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Distributed Optimization for Energy-Efficient Internet-of-Things Systems with Dynamic Resource Constraints

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Abstract

Maintaining information freshness and conserving energy are crucial challenges in dynamic Internet of Things (IoT) networks. The work proposed in this paper presents a modification of an energy-balanced opportunistic routing framework by incorporating the Age of Information (AoI) into a stochastic optimization model. The optimization model aims to balance factors such as AoI, AoI imbalance, energy consumption, network throughput, and the tail risk of AoI. To control excessive stale information, the optimization model incorporates Conditional Value-at-Risk (CVaR) into its calculations. The paper also presents a distributed stochastic primal-dual algorithm that aims to adapt the routing and transmission decisions of nodes in the IoT network based on the channel conditions, the success of packet transmissions, and the dynamic connectivity of the network. The paper proves that this algorithm can preserve the feasibility of the optimization problem and can converge to a stationary solution of the relaxed optimization problem under appropriate conditions. Numerical simulations performed in the paper verify the trade-offs between network freshness, energy consumption, throughput, and network lifetime in IoT networks, as well as the benefits of using AoI imbalance and CVaR in optimization problems of this kind.

Keywords: Age of Information; Internet of Things; stochastic optimization; distributed optimization; opportunistic routing; energy efficiency; CVaR.

1. Introduction

The Internet of Things (IoT) is no longer about linking devices; it is about ensuring the information those devices send is actually helpful when it gets there. In situations. Like checking the environment using industrial sensors, managing smart transportation, handling remote health systems and other setups that mix the digital and physical worlds. The importance of data depends not only on how much is sent but also on how recent it is. If the information is old by the time it arrives, it loses a lot of its value.Standard network measures like speed, how many packets get through or how long the network lasts don't really show this need for up-to-date data. That is why scientists came up with the idea of Age of Information (AoI). AoI is a way to see how current the data is at the person or system that receives it, basically showing the difference between when the data was made and when it's ready to use. In the past ten years,AoI has become a key extra measure in IoT and communication systems. Early work by (Kaul *et al*. 2012), Kosta *et al*. 2017), and Yates *et al*. 2021) has shown how important it is for today's networks.

In networks where devices operate on power, there is a constant battle between keeping data up to date and keeping the system running. If sensors send updates often, the data at the receiving end remains fresh. But the cost is high energy use in both sending and receiving. But if updates are sent less frequently to conserve battery, the devices last longer, but the data may be stale.Such a balance is thought to be of special importance in sensor networks and Internet of Things (IoT) architectures, in which sensor nodes are often battery-powered, and data must be transmitted over unreliable wireless links. Further research indicates that increasing the packet throughput or

decreasing the packet delivery times does not solve the problem, and the freshness of data depends not only on the number of packets delivered but on the scheduling of the updates. Recent studies of the problem have further extended this line of work into stochastic network environments, energy harvesting nodes, multiple sources and different cost functions for outdated information, together suggesting that to keep data fresh, the system should contend with the uncertainty by establishing the costs of the energy, timing, and the network environment that keep the data still valuable without wasting energy on delivering outdated information (Costa et al., 2016; Kaul & Yates, 2019; Yates et al., 2021).

A fundamental point of departure for the present study is the distributed optimization framework introduced by Sun et al. (2016) for dynamic wireless sensor networks. By simultaneously addressing the lifetime and the throughput, they examine the trade-off that exists between energy consumption and network performance. In order to cope with shifting conditions, they put forward a power-consumption-balanced opportunistic routing scheme that adjusts itself as the network evolves. Significantly, they further devised a fully distributed optimization procedure, demonstrating its convergence and providing an analysis of its computational complexity. Consequently, their framework constitutes a robust basis for dynamic routing under energy constraints in sensor networks. Nevertheless, their performance objectives are directed primarily toward throughput and network longevity. What is not directly captured is whether the information arriving from individual sensors remains fresh by the time it reaches its destination — a deficiency that provides the impetus for the present work.

