

Age-Optimal Power Allocation in Industrial IoT: A Risk-Sensitive Federated Learning Approach

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Abstract—This work studies a real-time environment monitoring scenario in the Industrial Internet of Things (IIoT), where wireless sensors proactively collect environmental data and transmit it to the controller. We adopt the notion of *risk-sensitivity* in financial mathematics as the objective to jointly minimize the mean, variance, and other higher-order statistics of the network energy consumption subject to the constraints on the AoI threshold violation probability and the AoI exceedances over a pre-defined threshold. We characterize the extreme AoI staleness using results in *extreme value theory* and propose a distributed power allocation approach by weaving in together principles of Lyapunov optimization and *federated learning* (FL). Simulation results demonstrate that the proposed FL-based distributed solution is on par with the centralized baseline while consuming 28.50% less system energy and outperforms the other baselines.

Index Terms—5G and beyond, industrial IoT (IIoT), smart factory, federated learning (FL), age of information (AoI), extreme value theory (EVT).

I. INTRODUCTION

Environment monitoring and control in smart factory scenarios are instances of mission-critical applications in 5G and beyond, where sensors, meters, and monitors generate and upload data to a central controller with real-time ultra-low latency. In particular, for real-time monitoring and control, the elapsed time of the generated data by a given sensor till its successful reception at the controller is key for the control performance. Such time duration is referred to as the *age of information* (AoI). If the AoI of the data grows unexpectedly, the outcome of the real-time environment monitoring will be poorly degraded [1]. The impact of AoI-aware resource allocation has been investigated in various communication systems [1]–[5]. The work [2] considers a multi-sensor industrial Internet of things (IIoT) scenario with finite blocklength transmission in which the controller instructs all devices to sample and upload environment data based on its AoI records. The objective therein is to minimize the sensors' power consumption. In [1], a mean-field game approach was proposed in a dense IIoT monitoring system. Aiming at minimizing the average AoI and average peak AoI using a Markov decision process, [3] investigates the tradeoff between AoI and energy cost and proposes an action policy for the devices. In [4], the authors assumed that the devices cannot upload data while wirelessly harvesting energy from the base station. As a result, the AoI exponentially increases

during the energy harvesting period. Finally, the authors in [5] considered a remote monitoring problem trading off the expected AoI and the AoI threshold violation probability.

Nevertheless, to reduce the AoI in a centralized manner, the proposed resource allocation approaches in [1]–[5] incur tremendous signaling overheads which are not negligible in ultra-low latency real-time monitoring, e.g., industrial automation. Under the ultra-low latency constraints, delegating the transmission decisions to the sensors provides a more realistic avenue, especially when the data sampling time is uncertain. Therefore, while accounting for the AoI threshold violation and the threshold-exceeding events, this work proposes a distributed and proactive power allocation approach that jointly minimizes the sensors' mean and variance energy consumption. We further leverage *extreme value theory* to characterize the AoI exceedance over a threshold using the observed historical data. Since the accuracy of this characterization is limited by the amount of sensor data. To improve the accuracy under limited sensor data availability, we resort to *federated learning* (FL), a collaborative and distributed model training framework [6], [7], and propose an FL-based distributed power allocation algorithm, using Lyapunov optimization. Numerical results show that the proposed approach is on a par with the centralized baseline while consuming less system energy for data transmission and model training.

II. SYSTEM MODEL AND PROBLEM FORMULATION

As shown in Fig. 1, we consider an industrial IoT network consists of a set \mathcal{K} of K intelligent sensors that monitor distinct and independent (but of the same type) environments and transmit the sampled data to a controller. The sensors cannot communicate with one another due to their geographical locations. We assume that the sensors' sampling operations are event-triggered, and the triggering time is random without any available statistical information. After a sensor samples status data, the data is transmitted immediately to the controller if the previously sampled one was uploaded. If the uploading procedure (of the previous data) has not been completed, the (new) data is queued in the buffer for the next transmission. Let us index the sequentially sampled data of each sensor by $i \in \mathbb{Z}^+$. To send the i th data with size N , sensor $k \in \mathcal{K}$ allocates transmit power $p_k(i)$ over its dedicated bandwidth

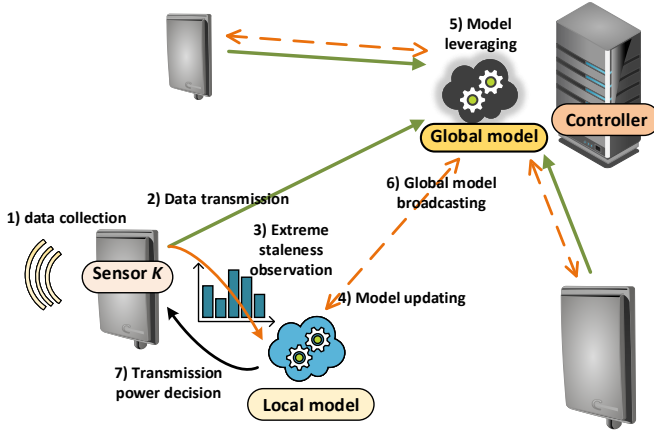


Figure 1: System architecture.

