Towards Optimized Connectivity in Health Internet of Things Device-to-Device Networks

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Abstract*— The Health Internet of Things (HIoT) enables Device-to-Device (D2D) communication among heterogeneous medical devices. However, optimal D2D connectivity is challenging due to traffic demand, the inherent environmental and device constraints. Prior works have characterized HIoT networks with single objective optimization models and either simplify or ignore device and environmental constraints, thus yielding poor scalability and limited practical value. Thus, this paper casts optimal HIoT D2D connectivity as a stochastic Multi-Objective, Mixed-Function and Mixed-Constraint (MO-MF-MC) problem. An analysis of why the HIoT D2D network is fundamentally stochastic is presented. In addition, the paper presents and formalizes two views to model optimal D2D connectivity. These are the Constraint Based (CB) and the Pareto Optimal Vector (POV) perspectives. The paper supports POV as most suitable. The contributions of this paper are: (1) an analysis of the challenges of modeling optimal HIoT D2D connectivity (2) the formulation of the stochastic D2D optimal connectivity from CB and POV perspectives, (3) justification of POV modeling for optimal D2D connectivity in HIoT. This work establishes the need for the design of lightweight, scalable, and adaptive protocols for sustainable, reliable real-time and optimal connectivity in HIoT D2D networks.

Keywords- Constraint based; Device-to-Device; Health Internet of Things; Optimization; Pareto vector.

I. INTRODUCTION

The Health Internet of Things (HIoT) connects medical sensors, wearables, clinical instruments and infrastructure for real-time patient diagnosis, treatment, and monitoring. A key enabler of the HIoT ecosystem is Device-to-Device (D2D) networks, which facilitate direct data transfer between devices, thereby reducing dependency on centralized infrastructure [1][2]. In healthcare scenarios, this is crucial because timely and reliable data transmission are essential for clinical decisions and emergency response. Thus, low latency, loss and jitter along with high data rate are required Quality of Service (QoS) [2][3]. However, HIoT D2D networks face unique challenges due to constraints imposed by their operational environment, the type of devices and traffic they support. Typically, these networks operate in Not-For-Wire (NFW) environments, which refer to any domain where wired connections are either infeasible, impractical, or undesirable. In such domains, devices exchange data by leveraging the wireless medium, which is shared, inherently unstable, and resource constrained. It is also characterized with limited bandwidth and data transmissions are prone to interference and high path loss. These conditions degrade and affect the network's performance to guarantee optimal connectivity essential for reliable communication within healthcare systems. Additionally, HIoT D2D devices are unconventional, miniature, and constrained in resources, such as computational power, memory, and battery life [4][5]. Traffic is diverse, ranging from data generated by patient monitoring, mission-critical and real-time operations to emergency alerts. These traffic streams require differentiated treatment and stringent QoS guarantees. However, the constraint imposed by devices, the unpredictability of the NFW environment coupled with the unique traffic types, introduces unpredictable conditions that cause stochastic connectivity and thus makes it difficult to guarantee QoS.

In HIoT D2D networks, connectivity implies that QoS demands by active traffic flows are simultaneously satisfied. QoS metrics include latency, jitter, throughput, and packet loss. The basic expression for connectivity is given by equation (1)

$$Connectivity \Leftrightarrow \forall i,\ f_i(x) \leq b_i \qquad (1)$$

where

- i: index over all QoS metrics
- $f_i(x)$: objective function of QoS metric i.
- b_i: the bound value for QoS metric i

Equation (1) states that connectivity is achieved, if and only if (iff), all QoS metrics indexed by i satisfy their respective bound (threshold). $f_i(x)$ represents the QoS performance under a given network configuration x, while b_i denotes the required bound that must be satisfied for each metric. For example, in a healthcare scenario, latency measured using $f_{latency}(x)$ must not exceed its critical bound $b_{latency}$ and similarly, packet loss must remain below its acceptable threshold. Quantifier ∀i ensures that QoS demand is simultaneously satisfied.

Consequently, sustaining QoS in HIoT D2D network requires protocols that utilize Multi-Objective, Mixed-function, Mixed-constraint (MO-MF-MC) optimization approach. The approach ensures that trade-offs between conflicting goals are carefully balanced. However, there is a lack of such protocols because most networking protocols were not designed to handle the multi-layer dynamics of QoS objectives, device constraints and uncertainty that exists in the NFW environments [6].

