Pr\{r_k(t) = 1\} = p_k$. We set $p_k = 0.15$, $k \in \mathcal{K}$. The weight parameters in (4) are set as $\beta_k = 1$, $\forall k \in \mathcal{K}$. For the value iteration method summarized in Algorithm 1, we set the threshold parameter as $\theta = 0.001$ and the discount factor as $\gamma = 0.99$. For the Q-learning method summarized in Algorithm 2, we set $\epsilon(t) = 0.02 + 0.98e^{-\epsilon_d t}$ with decay parameter $\epsilon_d = 10^{-7}$. The learning rate is set to $\alpha(t) = 0.5$ during the first $1/\epsilon_d = 10^7$ iterations and after that $\alpha(t) = 0.01$. 
B. Structure of Optimal Deterministic Policy

We analyze the structural properties of an optimal deterministic policy obtained by the value iteration algorithm for a particular sensor, i.e., sensor 1, and investigate the effect of the energy harvesting probability $\lambda_1$ and transmit success probability $\xi_1$.

Fig. 3 illustrates the structure of the obtained optimal deterministic policy for different values of the energy harvesting probability $\lambda_1$ with the transmit success probability $\xi_1 = 0.9$. Each point represents a potential state of the system as a pair of values of the battery level and AoI, $(b, \Delta)$. In particular, a red circle indicates that the optimal action in a given state is that the edge node does not command the sensor (i.e., $a = 0$), and a blue square indicates that the optimal action is that the edge node commands the sensor to send a status update (i.e., $a = 1$). The set of blue points is referred to as the command region hereinafter.

From Fig. 3(a)–(d), we observe that the optimal deterministic policy has a threshold-based structure with respect to the battery level and the AoI, which can be expressed as follows:

1) If the optimal action in state $s = \{b, \Delta\}$ is $a = 1$, then for all the states $s' = \{b', \Delta\}$, in which $b' \geq b$, the optimal action is $a = 1$ as well.

2) If the optimal action in state $s = \{b, \Delta\}$ is $a = 1$, then for all the states $s' = \{b, \Delta'\}$, in which $\Delta' \geq \Delta$, the optimal action is $a = 1$ as well.

To exemplify this threshold-based structure in Fig. 3(a), consider point $(5, 17)$. Since the optimal action at the point $(5, 17)$ is $a = 1$, we observe that the optimal action at all the points $(5, \Delta)$ where $\Delta \geq 17$, and all the points $(b, 17)$ where $b \geq 5$, is also $a = 1$.

By comparing Figs. 3(a)–(d) with each other, we observe that the command region (i.e., the set of blue square points) enlarges by increasing the energy harvesting probability $\lambda_1$. This is due to the fact that since the sensor harvests energy more often, the edge node commands the sensor to send fresh measurements more often. Note that Fig. 3(d) is associated with an extreme case in which the edge node always harvests energy at each time slot; in this case, there is always at least one unit of energy available in the battery of the sensor, and thus, for all the states with $b \geq 1$, the optimal action is $a = 1$.

Fig. 4 illustrates the threshold-based structure of the obtained optimal deterministic policy for different values of the transmit success probability $\xi_1$ with the energy harvesting probability $\lambda_1$. In Section V, we analytically proved this statement for the special case $\xi_k = 1$. In this section, we numerically show that an optimal policy has a threshold-based structure with respect to the AoI for all the values of $\xi_k$ as well.
λ₁ = 0.04. Figs. 4(a)–(d) illustrate that the command region expands by increasing the transmit success probability ξ₁. This is due to the fact that by increasing ξ₁, the communication link from the sensor to the edge node becomes more reliable, and thus, the edge node commands the sensor more often as it has more confidence about receiving the transmitted status update packet. Fig. 4(a) depicts an extreme case with ξ₁ = 0, in which the link from the sensor to the edge node is always in the failed state and the edge node never receives any commanded status update; to conserve the sensor’s battery, the optimal action is clearly a = 0.

C. Performance and Learning Behaviour of the Proposed Algorithms

We investigate the performance and learning behaviour of the proposed Q-learning algorithms with exact and partial battery knowledge. To this end, we analyze the performance of the proposed algorithms in terms of the long-term average costs defined in (5) and (7). As a remark, the value
iteration algorithm serves as a lower bound to the proposed Q-learning algorithms since it knows the exact statistical model of the environment, and consequently, the state transition probabilities of the underlying MDP. Similarly, the Q-learning method with the exact battery knowledge (referred to as \textit{Q-learning-exact} hereinafter) is a lower bound to the Q-learning algorithm having only the partial battery knowledge (referred to as \textit{Q-learning-partial} hereinafter).