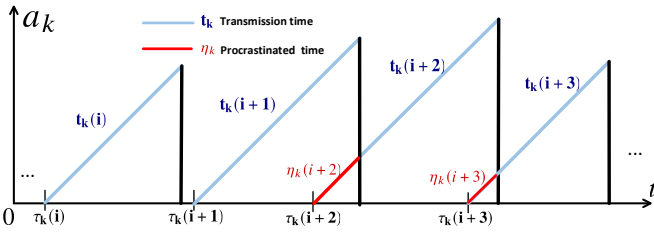


Figure 2: The AoI instances with data sampling and transmission. We have $\eta_k(i+1) = 0$, $\eta_k(i+2) > 0$, and $\eta_k(i+3) > 0$.

B in which the transmission time is

$$t_k(i) = \frac{N}{B \log_2 \left(1 + \frac{h_k(i)p_k(i)}{N_0 B} \right)}. \quad (1)$$

Here, $h_k(i)$ is the channel gain, including path loss and channel fading, between sensor k and the controller, and N_0 is the power spectral density of the additive white Gaussian noise. When the i th data is fully received at the controller, the time duration $a_k(i) = \eta_k(i) + t_k(i)$, including the procrastinated/queuing time $\eta_k(i)$ due to the previous transmission, has elapsed since the data was generated at time instant $\tau_k(i)$. Thus, $a_k(i)$ represents the AoI of the i th uploaded data at the reception time instant and is expressed in a recursive manner as

$$a_k(i) = [\tau_k(i-1) + a_k(i-1) - \tau_k(i)]^+ + t_k(i), \quad (2)$$

where $[x]^+ = \max\{x, 0\}$. Since the information ages in consecutive transmissions are entangled as per the recursive form (2), we should proactively account for the impacts of the allocated power on future AoI. The data sampling and uploading instances are schematically illustrated in Fig. 2. Note that the factory environment varies continuously, in which the stale information can degrade the control system performance. As a remedy, we impose a set of constraints on AoI in terms of the weighted expectation, AoI outage probability, and AoI exceedance. We firstly introduce a staleness function from [8] as $f_k(i) = \frac{[a_k(i)]^{(1-\beta)}}{1-\beta}$ for the AoI staleness with a predetermined value $\beta \leq 0$ and then consider a long-term

time-averaged constraint for every sensor k , i.e.,

$$\lim_{I \rightarrow \infty} \frac{1}{I} \sum_{i=1}^I \mathbb{E}[f_k(i)] \leq f_0, \forall k \in \mathcal{K}, \quad (3)$$

where f_0 is a pre-defined threshold. Additionally, we impose a probabilistic constraint on the AoI for each sensor k as

$$\lim_{I \rightarrow \infty} \frac{1}{I} \sum_{i=1}^I \Pr\{f_k(i) > f_0\} \leq \epsilon, \forall k \in \mathcal{K}, \quad (4)$$

in which $\epsilon \ll 1$ is the tolerable threshold violation probability. Although a very low occurrence probability of the AoI exceedance is ensured in (4), the uploaded data with an extremely large age can hinder the control performance. To mitigate this effect, a constraint on the AoI exceedances $q_k(i) = f_k(i) - f_0 > 0$ is imposed as follows:

$$\lim_{I \rightarrow \infty} \frac{1}{I} \sum_{i=1}^I \mathbb{E}[q_k(i)] \leq e_0, \forall k \in \mathcal{K}. \quad (5)$$

Here, we define the set of AoI exceedance of sensor k as $\mathcal{Q}_k \triangleq \{q_k(i) | \mathbb{1}_{\{q_k(i) > 0\}}, \forall i\}$, and e_0 is a pre-defined threshold. Finally, taking into account the sensors' limited-energy, we aim at not only minimizing the sensors' average energy consumption but also the variance for data uploading in order to reduce superabundant energy between each sensor. To this goal, denoting sensor k 's energy consumption for transmitting its i th data as $E_k(i) = p_k(i)t_k(i)$, we consider the entropic risk measure $\frac{1}{\rho} \ln(\mathbb{E}[e^{\rho E_k(i)}])$ as our objective, which incorporates the mean, variance, and higher-order statistics of energy consumption $E_k(i)$ [9]. The optimization problem is formally written as,

$$\underset{p_k(i)}{\text{minimize}} \quad \frac{1}{\rho} \ln \left(\lim_{I \rightarrow \infty} \frac{1}{I} \sum_{i=1}^I \mathbb{E}[e^{\rho E_k(i)}] \right) \quad (6a)$$

$$\text{subject to} \quad 0 \leq p_k(i) \leq p_{\max}, \forall i \in \mathbb{Z}^+, k \in \mathcal{K}, \quad (6b)$$

(3), (4), and (5),

where $\rho > 0$ reflects the weights of the variance and higher-order statistics in the risk minimization problem, and p_{\max} is the sensor's data transmission power budget. Since the objective (6a) and constraints (3), (4), and (5) are long-term time-averaged functions, we leverage Lyapunov optimization framework [10] to solve (6) as discussed next.