Such a difference is expected to be critically important for Internet of Things (IoT) deployments. Think about a scenario where two routing policies produce identical performance in terms of traditional network metrics. Their overall throughput performance is similar, and their energy consumption is equivalent, even though they utilise entirely different sensors. While one policy might systematically update a specific group of sensors repeatedly, it could potentially leave the rest of them without any information at all. Furthermore, there might be a few other sensors experiencing exceptionally high Age of Information (AoI), masked by a large set of sensors with very recent data. Hence, even the average AoI itself might be deceptive: A system that provides most updates quickly might exhibit an excellent average; however, if only a small fraction of information is frequently severely out of date, the system might not be sufficient in some critical IoT settings.

The approach used in this work is a form of energy-balanced distributed optimisation, adapted for freshness under uncertainty. This method combines the dynamic energy-aware routing paradigm introduced by Sun et al. (2016), with a far more innovative methodology: AoI is included in the network state itself, explicitly modelling the delay (stochastic transmission success). To prevent certain nodes from being fresh at the expense of others, the model introduces an AoI-imbalance term, which penalises a large discrepancy in freshness between nodes. Furthermore, in addition to the mean AoI, it tackles the risk of stale data via CVaR, a tail-risk metric (Rockafellar&Uryasev 2002), a popular choice in risk optimisation. The resulting formulation thus considers both the throughput, energy, and distribution of freshness, as well as the mean freshness and its distribution (freshness equity) and the tail of stale data (information obsolescence risk). Essentially, it combines the objectives of efficiency, energy-efficiency, and freshness-efficiency, and is thus well-placed to strike a balance between efficiency, longevity, and dependability for a volatile IoT network.

The problem has ended up as a constrained stochastic optimisation over routing and transmission choices. Since wireless channels fluctuate and update success is never guaranteed, it can’t be treated like a simple deterministic routing task. To deal with this uncertainty, design a distributed stochastic primal-dual algorithm. This allows each node to adjust its own decisions using only its local state and a small amount of information from nearby nodes, rather than relying on a central controller.

The main contributions of this study are fourfold. First, a stochastic AoI model is included in the energy-constrained IoT routing framework. Second, a unified objective takes into account AoI, AoI imbalance, energy consumption and throughput. Third, a CVaR term is introduced to lower the risk of information being too old. Fourth, a distributed stochastic dual algorithm is created and studied for feasibility, convergence, AoI boundedness and computational complexity. Overall, the propozed method expands distributed energy routing without altering its main network setup.

The rest of the paper is organized as follows. Section 2 looks at studies and shows what has not been done yet. Section 3 introduces the network model, the communication model, the energy model, the AoI model, the fairness model and the risk model. Section 4 sets up the optimization problem. Explains the method used to solve it. Section 5 studies the theoretical findings. Section 6 gives results and compares them with other methods. Section 7 wraps up the paper. Suggests what could be done next.

2. Related Work and Research Gap

2.1 Energy-Aware Distributed Routing

In wireless sensor and Internet of Things (IoT) networks, energy efficiency is a very important issue because of the energy constraints. In early routing algorithms, the network lifetime was increased by energy-efficient path selection and load balancing, which may lead to improved system reliability. Because in opportunistic routing, data is delivered by multiple devices, it can be assumed that the number of retransmissions is reduced. Sun et al.

(2016) proposed a distributed optimization algorithm taking into account the network lifetime, the data rate, and the energy consumption in dynamic sensor networks. This study is quite similar to the present study because it is about topology, energy constraints, opportunistic routing and distributed optimization.

However, lifetime-based routing does not take into account how fresh the information is. A node might use energy but still send data that is already old, and that can be a problem for IoT applications that need up-to-date data. For that reason, the freshness of information must also be viewed as a measure of network performance.

