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FLAM: Federated Learning-Based Age of Information Minimization for D2D-Enabled Healthcare-Centric SIoT Networks

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Abstract

The incorporation of Device-to-Device (D2D) communication into social Internet of Healthcare Things (SIoHT) networks necessitates rigorous requirements to reduce the Age of Information (AoI) and mitigate challenges stemming from the network's dynamic behavior. The proposed framework for optimizing the information freshness leverages a federated learning-based AoI minimization (FLAM) algorithm to ensure timeliness and energy-efficient data transmission. Additionally, it handles various issues arising from the network perturbation. We formulate an optimization problem to minimize the information freshness while ensuring efficient energy of the network. The FLAM algorithm is a federated learning-based approach that targets the distribution of resources across D2D users. Through extensive simulations, the proposed algorithm significantly reduces average AoI by 24.35%, enhances energy efficiency by 30.17%, and improves throughput by 16.17% over existing schemes. The proposed solution can be utilized for various applications such as real-time healthcare management, emergency response systems and patient-centric monitoring, within dynamic SIoHT environments.

Keywords: Federated Learning, Information Freshness, Perturbation Effect, Social Internet of Healthcare Things.

Introduction

Due to the increasing number of interconnected health-related devices, the need for energy efficient optimization and data transmission has become more critical in Device-to-Device (D2D)-enabled Social Internet of Healthcare Things (SIoHT)networks [1], [2]. The information freshness is a critical performance metric for ensuring data freshness, vital for healthcare applications requiring real-time monitoring and timely interventions to address such perturbations [3]. Despite the various advantages of D2D communication, it is still challenging to achieve low information freshness while maintaining reliable communication and energy efficiency. In this paper, we present a novel approach that involves implementing a Federated Learning (FL) algorithm for energy optimization and data dissemination. This approach can help minimize data freshness while ensuring privacy. The proposed method addresses the energy efficiency optimization and information freshness challenges in the SIoHT networks.

Related Work

Several studies have addressed the challenges of optimizing age of information (AoI) and resource allocation in various network environments. In [4], a deep reinforcement learning (DRL)-based framework was proposed to optimize AoI using finite blocklength coding, handling nonconvex multi-QoS constraints to minimize peak AoI violation probability. In [5], a learning-based robust resource allocation algorithm (LRRA-OIAoISR) was developed for ultradense Industrial IoT networks, addressing overlapping interference and AoI-sensitive service requirements through an interference hypergraph model and robust optimization under imperfect channel state information. In [6], an intelligent hybrid automatic repeat request-enabled rate-splitting multiple access framework was proposed, using Markov decision processes and Lyapunov drift functions to minimize AoI by adapting power allocation and retransmissions in 5G/6G networks. For mobile crowdsensing, authors in [7] employed contract theory to design incentive mechanisms and task allocation strategies, optimizing AoI by balancing sampling frequency and participant costs. An empirical study in [8] investigated FL implementation on IoT-edge devices, highlighting real-world challenges such as heterogeneity and on-device computation costs. In [9], a communication and sensing integration-driven FL framework for intelligent transportation systems was proposed, using polar coding and asynchronous updates to enhance transmission efficiency, model accuracy, and privacy under dynamic conditions. However, none of these works specifically address the joint optimization of AoI, throughput, and energy efficiency in D2D-enabled SIoHT networks using FL approach to mitigate dynamic perturbations.

The key issues identified based on the literature survey are as follows:

a) *Lack of consideration of Perturbation Issues:* Existing works lacks on addressing the perturbation effect on the AoI and energy efficiency, which significantly impacts the timely deliver the data freshness in healthcare applications.

b) *Lack of analysis on AoI in SIoHT Networks:* Recent works on D2D communication overlooks AoI minimization in heterogeneous healthcare scenarios.

The main contributions of this work is as follows:
We propose Federated Learning framework for D2D-enabled SIoHT networks to minimize AoI, using distributed models and strategies to counter dynamic network disruptions.

We develop an AoI optimization algorithm (FLAM) integrating federated learning for optimal power consumption, ensuring timely data delivery and energy efficiency under varying channel conditions.

We address AoI minimization challenges by dividing the problem into sub-tasks, using federated learning to minimize AoI, optimize energy use, and throughput, ensuring robust performance.