III. FL-BASED DISTRIBUTED POWER ALLOCATION

A. Distributed Power Allocation at the Sensor

In order to ensure the time-averaged constraints by Lyapunov optimization, we first introduce the virtual queues

$$\Gamma_k(i+1) = [\Gamma_k(i) + f_k(i) - f_0]^+, \quad (7)$$

$$\Upsilon_k(i+1) = [\Upsilon_k(i) + [q_k(i) - e_0] \mathbb{1}_{\{q_k(i) > 0\}}]^+, \quad (8)$$

for constraints (3) and (5), respectively. Additionally, by applying $\Pr\{f_k(i) > f_0\} = \mathbb{E}[\mathbb{1}_{\{q_k(i) > 0\}}]$ and scaling both sides of (4) as $\lim_{I \rightarrow \infty} \frac{1}{I} \sum_{i=1}^I f_k(i) \mathbb{E}[\mathbb{1}_{\{q_k(i) > 0\}}] \leq \lim_{I \rightarrow \infty} \frac{1}{I} \sum_{i=1}^I f_k(i) \epsilon$,

the virtual queue,

$$\Lambda_k(i+1) = [\Lambda_k(i) + (\mathbb{1}_{\{q_k(i)>0\}} - \epsilon)f_k(i)]^+, \quad (9)$$

is considered for the constraint (4). For notational simplicity, let $\Phi_k = [\Gamma_k(i), \Upsilon_k(i), \Lambda_k(i), \forall k \in \mathcal{K}]$ denote the combined queue vector. Due to the fact that minimizing (6a) is equivalent to minimizing $\lim_{I \rightarrow \infty} \frac{1}{I} \sum_{i=1}^I \mathbb{E}[e^{\rho E_k(i)}]$, the conditional Lyapunov drift (of the combined queue)-plus-penalty (based on the objective) is given by [10],

$$\mathbb{E}\left[\frac{1}{2}\Phi_k(i+1)\Phi_k(i+1)^T - \frac{1}{2}\Phi_k\Phi_k^T + V \sum_{k \in \mathcal{K}} \exp(\rho E_k(i))|\Phi_k\right], \quad (10)$$

where $(\cdot)^T$ denotes the transpose of a vector. Using $([Q + y]^+)^2 \leq Q^2 + 2Qy + y^2$, we can derive

$$(10) \leq \sum_{k \in \mathcal{K}} [\Delta_0 + V \exp(\rho E_k(i)) + F_k(i)]. \quad (11)$$

In (11), we have $F_k(i) = \theta_k^1(i)[f_k(i)]^2 + \theta_k^2(i)f_k(i)$ with $\theta_k^1(i) = \frac{1}{2}(1+\epsilon^2) + (1-\epsilon)\mathbb{1}_{\{q_k(i)>0\}}$ and $\theta_k^2(i) = \Gamma_k(i) - f_0 - \epsilon\Lambda_k(i) + [\Lambda_k(i) + \Upsilon_k(i) - f_0 - e_0]\mathbb{1}_{\{q_k(i)>0\}}$. Additionally, $\Delta_0 = \frac{1}{2}[f_0^2 - \Gamma_k(i) + [(f_0 + e_0)^2 - \Lambda_k(i)(f_0 + e_0)]\mathbb{1}_{\{q_k(i)>0\}}]$ is a constant. The solution of (6) can be obtained by minimizing the derived upper bound on the conditional Lyapunov drift-plus-penalty function [10], i.e., (11), in each transmission i by optimizing over the transmit power $p_k(i)$. Here, $V > 0$ is the tradeoff parameter between the lengths of the virtual queues and the optimality of the energy consumption in (6). To this end, each sensor $k \in \mathcal{K}$ locally solves its own problem

$$\underset{p_k(i)}{\text{minimize}} \quad V \exp(\rho E_k(i)) + F_k(i), \quad \text{subject to (6b)}, \quad (12)$$

for each transmission $i \in \mathbb{Z}^+$. In (12), we can straightforwardly prove the convexity of $F_k(i)$, but $\exp(\rho E_k(i))$ is non-convex with respect to $p_k(i)$. In order to tractably solve the non-convex problem (12), we adopt the notion of the convex-concave procedure (CCP) [11] by which we iteratively convexify $\exp(\rho E_k)$ by the first-order Taylor series expansion with respect to a reference point \hat{p}_k as