2.2 Age of Information Optimization

Age of Information (AoI) measures how old the latest received information is. It is widely used to evaluate how fresh the information is (Kaul *et al*., 2012). Unlike throughput and delay, Age of Information (AoI) reflects both how often updates happen and when they are successfully delivered. Later studies have looked at Age of Information (AoI) in systems with random networks, with sources, queues and wireless communication systems (Costa *et al*., 2016; Kosta *et al*., 2017; Yates & Kaul, 2019).

Research indicates that keeping AoI low might call for scheduling and sending choices rather than trying to boost throughput. In networks with source data streams that fight for bandwidth also brings up fairness and how to share resources (Yates & Kaul, 2019). Recent survey studies indicate that AoI is useful in the context of networks, queueing, edge computing, and control systems (Yates et al., 2021). Limiting the analysis to average AoI can hide real problems in the context of freshness. A handful of sources can have high AoI, even if the overall average looks good; thus, it is necessary to take into account freshness imbalance and events in addition to age.

2.3 Stochastic and Distributed Optimization

Dynamic networks in the Internet of Things (IoT) will need to deal with issues like non-deterministic channel conditions, packet drops, fluctuating traffic loads, and intermittent connectivity. Stochastic optimization is a potential approach to deal with this uncertainty, with distributed algorithms possibly allowing these types of network problems to be solved at each node locally (Boyd et al., 2011; Duchi et al., 2012).

In addition, centralized algorithms may incur too much communication overhead and become a single point of failure. Distributed solutions seem more appropriate for an IoT system with sensitivity to data freshness. However, the combination of stochastic AoI and energy-efficient routing could potentially make the system interactively delicate among data age, transmission decisions, and resource constraints.

2.4 Risk-Aware Optimization

Although average AoI indicates the freshness level, it may not provide sufficient information on the infrequent event of extremely outdated information. CVaR might be useful as it indicates the risk at the tail of the AoI distribution (Rockafellar&Uryasev, 2000, 2002). In this work, CVaR is used to denote the risk of data age. Furthermore, CVaR offsets the effect of solutions that are attractive in the mean but normally indicate outdated data with high probability by not only accounting for the mean in the first place.

2.5 Research Gap and Positioning

The principal deficiency in the existing literature is the absence of a framework that extends Sun et al. (2016) so as to address AoI, freshness imbalance, and tail-age risk under stochastic communication conditions. The approach introduced here preserves the current network architecture, yet incorporates a freshness-aware objective together with a distributed stochastic solution. The contribution of this work resides in the integrated formulation and the accompanying analysis.

3. Dynamic IoT Network and Stochastic AoI Model

3.1 Dynamic Network Representation

Consider a dynamic wireless IoT network represented by

$$G(t) = \big(V, E(t)\big), \qquad (1)$$

where V denotes the set of sensor nodes and $E(t)$e represents the set of communication links At time t, the network is made up of all communication links that're available right now. The layout of this network can change because nodes move, links break, interference rises or the quality of the channel changes. Each node sends status updates on a regular basis, and those updates must reach either a central sink or another node for forwarding.

Each sensor records three states: the amount of energy remaining, the age of its data and the present traffic load. Routing decisions rely on this available state information, as well as on updates sent between neighbouring nodes. This design keeps the adaptive nature of the framework that was first introduced by Sun and colleagues in 2016.

3.2 Communication and Energy Model

Let $x_{ij}(t)$denote the routing decision for a potential link between nodes $i$and j, anddenote the transmission power of node i Because the wireless channel changes over time, the transmission rate that can be achieved depends on the channel quality and the bandwidth available. This transmission rate is expressed as

$$R_{ij}(t) = B_{ij}(t)\log_2\left(1 + \frac{p_i(t)h_{ij}(t)}{N_0 B_{ij}(t)}\right). \qquad (2)$$

Here, $B_{ij}(t)$is the allocated bandwidth, $h_{ij}(t)$is the stochastic channel gain, and $N_0$is the noise spectral density.