For comparison, we consider two baseline policies: \textit{greedy} and \textit{random} policy. In the greedy policy, whenever the value of physical quantity $f_k$ is requested (i.e., $r_k(t) = 1$), the edge node commands sensor $k$ to send a status update (i.e., $a_k(t) = 1$), regardless of the battery stage and AoI; sensor $k$ sends a status update if the battery is non-empty, i.e., $b_k(t) \geq 1$. In the random policy, whenever the value of physical quantity $f_k$ is requested (i.e., $r_k(t) = 1$), the edge node selects a random action $a_k(t) \in \{0, 1\}$ according to the discrete uniform distribution.

Fig. 5 depicts the performance of each algorithm for the energy harvesting probabilities $\lambda_1 =
Figs. 5(a)–(c) are associated with the per-sensor long-term average cost ($\bar{C}_k$) for sensor 1, 2, and 3, respectively. Fig. 5(d) illustrates the long-term average cost over all the sensors ($\bar{C}$).

As it is shown in Fig. 5(d), Q-learning-exact performs close to the value iteration algorithm and the proposed RL algorithms outperform the baseline methods in terms of the long-term average cost. The Q-learning-exact, and also the value iteration algorithm, reduces the average cost approximately by a factor of 2 compared to the greedy algorithm. Furthermore, the average cost decreases roughly 30% for the Q-learning-partial compared to the greedy algorithm.

Interestingly, the gap between Q-learning-partial and Q-learning-exact is small, when the energy harvesting probability is high enough. As it is shown in Figs. 5(a)–(c), the largest gap

Fig. 5: Learning behaviour of the proposed value iteration algorithm and Q-learning algorithms in comparison to baseline policies.
occurs for the sensor with the lowest energy harvesting probability, i.e., sensor 1; on the contrary, the smallest gap is obtained for sensor 3 having the highest energy harvesting probability. This is due to the fact that when the energy becomes scarce, the edge node receives status updates more rarely; consequently, the information about the battery levels at the edge node becomes more outdated, i.e., more uncertain, inhibiting the capability of Q-learning-partial to take near-optimal actions as taken by Q-learning-exact. Overall, Fig. 5 demonstrates that the proposed algorithm for a realistic scenario has high performance even if the edge node performs actions based on the outdated battery information.

In Fig. 5(a), the greedy policy performs as poorly as the random policy, because the energy harvesting probability is low, and thus, it is highly sub-optimal to command the sensor at all states. As it can be seen in Figs. 5(a)–(c), the lowest long-term average cost is associated with the sensor that has the highest energy harvesting probability, i.e., sensor 3. This is because sensor 3 harvests energy more often, and thus, it can send status updates more frequently upon receiving a command from the edge node. Recall that the command region enlarges by increasing the energy harvesting probability, i.e., the edge node commands the sensor more frequently.

By comparing Figs. 5(a)–(c) with each other, we observe that by increasing the energy harvesting probability $\lambda_k$ the long-term average cost for the value iteration algorithm, and also for the Q-learning, moves toward the the long-term average cost for the greedy policy. This is because by increasing the energy harvesting probability, the command region enlarges, and thus, an optimal policy tends to the greedy policy.

VII. Conclusions

We investigated a status update control problem in an IoT sensing network consisting of multiple users, multiple energy harvesting sensors, and a wireless edge node. We modeled the problem as an MDP and proposed two reinforcement learning (RL) based algorithms: a model-based value iteration method relying on dynamic programming, and a model-free Q-learning method. Furthermore, we developed a Q-learning method for the realistic case in which the edge node does not know the exact battery levels. The proposed Q-learning schemes do not need any information about the energy harvesting model. Simulation results showed that an optimal policy has a threshold-based structure, and the proposed RL algorithms significantly reduce the long-term average cost compared to several baseline methods.
A. Proof of Proposition 1

Proof. As discussed in Section IV-A, the optimal state-value function \( v_k^*(s) \) can be computed iteratively by the value iteration algorithm. In the value iteration algorithm, the optimal state-value function of state \( s \) at iteration \( n = 1, 2, \ldots \), denoted by \( v_k^*(s)^{(n)} \), is updated as (see (16))

\[
\begin{align*}
v_k^*(s)^{(n)} &= \min_{a \in A_k} \sum_{s' \in S_k} \mathcal{P}_k(s'|s, a) \left[ c_k(s, a) + \gamma v_k^*(s')^{(n-1)} \right] \\
&= \min_{a \in A_k} q_k^*(s, a)^{(n-1)}, \quad \forall s \in S_k.
\end{align*}
\]

Thus, an optimal policy at \( n \)th iteration is given by

\[
\pi_k^*(a|s)^{(n)} = \begin{cases} 
1, & \text{if } a = \arg \min_{a \in A_k} q_k^*(s, a)^{(n)} \\
0, & \text{otherwise}
\end{cases}, \quad \forall s \in S_k.
\]