$$e^{\rho E_k(\hat{p}_k)} \left[t_k(\hat{p}_k) \left(1 - \frac{\hat{p}_k h_k t_k(\hat{p}_k)}{N(\hat{p}_k h_k + N_0 B) \ln 2} \right) (p_k - \hat{p}_k) + 1 \right]$$

and solve the convexified problem. Specifically, given the reference point \hat{p}_k^r in the r th iteration, we solve

$$\underset{p_k}{\text{minimize}} \quad V J(\hat{p}_k^r) p_k + F_k(p_k) \quad (13a)$$

$$\text{subject to} \quad 0 \leq p_k \leq p_{max}, \quad (13b)$$

with $J(\hat{p}_k^r) = e^{\rho E_k(\hat{p}_k^r)} t_k(\hat{p}_k^r) \left[1 - \frac{\hat{p}_k^r h_k t_k(\hat{p}_k^r)}{N(\hat{p}_k^r h_k + N_0 B) \ln 2} \right]$. The optimal solution to (13) is set as the reference point \hat{p}_k^{r+1} of the next iteration. After a large number of iterations, the optimal solution is converged, and we select \hat{p}_k^∞ as the sensor k 's power in the i th transmission. Afterwards, we update (2) and all virtual queues (7), (8), and (9). Note that the virtual queue length (8) varies when the AoI threshold violation occurs. However, since the tolerable violation probability in (4) is relatively small, we rarely change the value of $\Upsilon_k(i+1)$, resulting

in the slow convergence to the steady-state performance. To address this issue, we invoke results from extreme value theory and the principles of FL.

B. FL-Based Model Training for Excess AoI

Let us rewrite the virtual queue $\Upsilon_k(i)$ in (8) as

$$\begin{aligned} \Upsilon_k(i+1) &= \sum_{j=1}^i [q_k(j) - e_0]^+ \mathbb{1}_{\{q_k(j)>0\}} \\ &\geq \left[\sum_{j=1}^i [q_k(j) - e_0] \mathbb{1}_{\{q_k(j)>0\}} \right]^+ \\ &\stackrel{(a)}{=} \left[\frac{\sum_{j=1}^i q_k(j) \mathbb{1}_{\{q_k(j)>0\}}}{\sum_{j=1}^i \mathbb{1}_{\{q_k(j)>0\}}} - e_0 \right]^+ \sum_{j=1}^i \mathbb{1}_{\{q_k(j)>0\}} \end{aligned}$$

in which the first term in (a) represents the empirical average, which may have large variance due to limited historical data of the excess AoI. Nevertheless, if the mean of the AoI exceedance is available, we can estimate the steady-state average length of the virtual queue (8).

Theorem 1 (Pickands–Balkema–de Haan theorem [12]). *Given a random variable A with the cumulative distribution function $F_A(a)$ and a threshold a_0 , as $a_0 \rightarrow F_A(1)$, the excess value $Q = A - a_0 > 0$ can be approximately characterized by a generalized Pareto distribution (GPD) with the scale $\sigma > 0$ and shape $\xi \in \mathbb{R}$ parameters. The mean of the GPD is $\frac{\sigma}{1-\xi}$.*

Leveraging the results in Theorem 1, we characterize the statistics of $q_k(j)$ as a GPD whose parameters σ and ξ (i.e., the mean) can be estimated using maximum likelihood estimation. Given a sufficient amount of historical data, the GPD model (i.e., scale and shape parameters) of the excess AoI can be trained. However, owing to the sparsity of the excess AoI data at the sensor, it is time-consuming for each sensor to train the GPD model independently. To overcome this hurdle, we utilize the FL framework in which all sensors periodically update their locally-trained model to the controller. Then the controller aggregates the updated local models and feeds back the aggregated model to the sensors. Our FL-based model training is detailed as follows.

Assume that the local-model updating time interval is M , and each interval is indexed by $m \in \mathbb{Z}^+$. In every updating time interval, each sensor trains its model locally. In order to have sufficient independent data for local training, we set W observation time windows within which the sensor selects the largest excess AoI as a training sample. The observation time windows are indexed by $w \in \mathbb{Z}^+$, and the window size is O with $M/O = W \in \mathbb{Z}^+$, which should be sufficiently large to minimize the correlation between the selected data while being sufficiently small to prevent filtering out the data overmuch. Moreover, the selected extreme data at sensor k in the w th time window of the m th time interval is denoted by $\hat{q}_k^{m,w} = \max_{\tau_k(i) \in \mathcal{T}^{m,w}} \{q_k(i) | \mathbb{1}_{\{q_k(i)>0\}}\}$, where $\mathcal{T}^{m,w} \in [M(m-1) + O(w-1), M(m-1) + Ow]$. The selected data set