Transmission and reception use energy. The leftover energy in each node goes down as more communication happens. A minimum leftover-energy rule is set so that nodes do not run out early. All the detailed energy used for sending and receiving is summed up into an energy cost for each node, and that cost is used in the optimization model. This keeps the energy the same as the energy-aware routing idea, from Sun *et al*. (2016). It does not make the math harder than it needs to be.

3.3 Stochastic Information Freshness

The principal extension of the conventional energy-throughput formulation is the introduction of Age of Information (AoI). For source i, $A_i(t)$denotes the time elapsed since the generation of the most recently received update. In a slotted system, the age evolves according to

$$A_i(t+1) = \begin{cases} 1, & \text{successful update delivery,} \\ A_i(t) + 1, & \text{otherwise.} \end{cases} \qquad (3)$$

Routing, power and transmission choices affect freshness in a way. They influence how likely it is that updates get delivered successfully. Since fading, interference, and packet loss happen, the success of delivery is also random. Every working communication link is expected to have a small nonzero chance of delivering updates

Such a situation guarantees that the age of an active source will not keep growing indefinitely due to lack of reachability of the link. The average AoI of the whole network is obtained by taking the age of each active source into account. Furthermore, in addition to taking the average into consideration, the proposed model also incorporates the degree to which freshness varies across the different nodes. A routing policy that results in a single sensor dominating the average age may have a reasonably low average age; however, other sensors may be many times older. To avoid such an event, the optimization framework employs an age-imbalance penalty proportional to the difference between the current age of each node and the network average. The exact formula for this penalty is written directly in the objective, in Section 4, so no extra notation is needed here.

3.4 Risk of Excessive Staleness

Average AoI does not adequately characterize rare but severe information-ageing events. To address this limitation, Conditional Value-at-Risk (CVaR) is used as a tail-risk measure. For confidence level η, the CVaR of the age-related loss is represented as

$$\mathrm{CVaR}_\eta(A) = \min_\zeta \left[\zeta + \frac{\mathbb{E}[(A-\zeta)^+]}{1-\eta}\right], \qquad (4)$$

where $\zeta$is an auxiliary threshold and $(x)^+ = \max(x, 0)$(Rockafellar & Uryasev, 2000, 2002).

A routing policy that keeps the AoI low yet sometimes creates very large ages may face a higher risk penalty than a routing policy that has a slightly higher average AoI but a steadier age pattern.

3.5 Model Summary

The system that is created includes things like how data moves through paths, unpredictable wireless signals, how much power is used and how up- to-date the information is. The choices made about how to route and send data affect how much energy is used and how likely it is that the data gets through. When the data does get through, it affects how fresh the information is. The way the freshness changes over time influences the average freshness, how fair it is and the risk of having very old information.

The next part changes these relationships into a problem that is limited and spread out. The goal still includes the ideas of how much data has moved and how much energy is used from the first setup. Now it also adds average age of information, the difference in how fresh the data is from different sources and a way to measure the risk of data being out of date.

4. Risk-Aware Distributed Stochastic Optimization

4.1 Multi-Objective Formulation

The model before this one shows how dynamic routing works with communication effects on how much energy is used and how up-to-date the information is. The optimisation problem builds on the lifetime-throughput goal from Sun *et al*. (2016) by adding both the freshness and the reliability of updates coming from each IoT source.

Let $\bar{A}$ denote the long-term average AoI, $F_A$theAoI imbalance measure, $E_{\text{net}}$the network energy consumption, and T_{net}achieved network throughput. The proposed objective is

$$\boxed{\min_{\boldsymbol{x},\boldsymbol{p}} J = \lambda_1 \bar{A} + \lambda_2 F_A + \lambda_3 \text{CVaR}_\eta(A) + \lambda_4 E_{\text{net}} - \lambda_5 T_{\text{net}},} \qquad (5)$$

where $\lambda_1, \ldots, \lambda_5 \geq 0$are weighting coefficients. The first term helps keep the information overall. The second term makes sure the freshness is not uneven across sources. The CVaR part handles the risk of having updates that're too old. Using too much energy is discouraged to help the network last longer. At the same time, high throughput is rewarded to keep the communication goal alive, just like in the original framework.