The rest sections of this article is organized as follows: Section III defines the system model and problem formulation. Solution is proposed in Section IV. In Section V, we provide the simulation results and discussion. Section VI summarizes the article.

Network Model
We first introduce our network model for AoI-aware D2D communication in Social IoHT Networks followed by problem formulation from the identified lacunas in this section.

Network Model
We consider a D2D-enabled SIoHT Network consisting of a base station (BS), a set of cellular users (CUs) denoted by $\mathcal{C} = \{1, 2, \ldots, C\}$ and a set of D2D user pairs (DUs) denoted by $\mathcal{D} = \{1, 2, ..., D\}$. Each D2D pair $d \in \mathcal{D}$ consists of a transmitter T_{tx} and a receiver T_{rx}, sharing the same spectrum as CUs in an underlay mode to improve energy efficiency.

Let h_{ij} denote the complex channel coefficient between transmitter i and receiver j. The channel power gain is expressed as:

$$g_{ij} = |h_{ij}|^2 = \rho_o d_{ij}^{-\alpha} \quad (1)$$

where ρ_o represents the reference path loss at unit distance, d_{ij} is the Euclidean distance i and j, and α is the path-loss exponent. Each link experiences Rayleigh fading, such that $h_{ij} \sim \mathcal{CN}(0,1)$.

Each CU $c \in \mathcal{C}$ communicates with the base station (BS) while suffering interference from active D2D pairs sharing the same spectrum. The received signal strength with the presence of noise and interference (SINR) for cellular node c is:

$$\Gamma_c = \frac{P_c g_{c,BS}}{\sum_{d \in D} x_d P_d g_{d,BS} + \eta^2}, \quad (2)$$

where P_d and P_c denote the transmit powers of CU c and D2D user d, respectively, $x_d \in \{0,1\}$ is the D2D resource indicator, and η^2 is the noise power spectral density.

Each D2D receiver experiences interference from both other D2D pairs and CUs. The SINR for D2D pair d is given as:

$$\Gamma_d = \frac{P_d g_{d,d}}{\sum_{j \in \mathcal{D}, j \neq d} x_j P_j g_{j,d} + \sum_{c \in \mathcal{C}} P_c g_{c,d} + \eta^2}, \quad (3)$$

The achievable instantaneous throughput for each CU and D2D user is defined by the Shannon capacity formula:

$$\mathcal{R}_c = \mathcal{B} \log_2(1 + \Gamma_c), \ \forall c \in \mathcal{C}, \quad (4)$$

$$\mathcal{R}_d = \mathcal{B} \log_2(1 + \Gamma_d), \ \forall d \in \mathcal{D}, \quad (5)$$

Where $\mathcal{B}$ is the bandwidth allocated to each resource block.
The total system throughput is:

$$\mathcal{R}_{sum} = \sum_{c \in \mathcal{C}} \mathcal{R}_c + \sum_{d \in \mathcal{D}} \mathcal{R}_d \quad (6)$$

Information Freshness Model
For each D2D transmitter T_{tx}, packets are generated and transmitted to its receiver T_{tx} periodically. The AoI at the receiver is given by:

$$\psi_d(t) = t - \delta_d(t), \quad (7)$$

where $\delta_d(t)$ denotes the most recently received packet.
The AoI evolution for each time slot is defined as:

$$\psi_d(t+1) = \begin{cases} 1, & \text{if a packet from } T_{tx} \text{ is successfully received at } T_{rx} \\ \psi_d(t) + 1, & \text{otherwise} \end{cases} \quad (8)$$

The average AoI over a period τ is:

$$\bar{\psi} = \frac{1}{\tau} \sum_{t=1}^{\tau} \psi_d(t) \quad (9)$$

The energy efficiency (EE) of D2D user d is expressed as:

$$\lambda_d = \frac{\mathcal{R}_d}{P_d + P_{crkt}}, \quad (10)$$

Where P_{crkt} represents the static circuit power consumption. The overall network energy efficiency is:

$$\lambda_{ee} = \frac{\sum_{d \in \mathcal{D}} \mathcal{R}_d}{\sum_{d \in \mathcal{D}} (P_d + P_{crkt})} \quad (11)$$

Problem Formulation
To jointly minimize the average AoI and throughput while ensuring energy-efficient network, we formulate a joint optimization problem:

$$\min_{\{x_d, P_d\}} \left(\sum_{d \in \mathcal{D}} \mu_d \bar{\psi}_d - \sum_{d \in \mathcal{D}} \sigma_d \mathcal{R}_d + \xi_e \sum_{d \in \mathcal{D}} P_d \right), \quad (12)$$

s.t.