These dynamics highlight the importance of treating optimal D2D connectivity in HIoT as a stochastic MO-MF-MC problem. It is also desirable to have protocols that facilitate optimal D2D connectivity. To address these gaps, this paper focuses on:

"How optimal connectivity can be achieved despite the tradeoff that exists in meeting conflicting and stringent QoS demands of mission-critical traffic traversing the constrained HIoT D2D network operating under stochastic conditions"

The contributions of this paper are: 1) analysis of the inherent challenges for optimal connectivity and the limitations of single-objective optimization models in HIoT D2D networks 2) formulation of optimal connectivity with a stochastic MO-MF-MC model under the Constraint Based (CB) and Pareto Optimal Vector (POV) perspectives. 3) justification of POV as the perspective that best captures the realistic trade-offs among QoS metrics subject to device and environment constraints. Moreover, one of the challenges for optimal connectivity identified and introduced in this paper, is the unique characteristic of HIoT D2D traffic flow, which has been termed "Mixed-criticality, Bound-assured, Mission-synchronous" (MC-BAMS). The term is explained in Section II. Lastly, the paper provides insight into a framework to be adopted in the design of next generation communication protocols for HIoT D2D networks. The future work that builds upon this paper includes a lightweight protocol that operationalizes the POV framework. The paper's content is as follows: Section II presents the challenges for optimal D2D connectivity in HIoT, Section III discusses optimization in HIoT, Section IV presents the optimal connectivity model and Section V concludes the paper.

II. Challenges for Optimal Connectivity

Within the HIoT D2D networks, three main challenges impose the need for tailored protocols to facilitate optimal connectivity. These are operational challenges, which affect QoS performance objectives and in turn impacts connectivity. They stem from environmental and device constraints, and heterogeneity of data traffic, which are discussed as follows.

A. Not-For-Wire (NFW) Environmental conditions

The operational domain of HIoT D2D networks is often a NFW setting where links are wireless. Conditions within such settings are inherently unpredictable due to co-located medical systems, patient movement and deteriorating signal strength. These conditions introduce interference and fluctuations that cause connectivity to be stochastic thus, making QoS guarantees difficult to sustain [3][7]. While deterministic connectivity models may suffice in stable networks, the instability of NFW environmental conditions favors stochastic modeling especially in healthcare systems where millisecond delays can impact outcomes [7][8]. An example of the NFW environment is smart Intensive Care Units (ICUs) where ventilators, infusion pumps, and monitors exchange critical data simultaneously over the shared wireless spectrum. The setting reduces cable clutter and improves safety but raises signal interference risk [8]. In homecare, data generated by wearable ECG patches and implantable glucose sensors is wirelessly sent to smartphones or clouds systems and thus allow patient mobility. However, these medical devices contend with home appliance operating in the same frequency bands and patient mobility can affect link quality [9]. Mobile emergency care further highlights the stochasticity in NFW environments. The ambulances stream vital signs en route, so low latency and negligible error rates are essential for pre-arrival interventions, yet handoffs and fading continually perturb the wireless links [7][10]. HIoT D2D networks need robust, adaptive mechanisms that handle environmental variability while preserving the performance of life-critical traffic. Therefore, optimization frameworks should explicitly model NFW uncertainty and guarantee QoS bounds [7][8][9].

B. Device Constraints

In D2D networks, devices are often miniature embedded systems designed with strict size for comfort and usability requirements. Smartwatches, biosensors, and implantable medical devices prioritize patient convenience and portability but at the cost of battery capacity, memory, and processing power [11]. Limited energy prevents prolonged high data rate thus making it challenging to guarantee continuous, low-latency transmission. Memory and computational limitations further restrict the use of conventional protocols, which often require data buffering, complex computations and large memory [4]. For instance, real-time ECG monitoring generates massive data streams, but devices often lack the capacity to buffer or preprocess data locally [12]. This constraint forces reliance on lightweight, efficient communication mechanisms tailored for low-resource devices. Additionally, battery longevity is a critical factor. Many implantable wearable devices must function for months or even years without replacement and frequent recharging is impractical. Battery power constraint impacts not just transmission occurrence rate but also the complexity of protocols that can be executed.

C. Traffic Characteristics

The data traffic in HIoT D2D networks is highly heterogeneous. It includes data generated by routine updates, monitoring devices and mission-critical alerts from pacemakers. Diversity means that different traffic streams require differentiated QoS guarantees. For healthcare traffic, timeliness is as crucial as accuracy [13]. Inherently, traffic is generated in real-time and delayed data may become irrelevant, thus reducing their utility for clinical decisions. For example, a physician monitoring a remote patient's heart rhythm requires data to be streamed in near real time. A delayed transmission of the same data will lose diagnostic value. However, while routine patient monitoring data can tolerate modest delays, mission-critical signals must be delivered with minimal latency and low jitter [13]. The diverse traffic requirements make prioritizing traffic during resource allocation difficult. High-priority emergency traffic must preempt less urgent transmissions without entirely starving background data streams, such as periodic wellness updates. Thus, the nature of traffic flow is such that they are "mixed-criticality, bound-assured, mission-synchronous" (MC-BAMS). MC-BAMS implies that "At any time, there exist diverse traffic flow with different criticality level and QoS bounds that must be simultaneously guaranteed and transmitted in a shared, unpredictable, and resource-constrained environment, where no traffic can be deferred". This traffic flow characteristic is unique to HIoT D2D networks. Consequently, designing scheduling and resource allocation protocols to facilitate fair differentiated service by supporting MC-BAMS traffic flows under device and environmental constraints remains a challenge.