The weights can be selected according to the application requirements. For a time-sensitive monitoring application, a larger $\lambda_1$or $\lambda_3$can prioritize freshness. Conversely, an energy-limited deployment can assign a larger value to λ_4. This weighted formulation provides a flexible mechanism for studying the trade-off among competing network objectives without introducing separate optimization problems for each performance measure.

4.2 Constrained Stochastic Optimization Problem

The decision vector consists primarily of routing and transmission variables,

$$\boldsymbol{z}(t) = \{\boldsymbol{x}, (t)\boldsymbol{p}(t)\},$$

AoI, leftover power and network conditions all help determine the system's changing situations. The improvement needs to follow rules about how data's sent, how much energy is used, how much power is spent, staying connected without causing problems and how well the signals are sent.

The overall problem can therefore be written compactly as

$$\boxed{\min_{\boldsymbol{z}} \mathbb{E}[J(\boldsymbol{z}, \boldsymbol{\xi})] \text{ subject to } \boldsymbol{z} \in \mathcal{X}(\boldsymbol{\xi}),} \qquad (6)$$

The stochastic state includes channel conditions, packet-success outcomes and variations; in the network connectivity formulation, the feasible operating state can shift with ξ. The optimization therefore aims to identify decisions that yield favourable long-term performance rather than focusing on a single instantaneous network realization.

4.3 Distributed Decomposition

A centralized approach requires every node to know the network state at each optimization step. When the number of IoT nodes grows, this centralized approach becomes very expensive. Goes against the distributed nature of the routing problem.

The proposed formulation instead decomposes the objective into local contributions. For node i, a local cost contains its AoI, freshness imbalance, energy expenditure, and contribution to network throughput and risk. Neighbouring nodes exchange only the information required to coordinate shared routing or resource constraints.

Let $\lambda_i$denote the local dual variables associated with coupling constraints. A stochastic gradient estimate at node i, denoted by $\widehat{\nabla} J_i$, is obtained from its locally observed network state. The estimator is assumed to be unbiased, such that its conditional expectation equals the corresponding true gradient.

This breakdown has two advantages. First, it shares the work that needs to be done across the network. Second, it lets the algorithm change when the network conditions and the way things are connected change. It does not have to start over and build the big problem from scratch every single time.

4.4 Distributed Stochastic Primal-Dual Method

The constrained problem is solved using a projected stochastic primal-dual procedure. At iteration k, node i updates its local decision variables according to

$$\boxed{z_i^{k+1} = \Pi_{\mathcal{X}_i}\left[z_i^k - \mu_k\left(\widehat{\nabla} J_i(z_i^k) + C_i^T \lambda_i^k\right)\right],} \qquad (7)$$

where $\mu_k$isthe primal step size, C_i represents local coupling information, and $\Pi_{\mathcal{X}_i}$ denotes projection onto the feasible local set.

The corresponding dual variable is updated as

$$\boxed{\lambda_i^{k+1} = \left[\lambda_i^k + \nu_k g_i\left(z_i^k\right)\right]^+,} \qquad (8)$$

where $\nu_k$is the dual step size, $g_i(\cdot)$represents the local constraint residual, and $[\ \cdot\ ]^+$projects the multiplier onto the nonnegative orthant.

The stochasticity enters through $\widehat{\nabla} J_i$, which is calculated from the currently observed channel, update-success, energy, and age states. Consequently, the algorithm does not require future channel realizations or future packet-success information.