Accordingly, an optimal action in state \( s \) at \( n \)th iteration, denoted by \( a_k^*(s)^{(n)} \), is expressed as

\[
a_k^*(s)^{(n)} = \arg \min_{a \in A_k} q_k^*(s, a)^{(n)}.
\]

For any arbitrary initialization \( v_k^*(s)^{(0)} \), the sequence \( \{v_k^*(s)^{(n)}\} \) can be shown to converge to the optimal state-value function \( v_k^*(s) \) [34, Sect. 4.4]. This fact can be expressed as

\[
\lim_{n \to \infty} v_k^*(s)^{(n)} = v_k^*(s).
\]

(i) In order to prove that \( v_k^*(s) \) is non-decreasing with respect to the AoI, let us define two states \( s = \{b, \Delta\} \) and \( \bar{s} = \{b, \bar{\Delta}\} \), where \( \Delta \geq \bar{\Delta} \). We show that \( v_k^*(s) \geq v_k^*(\bar{s}) \). According to (22), it suffices to prove that \( v_k^*(s)^{(n)} \geq v_k^*(\bar{s})^{(n)} \), \( \forall n \). We prove this by mathematical induction. The initial values can be chosen arbitrarily, e.g., \( v_k^*(s)^{(0)} = 0 \) and \( v_k^*(\bar{s})^{(0)} = 0 \), thus, the relation \( v_k^*(s)^{(n)} \geq v_k^*(\bar{s})^{(n)} \) holds for \( n = 0 \). Assume that \( v_k^*(s)^{(n)} \geq v_k^*(\bar{s})^{(n)} \) for some \( n \). We need to prove that \( v_k^*(s)^{(n+1)} \geq v_k^*(\bar{s})^{(n+1)} \) as well. From (19) and (21), we have

\[
\begin{align*}
v_k^*(s)^{(n+1)} - v_k^*(\bar{s})^{(n+1)} &= \min_{a \in A_k} q_k^*(s, a)^{(n)} - \min_{a \in A_k} q_k^*(\bar{s}, a)^{(n)} \\
&= q_k^*(s, a_k^*(s)^{(n)})^{(n)} - q_k^*(\bar{s}, a_k^*(\bar{s})^{(n)})^{(n)} \\
&\leq q_k^*(s, a_k^*(s)^{(n)})^{(n)} - q_k^*(\bar{s}, a_k^*(\bar{s})^{(n)})^{(n)},
\end{align*}
\]

where (a) follows from the fact that taking action \( a_k^*(s)^{(n)} \) in state \( s \) is not necessarily optimal. We show that \( q_k^*(s, a_k^*(s)^{(n)})^{(n)} - q_k^*(\bar{s}, a_k^*(\bar{s})^{(n)})^{(n)} \leq 0 \) for all possible actions \( a_k^*(s)^{(n)} \in \{0, 1\} \). We present the proof for the case corresponding to (18d) where \( b \geq 1 \) and \( a_k^*(\bar{s})^{(n)} = 1 \); for the other three cases corresponding to (18a)–(18c), the proof follows similarly. We have
\[ q_k^*(s, 1)^{(n)} - q_k^*(s, 1)^{(n)} \]
\[ = \sum_{s' \in S_k} P_k(s'|s, 1) \left[ c_k(s, 1) + \gamma v_k^*(s') \right] - \sum_{s' \in S_k} P_k(s'|s, 1) \left[ c_k(s, 1) + \gamma v_k^*(s') \right] \]
\[ = \lambda_k \xi_k (1 + \gamma v_k^*(b, 1)) + (1 - \lambda_k) \xi_k (1 + \gamma v_k^*(b - 1, 1)) \]
\[ + \lambda_k (1 - \xi_k) \left( \min \{ \Delta + 1, \Delta_{k, \text{max}} \} + \gamma v_k^*(b, \min \{ \Delta + 1, \Delta_{k, \text{max}} \}) \right) \]
\[ + (1 - \lambda_k) (1 - \xi_k) \left( \min \{ \Delta + 1, \Delta_{k, \text{max}} \} + \gamma v_k^*(b - 1, \min \{ \Delta + 1, \Delta_{k, \text{max}} \}) \right) \]
\[ - \lambda_k \xi_k (1 + \gamma v_k^*(b, 1)) - (1 - \lambda_k) \xi_k (1 + \gamma v_k^*(b - 1, 1)) \]
\[ - \lambda_k (1 - \xi_k) \left( \min \{ \Delta + 1, \Delta_{k, \text{max}} \} + \gamma v_k^*(b, \min \{ \Delta + 1, \Delta_{k, \text{max}} \}) \right) \]
\[ - (1 - \lambda_k) (1 - \xi_k) \left( \min \{ \Delta + 1, \Delta_{k, \text{max}} \} + \gamma v_k^*(b - 1, \min \{ \Delta + 1, \Delta_{k, \text{max}} \}) \right) \]
\[ = (1 - \xi_k) \left( \min \{ \Delta + 1, \Delta_{k, \text{max}} \} - \min \{ \Delta + 1, \Delta_{k, \text{max}} \} \right) \]
\[ + \gamma \lambda_k (1 - \xi_k) \left( v_k^*(b, \min \{ \Delta + 1, \Delta_{k, \text{max}} \}) \right)^{(n)} - v_k^*(b, \min \{ \Delta + 1, \Delta_{k, \text{max}} \})^{(n)} \]
\[ + \gamma (1 - \lambda_k) (1 - \xi_k) \left( v_k^*(b - 1, \min \{ \Delta + 1, \Delta_{k, \text{max}} \}) \right)^{(n)} - v_k^*(b - 1, \min \{ \Delta + 1, \Delta_{k, \text{max}} \})^{(n)} \leq 0, \]