D. Architectural Overview of HIoT D2D Networks

Figure 1 depicts a simplified architectural overview of the challenges for optimized connectivity in HIoT D2D networks. Typically, such networks integrate multiple types of medical and wearable devices that communicate directly without relying exclusively on centralized infrastructure. The devices include implantable sensors, wearable glucose monitors, smartwatches, infusion pumps, ventilators, and imaging systems. Each device is constrained by size, memory, computational capacity, and battery power, limiting its ability to process and transmit continuous high-volume traffic.

These limitations necessitate lightweight optimization strategies to maintain network reliability. The environment is depicted as a Not For Wire (NFW) medium, characterized by interference, unpredictability, mobility, and shared spectrum resources. Within this environment, different types of traffic coexist.

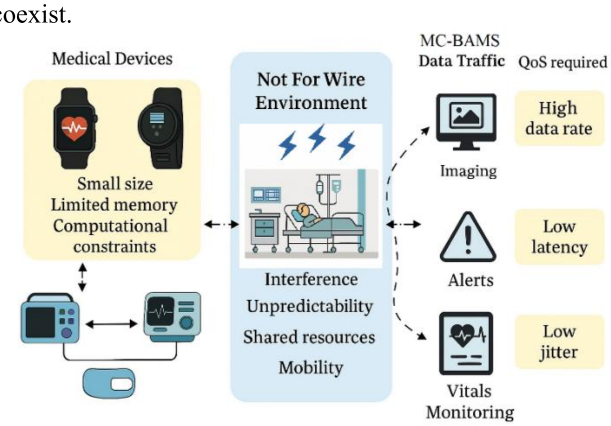

Figure 1. Architectural Challenges for Optimized Connectivity in HIoT D2D Networks.

Each traffic type has unique QoS requirements as outlined:

- Imaging data (high bandwidth, moderate latency tolerance).
- Alerts (ultra-low latency, mission-critical).
- Vitals monitoring (periodic updates, moderate QoS).

The figure illustrates how device limitations, volatile environments, and heterogeneous traffic demands combine to create optimization challenges for HIoT D2D networks.

E. Need for lightweight protocols

Commonly used standardized networking protocols were not designed for the highly unstable and constrained condition of the HIoT D2D network. Those protocols function with high signaling overhead, computational processes and memory resources, which cannot be supported by miniature medical devices. Moreover, most do not adapt to the NFW environments where connectivity is stochastic. Furthermore, these protocols do not implement mechanisms that can cater for the unique nature of MC-BAMS traffic flow in HIoT D2D. Thus, making them inadequate for mission-critical health applications where real-time medical signals require stringent QoS guarantees simultaneously. Due to these limitations, HIoT D2D networks require lightweight, adaptive protocols that will optimize and allocate resources fairly while meeting stringent QoS requirements of heterogeneous medical traffic. Such tailored protocols should be based on optimization models that will ensure that life-critical communications are reliably sustained under device, environmental and traffic requirement constraints.

III. Optimization in Health Internet of Things (HIoT)

In this section, a comparison of single and multi-objective optimization techniques for HIoT is presented. Existing approaches and gaps are also discussed.

A. Single objective vs. Mult objective Optimization

Single-objective optimization approaches focus on one metric at a time, for example, minimizing latency or maximizing data rate. They are simple, computationally less intensive and easier to interpret thus appear appealing for modeling constrained environments [14]. However, their weakness lies in oversimplification and the inability to combine multiple metrics' objectives simultaneously. For example, minimizing latency without regarding data rate forces very short traffic inter-arrival times and high scheduling frequency, which inflates protocol overhead and reduce effective data rate. Conversely, if data rate is maximized without regard for latency, large data aggregation, and buffering raise queueing delays (and jitter), thus impacting end-to-end latency.

In real-world HIoT D2D network applications, where performance dimensions are highly interdependent, single-objective approaches often fail to capture the true complexity of the problem. By contrast, multi-objective optimization models recognize trade-offs across multiple metrics [14][15]. These models enable the design of protocols that can generate sets of optimal solutions instead of committing to a single "winner." This is valuable in HIoT D2D networks, where objectives of guaranteeing multiple QoS demands such as minimizing latency, maximizing data rate and minimizing data error and loss are simultaneously critical.