within the m th time interval is denoted by $\mathcal{Q}_k^m = \{q_k^{m,w}\}_{w=1}^W$. After collecting the samples \mathcal{Q}_k^m , we train the sensor k 's GPD model $\theta_k^m = \{\sigma_k^m, \xi_k^m\}$ via a *tilted empirical risk minimization* (ERM) [13], i.e.,

$$\begin{aligned} & \underset{\theta_k^m}{\text{minimize}} \tilde{\mathcal{L}}(\theta_k^m | t, \mathcal{Q}_k^m) \\ & \equiv \underset{\theta_k^m}{\text{minimize}} \frac{1}{t} \ln \left(\frac{1}{|\mathcal{Q}_k^m|} \sum_{\mathcal{Q}_k^m} G(\theta_k^m | \mathcal{Q}_k^m)^{-t} \right). \end{aligned} \quad (14)$$

Here, $G(\sigma, \xi | q) = \frac{1}{\sigma} (1 + \frac{\xi q}{\sigma})^{-(\frac{1}{\xi} + 1)}$ is the GPD's likelihood function while t is the tilted factor. In contrast with conventional ERM, in which the average of the loss function is minimized, tilted ERM considers the entropic risk measure $\frac{1}{t} \ln(\mathbb{E}_X[e^{tX}])$ of the loss functions as the objective which jointly incorporates the mean, variance, and other higher-order moments [9]. In this regard, by setting $t < 0$ in (14), we can account for the outliers and other extreme events. Subsequently, based on the global model $\theta^{m-1} = \{\sigma^{m-1}, \xi^{m-1}\}$ received in the $(m-1)$ th interval, each sensor k updates the local model parameters as per

$$\theta_k^m = \theta^{m-1} - \delta_\theta \nabla_{\theta_k^m} \tilde{\mathcal{L}}(\theta_k^m | t, \mathcal{Q}_k^m), \quad (15)$$

with the initial value θ^0 and sends θ_k^m to the controller. In (15), δ_θ is the step size. The gradient of $\tilde{\mathcal{L}}(\theta_k^m | t, \mathcal{Q}_k^m)$ with respect to θ_k^m is given by

$$\begin{aligned} & \nabla_{\theta_k^m} \tilde{\mathcal{L}}(\theta_k^m | t, \mathcal{Q}_k^m) = \\ & \frac{-\sum_{\mathcal{Q}_k^m} \nabla_{\theta_k^m} G(\theta_k^m | \mathcal{Q}_k^m) \times G(\theta_k^m | \mathcal{Q}_k^m)^{-t-1}}{\sum_{\mathcal{Q}_k^m} G(\theta_k^m | \mathcal{Q}_k^m)^{-t}}, \end{aligned} \quad (16)$$

and

$$\begin{aligned} \frac{\partial G(\theta | \mathcal{Q})}{\partial \sigma} &= \frac{Q - \sigma}{\sigma^3} \left(1 + \frac{\xi Q}{\sigma} \right)^{-2 - \frac{1}{\xi}}, \\ \frac{\partial G(\theta | \mathcal{Q})}{\partial \xi} &= \frac{(1 + \frac{\xi Q}{\sigma})^{-1 - \frac{1}{\xi}}}{\sigma \xi} \left(\frac{-(\xi + 1)Q}{\sigma + \xi Q} + \frac{\ln(1 + \frac{\xi Q}{\sigma})}{\xi} \right). \end{aligned}$$

Here, the notations m and k are neglected for simplicity. The controller then calculates the global model of the m th updating time interval as

$$\theta^m = \frac{\sum_{k=1}^K (|\mathcal{Q}_k^m| \theta_k^m)}{\sum_{k=1}^K |\mathcal{Q}_k^m|}. \quad (17)$$

Finally, after receiving the global feedback model θ^m , each sensor k replaces the virtual queue value with

$$\Upsilon_k(\hat{i} + 1) = \left[\frac{\sigma^m}{1 - \xi^m} - e_0 \right]^+ \mathbb{E}_{\mathcal{K}} \left[\sum_{j=1}^{\hat{i}} \mathbb{1}_{\{q_k(j) > 0\}} \right], \quad (18)$$

in which $\hat{i} = \arg \min_{\forall i} \{\tau_k(i) - Mm \geq 0\}$, and proceeds with the next local-model training θ_k^{m+1} . The proposed FL-based distributed power allocation is outlined in Algorithm 1.

IV. NUMERICAL RESULTS

We simulate a factory environment with $K = 50$ sensors with 50 Hz data-sampling frequency in Poisson. The considered path loss model is $32.45 + 31.9 \log 20 + 20 \log 3.5$

Algorithm 1 FL-Based Distributed Power Allocation Mechanism

Input: transmission parameters in (1), $\beta, \theta^0, \delta_\theta, M, O$.