C1: $0 \le P_d \le P_{\max}, \forall d \in \mathcal{D}$

C2: $\Gamma_d \ge \Gamma_d^{th}, \Gamma_c \ge \Gamma_c^{th}, \forall c \in \mathcal{C}, d \in \mathcal{D}$

C3: $\sum_{d \in \mathcal{D}} x_d P_d g_{d,BS} \le \phi_d^{th}$

C4: $x_d \in \{0,1\}, \forall d \in \mathcal{D}$

where μ_d controls the AoI weight parameter, σ_d denotes the throughput weight, and $\xi_e = \bar{\mathcal{R}}/P_{\max}$ represents the constant design parameter. The optimization problem in equation (12) is dependent on the following constraints. C1 represents the power constraints of the D2D users. C2 denotes the threshold SINR constraint for maintaining the reliable connectivity of the networks. Constraint C3 defines the scheduling constraints. To address this problem, we propose a Federated Learning (FL)-based approach that provides an optimal solution, shall be discussed in the next section.

Proposed Federated-Learning Based Age of Information Minimization Algorithm

In this section, we will derive the efficient solution of formulated problem in in equation (12) using Federated Learning (FL)-based approach [10]. The proposed approach is mathematically modeled with the help of distributed scheduling and power-control policy and optimized through federated training across channel link gains and power levels. Each device autonomously fetches local observations, including states, actions, and rewards to optimize an objective function that balances throughput and AoI. A central server periodically aggregates the locally computed model updates from D2D users and disseminates the refined global model to all participating devices. Each device leverages the learned policy to make real-time decisions on transmission scheduling and power allocation in a privacy-preserving and communication-efficient manner. The subsequent subsections elaborate the FL through policy parameterization, rewards calculation, and federated aggregation.

Policy parameterization

We parameterize a per-device policy π_θ with shared parameters θ. The policy maps a local observation $o_i(t)$ to a stochastic action $a_i(t)$ that contains transmission decision $x_i(t) \in \{0,1\}$ and power level selection $P_i(t) \in [0, P_i^{\max}]$.

A simple, effective parameterization is a small neural network that output contains transmit probability $q_i(t) = \sigma(f_\theta(o_i(t))_1) \in (0,1)$, normalized power factor $u_i(t) = \tanh(f_\theta(o_i(t))_2) \in (-1,1)$ mapped to $P_i(t) = \frac{P_i^{\max}}{2}(u_i + 1)$, and action sampling $x_i(t) \sim Bernoulli(q_i(t))$, if $x_i(t) = 1$ set $P_i(t)$ as high, else $P_i(t) = 0$.

Local observation $o_i(t)$ may include $\psi_i(t)$, $\hat{h}_{ii}(t)$, moving average of h_{ii}, recent success $S_i(t-1)$, local queue length, neighbor interference estimate.

Rewards in Federated Learning

We use an instantaneous per-slot reward that reflects throughput and AoI improvements. Let instantaneous reward for device i at slot t be

$$\Delta_i(t) = \sigma_i \mathcal{R}_i(t) + \mu_i(\psi_i(t) - 1) S_i(t) - \xi_e P_i(t), \tag{13}$$

where $\mathcal{R}_i(t)$ is the instantaneous rate, $S_i(t)$ is 1, then successful reception, $\sigma_i \ge 0$ is throughput weight, $\mu_i > 0$ rewards AoI reduction, and $\xi_e \ge 0$ is an energy penalty coefficient.

Algorithm 1: Federated Learning (FL)-based AoI Minimization (FLAM) Algorithm

Input: Channel state information h, D2D users $\mathcal{D}$, training episodes $\mathcal{D}_{ep}$, number of communication rounds R, local training epochs E, AoI weights μ, throughput weights σ, maximum transmission power Pmax, SINR threshold Γ^{th}.

Output: Optimized global model parameters θ for AoI-aware resource allocation and power control.