where in step (a) we use the result of \([18a]\), step (b) follows from the assumption \( \Delta \leq \Delta \), and steps (c) and (d) follow from the induction assumption.

(ii) In order to prove that \( v_k^*(s) \) is non-increasing with respect to the battery level, we define two states \( s = \{ b, \Delta \} \) and \( s = \{ b, \Delta \} \), where \( b \geq b \). By using induction and following the similar steps as we have done in (i), one can easily show that \( v_k^*(s) \geq v_k^*(s) \). \( \square \)

B. Proof of Proposition \([2]\)

**Proof.** We define two states \( s = \{ b, \Delta \} \) and \( s = \{ b, \Delta \} \), where \( \Delta \geq \Delta \). We show that \( \delta q_k^*(s) \geq \delta q_k^*(s) \), which can be rewritten as \( q_k^*(s, 1) - q_k^*(s, 1) - q_k^*(s, 0) + q_k^*(s, 0) \geq 0 \). We present the proof for the case where \( 1 \leq b < B_k \); for the other two cases, i.e., \( b = 0 \) and \( b = B_k \), the proof follows similarly. We have
\[ q_k^*(s, 1) - q_k^*(s, 1) - q_k^*(s, 0) + q_k^*(s, 0) \]
\[ = \sum_{s' \in S_k} P_k(s'|s, 1) \left[ c_k(s, 1) + \gamma v_k^*(s') \right] - \sum_{s' \in S_k} P_k(s'|s, 1) \left[ c_k(s, 1) + \gamma v_k^*(s') \right] \]
\[ = \lambda_k (1 + \gamma v_k^*(b, 1)) + (1 - \lambda_k) (1 + \gamma v_k^*(b - 1, 1)) \]
\[ - \lambda_k (1 + \gamma v_k^*(b, 1)) - (1 - \lambda_k) (1 + \gamma v_k^*(b - 1, 1)) \]
\[-\lambda_k \left( \min\{\Delta + 1, \Delta_{k, \text{max}}\} + \gamma v_k^*(b + 1, \min\{\Delta + 1, \Delta_{k, \text{max}}\}) \right) \]
\[-(1 - \lambda_k) \left( \min\{\Delta + 1, \Delta_{k, \text{max}}\} + \gamma v_k^*(b, \min\{\Delta + 1, \Delta_{k, \text{max}}\}) \right) \]
\[+ \lambda_k \left( \min\{\Delta + 1, \Delta_{k, \text{max}}\} + \gamma v_k^*(b + 1, \min\{\Delta + 1, \Delta_{k, \text{max}}\}) \right) \]
\[+ (1 - \lambda_k) \left( \min\{\Delta + 1, \Delta_{k, \text{max}}\} + \gamma v_k^*(b, \min\{\Delta + 1, \Delta_{k, \text{max}}\}) \right) \]
\[= \left( \min\{\Delta + 1, \Delta_{k, \text{max}}\} - \min\{\Delta + 1, \Delta_{k, \text{max}}\} \right) \]
\[+ \gamma \lambda_k \left( v_k^*(b + 1, \min\{\Delta + 1, \Delta_{k, \text{max}}\}) - v_k^*(b + 1, \min\{\Delta + 1, \Delta_{k, \text{max}}\}) \right) \]
\[+ \gamma (1 - \lambda_k) \left( v_k^*(b, \min\{\Delta + 1, \Delta_{k, \text{max}}\}) - v_k^*(b, \min\{\Delta + 1, \Delta_{k, \text{max}}\}) \right) \geq 0, \]

where step (a) follows from the assumption $\Delta \leq \Delta$, and steps (b) and (c) follow from Proposition 1. \hfill \square

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