Output: The result of objective (6a)

Initialize: create i_k for data indicator, $i_k = 1, \forall k$,

$a_k(0) = 0, \eta_k(1) = 0, \tau_k(i_k | i_k = 0, 1) = 0, \forall k$,

$\{A_k(1), \Gamma_k(1), \Lambda_k(1), \Upsilon_k(1)\} = 0$.

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1: for  $m = 1, 2, \dots$  do // for global model updating interval
2:   for  $k = 1, \dots, |K|$  do
3:      $w = 1, \mathcal{Q}_k^m = \{\}$ , // check each observation window
4:     if  $\tau_k(i_k) \leq Mm$  &&  $w \leq W$  then
5:       while  $\tau_k(i_k) \leq M(m-1) + Ow$  do
6:         update  $\eta_k(i_k), \theta_k^1(i_k), \theta_k^2(i_k), \theta_k^3(i_k)$ ,
7:         form  $u_k(i_k)$  by (11) and solve  $p_k^*(i_k)$  by CCP.
8:         count  $t_k^*(i_k)$  by (1),  $E_k^*(i_k), a_k(i_k), f_k(i_k), q_k(i_k)$ ,
9:         update  $A(i_k), \Gamma_k(i_k), \Lambda_k(i_k), \Upsilon_k(i_k)$ ,
10:         $i_k = i_k + 1$ ,
11:      end while
12:      Count  $\hat{q}_k^{m,w}$ , update  $\mathcal{Q}_k^m = \{\mathcal{Q}_k^m, \hat{q}_k^{m,w}\}$ ,
13:       $w = w + 1$ ,
14:    else  $\mathcal{Q}_k^m = \{\}$ ,
15:    end if
16:    train  $\theta_k^m$  with (15), (16) by  $\mathcal{Q}_k^m$  and update them to Controller,
17:  end for
18:  Controller updates  $\theta^m$  with  $\theta_k^m$  by (17), and broadcasts to IDs,
19:   $\forall k, \Upsilon_k(i_k)$  is replaced with  $\hat{\theta}^m$  by (18).
20: end for

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(dB) given 3.5 GHz carrier frequency and a 20-meter sensor-controller distance [14]. The wireless channel experiences Rayleigh fading with unit variance. The remaining simulation parameters are $N = 3000$ bytes, $B = 180$ kHz, $N_0 = -174$ dBm, $p_{max} = 23$ dBm, $\beta = -2$, $f_0 = 5 \times 10^{-4}$, $e_0 = 10^{-4}$, and $\epsilon = 2 \times 10^{-3}$, $M = 30$ ms, $O = 10$ ms, $\theta^0 = [0.0002, 0.02]$, $\delta_\theta = [10^{-9}, 10^{-3}]$, and $t = -10$. For performance comparison, we consider four baselines: i) **Centralized model-training** (CENT) scheme which trains the extreme staleness GPD model at the central controller with all sensors' exceedance data. ii) **Local model-training** (LOCAL) scheme in which the sensors only train the GPD model individually without any information exchange. iii) **Non-model-training** (NonT) scheme which directly solves problem (12) without renewing the virtual queue $\Upsilon_k(i)$ in (8) via the training result of GPD model. iv) **Excess staleness-agnostic** (ESA) scheme which does not take extreme staleness into consideration, i.e., neglecting constraints (4) and (5) in problem (6). In addition to the performance of the objective (6a), we further investigate the expected system energy consumption $\mathbb{E}[E_{sys}] = \mathbb{E}[E_k] + \mathbb{E}[E_{comp}^{train}] + \mathbb{E}[E_{tx}^{train}]$, including the sensor's monitored data-updating energy E_k , the computation energy in GPD-model training $E_{comp}^{train} = 10^{-27} f_{cpu}^2 N_{tr} l_{req}$, and the energy consumption in model-uploading $E_{tx}^{train} = p_{max} N_{tr} / (B \log_2 (1 + \frac{h_k p_{max}}{N_0 B}))$. Here, $f_{cpu} = 2 \times 10^{11}$ cycle/s and $f_{cpu} = 10^9$ cycle/s are the controller's and sensor's computation capabilities for model training [9]. $N_{tr} = 30$ bytes is the single-data size in GPD-model training, and $l_{req} = 87.8$ cycle/bit is the required computation frequency.