1: Initialize global parameters θ at the central server.
2: **for each** training episode $i \in [1, \mathcal{D}_{ep}]$ **do**
3: Initialize buffers and AoI states $\psi_i(0)$ for all D2D pairs.
4: Establish D2D underlay links coexisting with cellular users.
5: Empty local experience memory buffers at all D2D devices.
6: **for each** time step $t \in [1, \tau]$ **do**
7: Packets arrive at D2D transmitters' buffers.
8: Update instantaneous AoI states $\psi_i(t)$ for each D2D pair.
9: Each D2D device observes local state
10: $o_i(t) = \{\psi_i(t), h_i(t), q_i(t)\}$
11: Select transmission action $a_i(t) = \{x_i(t), P_i(t)\}$ using current local policy π_θ.
12: Execute transmission over D2D underlay channel with power $P_i(t)$ while ensuring interference constraint with cellular users.
13: Compute SINR $\Gamma_i(t)$ and achievable rate $\mathcal{R}_i(t)$.
14: Update AoI based on successful packet delivery indicator $S_i(t)$.

Compute reward $\Delta_i(t)$ reflecting AoI minimization and energy efficiency trade-off.

Store transition $\{o_i(t), a_i(t), \Delta_i(t), o_i(t+1)\}$ in local memory buffer.

end for

Each D2D device performs E local gradient updates on θ using stored experiences.

Obtain updated local model parameters θ_i.

if i mod $\mathcal{R} = 0$ **then**

for each selected D2D device $l \in [1, K]$ **do**

Transmit local parameters θ_i to the central server.

end for

The central server aggregates local updates using:

$\theta \leftarrow \sum_i \left(l_i / \sum_j l_j \right) \theta_i$

Broadcast the updated global parameters θ to all D2D users.

Empty local experience buffers at each D2D node.

end if

end for

Objective is to maximize expected cumulative reward (or minimize negative reward). For client i over a local trajectory of τ slots:

$$\mathcal{L}_i(\theta) = -\mathrm{E}\left[\sum_{t=0}^{\tau-1} \Delta_i(t)\right] \tag{14}$$

Expectation with respect to policy stochasticity and channel randomness. Users use an on-device policy-gradient estimator to compute $\partial_\theta \mathcal{L}_i(\theta)$. For a trajectory $\{o, a, \Delta\}$, the gradient estimator is expressed as

$$\partial_\theta \mathcal{L}_i(\theta) \approx -\sum_{t=0}^{\tau-1} \widehat{G}_i(t) \partial_\theta \log \pi_\theta\left(a_i(t) \middle| o_i(t)\right), \tag{15}$$

where $\widehat{G}_i(t)$ is a discounted factor that return $\sum_{t' \geq t} \Delta_i(t') - \upsilon$, with variable υ is used to reduce variance.

Federated aggregation

We use federated aggregation at communication round k, server has $\theta^{(k)}$, server selects a subset of clients $\mathcal{C}^{(k)}$ each client $i \in \mathcal{C}^{(k)}$ initializes local model $\theta^{(k)}$, runs E local training epochs on its collected local data, resulting in $\theta_i^{(k+1)}$. D2D users send updates $\omega_i^{(k)} = \theta_i^{(k+1)} - \theta^{(k)}$ to server. Server aggregate is expressed as

$$\theta^{(k+1)} = \sum_{i \in \mathcal{C}} \frac{l_i}{\sum_{j \in \mathcal{C}^{(k)}} l_j} \theta_i^{(k+1)}, \tag{16}$$

where l_i is the local data size.

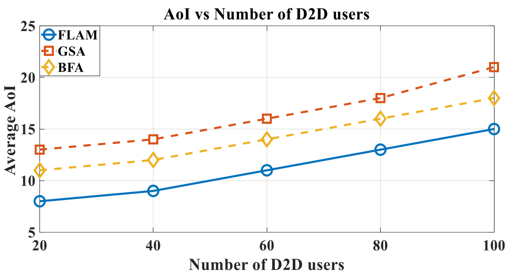
This global model guides AoI-aware power allocation and scheduling decisions across the SIoHT network. The pseudo code of the proposed FL-based AoI minimization algorithm is shown in Algorithm 1.