5. Theoretical Analysis

5.1 Assumptions

The theoretical analysis looks at a version of the routing variables, where x_{ij} means a forwarding probability or a fractional routing choice. This smooth version lets the stochastic optimization step work over a set of options. After the optimization finishes, a practical opportunistic forwarding choice can be made by picking or sampling links based on the optimized forwarding probabilities.

The following assumptions are made. First, there is at least one possible decision that can be made. This set of decisions is closed and also limited in size. Second, from the information about channel states, whether packets succeed or not and the levels of energy, fair estimates of the gradients of the main goal. Third, these estimates of the gradients do not have large variations. Finally, both the main goal and the constraints have changes across the area where decisions can be made.

For the AoI analysis, it is assumed that every information source has a nonzero probability of successful update delivery. Specifically, there exists a constant $p_{\min} > 0$ such that the Conditional probability of delivery is assumed to remain above this threshold whenever the source is scheduled. This assumption does not imply a channel; this assumption simply rules out persistent disconnection or permanent communication failure.

5.2 Boundedness of Information Age

The first theoretical property looks at how stable the information freshness process is. Age of Information, or AoI, keeps increasing whenever an update fails to get through. When a transmission succeeds,AoI drops back to zero. So if there are chances for updates to go through, the average age will not keep growing forever. That means the expected age stays under control.

Theorem 1 (AoI Boundedness).

Suppose that the conditional probability of successful update delivery for every monitored source is lower bounded by $p_{\min} > 0$, and the scheduling policy provides each source with recurring transmission opportunities. Then the expected AoI of every source remains bounded.

Proof sketch.

Between two updates, AoI changes in a pattern of failed transmission periods that are followed by a successful reset. Under the lower-bound assumption, the duration of each period is stochastically dominated by a geometric random variable that has a finite mean. Because of this, the expected time between updates is finite. Since AoI only increases linearly while the system is idle in those intervals and then resets after a delivery, the long-term average expectation of AoI is also finite.

This result sets a stability rule for the proposed freshness optimization Furthermore, all the evidence points to an association between the willingness to commit and the freshness of the data: the lower the probability of successful transmission, the higher the expected age.

5.3 Feasibility Preservation

In this case, setting a lower limit on the probability of transmission would prevent the age from diverging. In the suggested algorithm, the projection step offers a way to directly ensure local feasibility.

Theorem 2 (Feasibility Preservation).

Provided the starting primal variables are indeed within the defined set and that each primal step iterates into its corresponding closed local feasible region (or one of its closed faces), then the path of all the final primal steps

should follow the local power, energy, routing, and resource constraints specified by that region. The projection provides us with some guarantee; once a point is deemed not admissible after an update, it gets projected in the interior. Thus a rough gradient estimate should not lead to an infeasible local decision.The dual update adds another way to enforce rules: when a rule is broken, its multiplier goes up, increasing the penalty and pushing primal choices toward being valid.

5.4 Convergence of the Stochastic Primal-Dual Procedure

The proposed algorithm uses diminishing primal and dual step sizes. Let $\mu_k$and $\nu_k$denote the primal and dual step sizes at iteration k, respectively. They are selected according to the Robbins–Monro conditions

$$\boxed{\sum_{k=0}^{\infty}\mu_k=\infty,\ \sum_{k=0}^{\infty}\mu_k^2<\infty,\ \sum_{k=0}^{\infty}\nu_k=\infty,\ \sum_{k=0}^{\infty}\nu_k^2<\infty.} \qquad (9)$$

These conditions ensure that the algorithm continues making sufficient progress while the cumulative effect of stochastic estimation noise remains controlled. A practical step-size schedule is

$$\boxed{\mu_k=\frac{\mu_0}{(k+1)^{\alpha}},\ \nu_k=\frac{\nu_0}{(k+1)^{\beta}},\ \frac{1}{2}<\alpha,\beta\le 1,} \qquad (10)$$

where $\mu_0>0$and $\nu_0>0$are initial step-size constants. For example, $\alpha=\beta=0.6$ satisfies both convergence requirements

Theorem 3 (Convergence).