The impact of the tradeoff parameter V in the Lyapunov optimization on energy consumption is shown in Fig. 3. We first examine the performance of the objective (6a) in Fig. 3a as a function of V . It can be noted that the objective is a decreasing function of V since the importance of energy

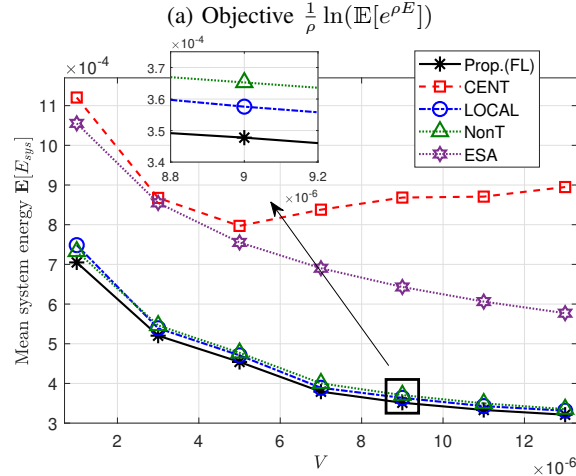
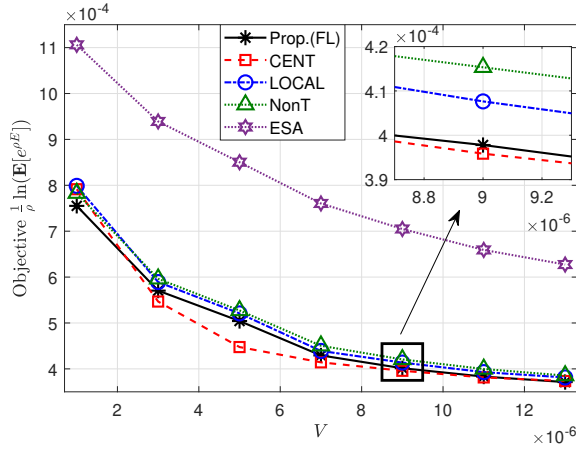


Figure 3: Energy consumption versus V with $\rho = 2$.

reduction increases with increasing V . Although CENT almost outperforms the other schemes across various V values due to the GPD model training over the global dataset, the performance of our proposed scheme is close to CENT with only 0.48% – 11.26% increments in the objective. Compared with LOCAL and NonT, the proposed FL scheme decreases the objective cost up to 5.45% and 5.56%, respectively, showing the benefit of FL model training. In addition, LOCAL outperforms NonT, manifesting the advantage of model training even without any information exchange. Being agnostic to extreme staleness, ESA may incur a high instantaneous AoI, which results in larger energy consumption. In this regard, ESA has a higher objective cost (up to 44.75% increase) than the cost of the proposed scheme.

In Fig. 3b, we further verify the advantages of our proposed approach in terms of the expected system energy consumption. In CENT, all sensors have to deliver every observed extreme staleness data to the controller, consuming high energy for information exchange. Note that as V increases, all schemes tend to save more power in environmental data transmission based on the Lyapunov optimization framework but increases the occurrence chance of extreme staleness. In this situation, the sensors in CENT have to consume more energy to upload

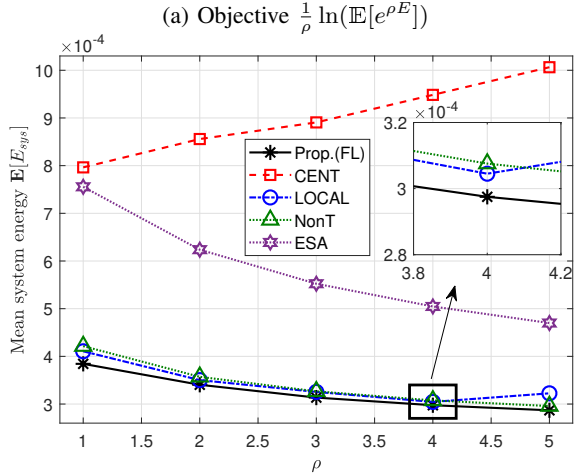
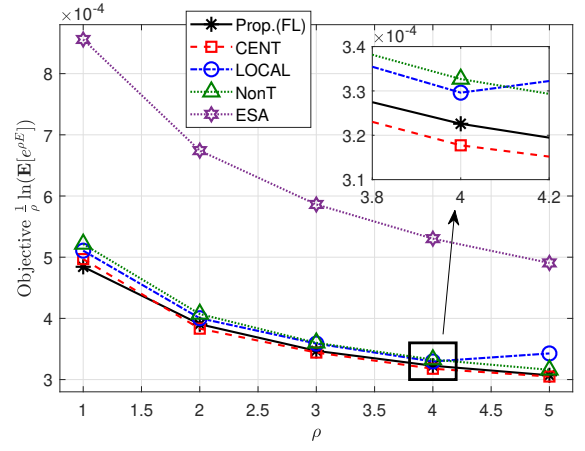


Figure 4: Energy consumption versus ρ with $V = 10^{-5}$.

more model-training data to the controller. Therefore, the expected system energy of CENT grows gradually with V in Fig. 3b. In the proposed FL-based approach, since the sensors train the GPD models locally and only upload the model parameters to the controller, the energy consumption is significantly reduced. In this regard, our approach can save up to 64.11% in system energy compared to CENT. In contrast with NonT and LOCAL, our approach spends extra energy on FL model training and information exchange. Nevertheless, our energy-saving benefit with respect of $\mathbb{E}[E_k]$ compensates this expenditure. Where the proposed scheme can save up to 5.82% and 6.21% in system energy then LOCAL and NonT. The objective performance and expected system energy consumption by varying ρ are shown in Fig. 4. As per (12), all the schemes put more focus on energy deduction as ρ grows.