Numerical Simulations

In this section, we provide the simulation results for the validation and effectiveness of our proposed Federated Learning (FL)-based AoI minimization (FLAM) algorithm. The simulation environment models a SIoHT network with D2D communication, where the BS coverage is a circular area with a radius of 500 m, the maximum transmission power is set to 23 dBm, and the number of D2D devices varies from 20 to 100. In order to evaluate the effectiveness of the proposed approach, the performance is compared with other existing schemes as Greedy (GA) [11] and Brute-Force Algorithms (BFA) [12]. Numerical simulation parameters are defined in Table 1.

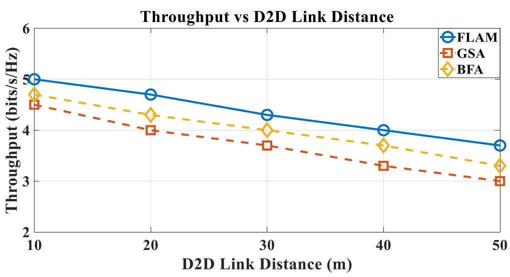
System simulation settings parameters

Control Parameters	**Value**
X and Y coordinates of Network	(500,500) m
Number of D2D nodes	100
D2D link distance	50 m
Bandwidth	10 MHz
SINR threshold	12 dB
Pathloss exponent	4
Maximum power transmitted at D2D node	23 dBm
Power transmitted from circuit	8 dBm
Noise Power	-174 dBm/Hz



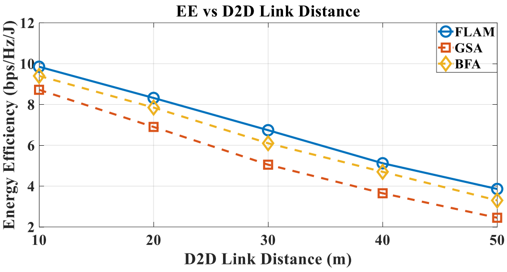
Impact of D2D users on Averga AoI.

Fig. 1 shows the impact of D2D node variation on Average AoI. As we can observe from the figure that AoI increases throughout the various schemes due to rising demand for limited communication resources and higher scheduling delays with an increase in density of users. The proposed FLAM approach consistently yields the lowest AoI, shows updated information freshness. When the number of D2D users deployed is 100, proposed FLAM schemes reduces average AoI by 15.38% and 33.33% compared to existing schemes, respectively.



Impact of D2D link distance on Throughput.

Fig. 2 illustrates the variation in throughput by varying the threshold D2D pair distance between transmitter and receiver. There is decrement in throughput for all the schemes as distance between D2D pair is varied due to higher path loss and reduced SINR. Short D2D link distance support higher data rates through improved signal strength because D2D users transmits more power to deliver the data. The proposed FLAM approach maintains enhance throughput and significantly outperforms the benchmark schemes by 11.43% and 20.89%, respectively.



Impact of variation in the distance between D2D users on Energy Efficiency of the network.

Fig. 3 demonstrates the impact of variation in D2D pair distance on energy efficiency (EE) parameter in D2D-enabled SIoHT networks. Greater the D2D link distance, lowers EE due to increased power demands and signal attenuation. The proposed FLAM approach significantly achieves the highest EE, which optimizes the power efficiently. When D2D transmitter and receiver distance is 50 m, proposed approach significantly outperforms the benchmark schemes by 15.64% and 44.69%, respectively.

Conclusion

In this paper, we investigated the AoI dynamics in D2D communication for SIoHT networks, focusing on the joint optimization of energy efficiency and AoI under dynamic perturbation conditions. The dynamic allocation of transmission power and scheduling resources significantly impacts the AoI of healthcare data flows, while varying AoI influence the resource management decisions. To address these issues, we formulated an optimization problem and proposed a Federated Learning-based AoI Minimization (FLAM) algorithm that jointly optimizes the AoI and energy efficiency with minimum power consumption. Simulation results demonstrate that the FLAM algorithm achieves up to 24.35% reduction in average AoI, and improves energy efficiency and throughput by 30.17% and 16.17%, respectively, compared to benchmark schemes. In future work, we plan to extend this framework to Digital Twin-enabled SIoHT environments, where real-time virtual replicas of healthcare networks can enhance predictive resource optimization and further improve AoI performance.

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