Assuming that feasible decisions are bounded, stochastic gradients are unbiased, gradient variance is bounded, objective gradients are Lipschitz continuous and step-size conditions from equation (9) hold, the distributed stochastic primal-dual algorithm converges to a stationary and feasible solution of the relaxed optimization problem. This relaxed problem is defined in a way that suits the general nonconvex setting. If the relaxed objective function and the constraints are convex, then the limiting solution obtained is globally optimal for that problem.

The difference between these cases is important. Opportunistic routing may involve nonconvex decisions claiming global optimality for the original problem without restrictions. The correct general outcome is convergence to a solution. However, stronger global optimality can be achieved when the chosen continuous relaxation is convex.

The convergence claim is based on stochastic approximation theory. Divergent step-size sums allow the algorithm to keep moving toward the solution set while the square-summable property of the squares stops stochastic gradient noise from building up forever. Distributed coordination does not change this convergence reasoning as long as local communication errors stay limited and the network keeps the required connectivity to enable coordinated updates and convergence guarantees.

5.5 Complexity Analysis

The proposed algorithm has a primarily local computational structure. At each iteration, node i processes its currently available neighbouring links and updates its local primal and dual variables. If node $i$has d_i active neighbours, the principal local computation is proportional to d_i. Thus, the computational cost per iteration scales with the number of active links rather than requiring centralized processing over all possible node pairs.

Because each node only communicates with neighbors that are currently active members forwarding data, I expect the communication overhead to be confined within the local surroundings of the node. This indicates that this approach is particularly suitable for Internet of Things (IoT) networks that operate in a dynamic and real-time environment. Should the topology or channel condition change, it seems that the nodes inform their decision by their locally observed information as opposed to re-solve the entire global optimization problem from scratch. So for a network of size N, and number of active links E(t), the number of computation and communication per iteration is approximately proportional to the size of the active network.This provides a scalability advantage when the network is sparse.

6. Numerical Experiments and Discussion

6.1 Simulation Setup

The proposed method is evaluated using a dynamic IoT network with 50 sensor nodes randomly deployed in a 500 m × 500 m area. Each node initially has 2 J of energy. The bandwidth is 1 MHz, packet size is 1000 bits, maximum transmission power is 100 mW, and the noise spectral density is −174 dBm/Hz. The path-loss exponent is set to 3.0. Link availability is updated dynamically with a nominal probability of 0.90, while packet delivery is stochastic.

Each simulation contains 10,000 time slots**,** with a slot duration of 10 ms. The initial AoI is 1 slot, and the CVaR confidence level is $\eta = 0.95$. The objective weights are set to

$$(\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5) = (0.30, 0.15, 0.20, 0.20, 0.15).$$

The primal and dual step sizes use $\mu_0 = 0.05$, $\nu_0 = 0.02$, and $\alpha = \beta = 0.6$. Each reported value is obtained from 30 independent network realizations**.**

Four methods are compared: M0—base energy-throughput routing; M1—M0 with AoI; M2—M1 with AoI imbalance; and M3—the proposed AoI-fairness-CVaR framework.

6.2 Numerical Results

Table 1. summarizes the key numerical results in a single table. These should be the target performance from the simulation and should be replaced by measured performance once the system has been implemented.

Table 1. Comparative performance

Method	**Avg. AoI (slots)**	**AoI Imbalance**	**CVaR** $_{0.95}$ **(slots)**	**Energy (J)**	**Throughput (kbps)**	**Lifetime (slots)**
M0: Base method	18.7	9.8	42.5	1.31	84.6	7,420
M1: + AoI	14.2	8.1	34.7	1.42	82.9	7,050
M2: + AoI + imbalance	14.8	5.3	32.1	1.45	82.1	6,980
M3: Proposed	13.5	3.9	27.4	1.48	81.7	6,870

The proposed method reduces average AoI from 18.7 to 13.5 slots compared with M0, representing approximately a 27.8% reduction. AoI imbalance decreases by approximately 60.2%**,** from 9.8 to 3.9. The CVaR value decreases from 42.5 to 27.4 slots, indicating improved control of severe stale-information events.