The capability of extreme staleness control is manifested in Fig. 5. Given a specific amount of expected status-updating energy $\mathbb{E}[E_k]$, the proposed approach, CENT and LOCAL benefited from the GPD-model training showcase the lowest excess staleness values, whereas ESA, which is agnostic to the extreme AoI, has much higher excess staleness. However, if we further take into account the energy consumption in model training, our proposed approach (compared with CENT

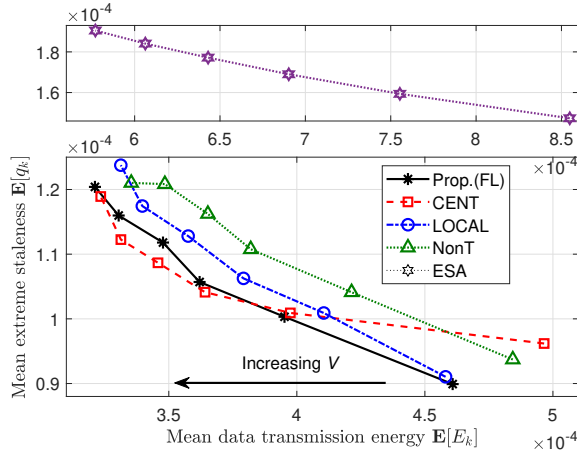


Figure 5: Extreme AoI versus average transmission energy with $\rho = 2$.

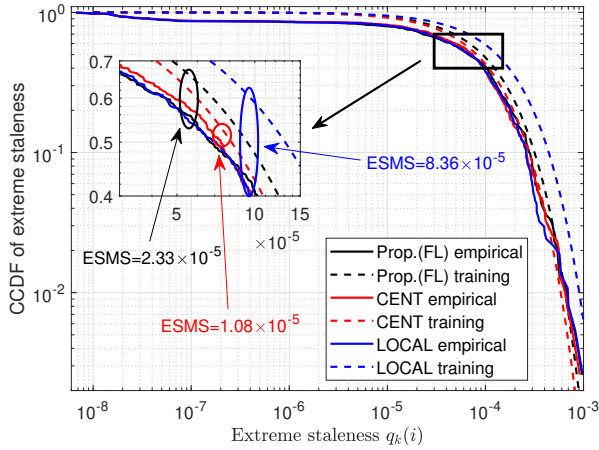


Figure 6: CCDF of extreme AoI with $\rho = 2$ and $V = 10^{-5}$.

and LOCAL) consumes less energy while achieving the same extreme staleness performance.

Finally, we discuss the performance of GPD-model training in terms of the complementary cumulative distribution function (CCDF) of extreme staleness in Fig. 6. As shown, the predicted extreme staleness mean $\sigma/(1 - \xi)$ is always higher than the empirical one. The reason is that the predicted extreme staleness mean values in both schemes are leveraged to suppress the extreme staleness further. The more precise the estimation is, the more accurate the decision. The centralized approach, i.e., CENT, estimates the GPD model closer to the empirical one, saving more energy to control the extreme staleness. In this regard, the proposed FL scheme and CENT, respectively, possess 2.33×10^{-5} and 1.08×10^{-5} in terms of the estimation-statistic mean surplus (ESMS) value between the trained model and empirical curve. On the other hand, the localized approach, i.e., LOCAL, has the highest ESMS 8.36×10^{-5} for the sake of lacking global estimation. Such results reflect on the least objective performance in Fig. 3a and 4a. However, the mean extreme staleness from the proposed scheme is 3.54% higher than CENT, underscoring that

increasing transmission energy based on inaccurate predictions cannot effectively suppress extreme values.

V. CONCLUSIONS

In this work, we considered an industrial IoT real-time monitoring scenario with intelligent sensors proactively collecting changing environmental data and autonomously transmitting data to the controller. To avoid stale data delivery hindering the monitoring performance, we have formulated an entropic risk-minimizing problem subject to data staleness constraints. To confront extreme staleness regimes, we invoked results in extreme value theory and trained a GPD model by leveraging FL. Numerical results have shown that the proposed FL scheme is on a par with the centralized model-training scheme and consumes less system energy.

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