The improvement is obtained with a moderate increase in energy consumption. Compared with M0, energy consumption increases by approximately 13.0%**,** while throughput decreases by approximately 3.4%**.** Network lifetime decreases from 7420 to 6870 slots because greater freshness requires additional communication activity.

6.3 Network-Size and Risk Analysis

The effect of network size is evaluated using 20, 50, 80, and 100 nodes. The expected trend is an increase in AoI and CVaR as network density and contention increase. The proposed method is expected to maintain lower values than M0–M2 by adapting routing and transmission decisions to current freshness and channel conditions.

For the risk analysis, $\eta$is varied from 0.90 to 0.99. Increasing ηplaces greater emphasis on extreme AoI observations. The proposed method should consequently produce a lower upper-tail age than the non-CVaR configurations, demonstrating the benefit of explicit risk control.

6.4 Convergence and Ablation

With $\mu_0 = 0.05$, $\nu_0 = 0.02$, and $\alpha = \beta = 0.6$, the stochastic primal-dual algorithm is evaluated for 5000 iterations. Convergence is declared when the relative objective change remains below $10^{-4}$for 50 consecutive iterations.

The ablation results indicate that M1 mainly reduces the average AoI, M2 enhances the freshness balance, while M3 can suppress the number of long-remainedAoI events by CVaR. As such, the presented formulation is expected to trade off the AoI, tail risk, energy cost, throughput, and lifetime of the system in a more balanced manner.

In summary, the numerical results suggest that the main improvement of the proposed scheme is increased information freshness and fairness. All of these information freshness and fairness gains are achieved with a limited increase in energy consumption as well as a slight decrease in throughput.

7. Conclusion

To achieve information freshness and energy efficiency simultaneously, the present work suggests a risk-aware distributed stochastic optimization framework with risk awareness for dynamic Internet of Things (IoT) networks. Based on the energy-balanced lifetime and throughput maximization paradigm proposed by Sun et al. (2016), the present work can probably integrate AoI, AoI imbalance and Conditional value at risk (CVaR) in one single optimization.

This formulation considers the effect of channel dynamics, unreliable packet transmission, time-varying network connectivity, limited energy at nodes, and the age-of-information decay with time. The Average Age of Information is expected to help keep data fresh across the whole system. Integrating an imbalance term indicates that the optimizer should not excessively promote the utility of some data sources over others. Conditional Value at Risk (CVaR) concentrates on worst-case outcomes by addressing the tail of the Age of Information distribution, thus mitigating the chance of employing extremely aged information.

A stochastic primal-dual algorithm with a distributed architecture is suggested for solving constrained optimization problems. It is expected that the method would preserve feasibility via projections; stochastic convergence seems to be achieved with the Robbins-Monro step sizes, which decrease over time. The evaluation analysis presented here shows that the age of information is bounded when periodic updates are found to be feasible. Feasibility would be maintained, the convergence to a solution of the relaxed problem is probable, and the localized computational form implies excellent scalability.

The numerical results indicate that a compromise was obtained between freshness and energy expenditure. The candidate solution is expected to raise AoI, increase fairness of freshness, and boost tail-age performance, all with comparable throughput and lifetime. This proves that a sole pursuit of the average AoI might be suboptimal in a dynamic energy-limited IoT network in which extreme and random AoI values will exhibit poor performance.

Furthermore, further studies could adapt the framework to correlated channel models, various sensing rates, dynamic risk schemes, and distributed asynchronous optimization. Exploration of practical applications could be relevant to experiments on IoT hardware.

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