While single-objective optimization provides clarity, it lacks realism for HIoT D2D applications. Multi-objective models, though more complex, provide the flexibility and adaptability needed to balance diverse, and often conflicting requirements exhibited by the MC-BAMS traffic flow in a NFW, device constrained healthcare-focused D2D networks.

B. *Optimization aproaches in IoT and HIoT*

Optimization in the IoT has been widely studied. Particularly, wireless sensor networks (WSNs) formed the basis of many early optimization frameworks. These networks highlighted the challenges of balancing multiple objectives such as data rate and latency. In [15] the authors provided comprehensive taxonomies of Multi-Objective Optimization (MOO) in WSNs. They examined both scalarization approaches (e.g., weighted sums) and evolutionary algorithms. Such methods laid the groundwork for extending optimization approaches into the more complex domain of HIoT.

In the HIoT context, optimization approaches have focused on areas such as task scheduling, device allocation, and network resource management. Nucci et al presented a bi-objective scheduling framework. It minimizes operational costs, maximizes quality of care simultaneously with non-dominated sorting genetic algorithm II (NSGA-II**)** heuristics. The framework takes into consideration device constraints such as compatibility, limited battery capacity, and setup overheads. This dual-focus design underscores the necessity of balancing operational efficiency with service quality in life-critical environments. Similarly [17] focused on multi-objective model for IoT application placement (MAPO) to address application placement by balancing latency, energy consumption, and operational costs. Such approach demonstrates particular relevance for medical applications, where offloading and distributed computing reduces stress on resource-constrained devices while still meeting stringent latency and reliability requirements.

More recently, adaptive strategies leveraging evolutionary and reinforcement learning have been introduced. Evolutionary Multi-Objective Optimization (EMO) techniques have shown promise in handling the scale and complexity of large HIoT deployments [18]. Furthermore, Multi-Objective Reinforcement Learning (MORL) has emerged as a dynamic solution, capable of learning adaptive trade-off policies under uncertain environments without relying on predefined training data [19]. Such methods are increasingly attractive for HIoT networks.

C. *Gaps: lack of real world conditions*

Despite advancements in optimization frameworks, existing models often fall short in their applicability in real-world HIoT scenarios. Many rely on idealized assumptions such as stable wireless channels, unconstrained processing power, and predictable traffic patterns. These assumptions do not reflect the stochastic nature of the NFW environment of HIoT D2D networks. Most models assume deterministic QoS guarantees by discounting the reality of fluctuating NFW settings and the constraints of miniature devices.

Scalability presents another significant challenge. While evolutionary algorithms are robust in generating optimal solutions, their computational complexity grows exponentially with the number of objectives or devices [18]. Consequently, this can create a bottleneck in large-scale deployments of real-time HIoT D2D applications, where instantaneous decision-making is critical. Optimizing all data traffic QoS demand across hundreds of devices simultaneously can exceed the practical computational capacity of even fog-enabled networks.

Moreover, most of the existing frameworks do not integrate dynamic, stochastic constraints into their models. Real-world HIoT D2D networks may be subject to fluctuating interference and unpredictable error rate, which leads to unstable connectivity for traffic flows with diverse criticality levels. Yet most optimization studies often treat constraints as static, ignoring temporal variations and unpredictability [17]. Finally, the lack of lightweight protocols derived from optimization insights remains a critical concern. Current optimization research tends to stop at theoretical modeling, without translating results into deployable protocols that resource-constrained devices can implement.

These gaps undermine the delivery of consistent QoS in real medical environments, where momentary lapses in connectivity can jeopardize patient safety. Addressing these gaps require developing scalable, adaptive, and lightweight MO-MF-MC frameworks that integrate stochastic constraints and translate directly into operational protocols suitable for HIoT D2D networks.

IV. OPTIMAL CONNECTIVITY MODEL

A. *Stochastic Nature of Connectivity*

Connectivity is achieved in HIoT D2D networks if and only if all QoS requirements are simultaneously satisfied. This reflects the mission-critical nature of such networks, where failing in one metric implies network failure. However, the stochastic nature of connectivity, due to the NFW environmental conditions, makes it challenging to satisfy simultaneous demands. As a result, QoS metrics cannot be taken on fixed values but rather be modeled as random variables with probability distributions [20]. For example, the probability of maintaining latency below a certain threshold may vary significantly depending on interference levels, which means deterministic guarantees are impossible. Instead, probabilistic QoS guarantees, e.g., $P(\text{latency} \leqslant \tau) \geqslant 0.95$ must be incorporated into optimization formulations to account for the stochastic nature of connectivity. However, the stochasticity also complicates optimization because even when devices operate under optimal configurations, performance guarantees may not be met due to environmental variations. For example, significant loss of data may occur due to unpredictable interference bursts, even if optimal QoS targets have been initially met. Hence, connectivity optimization frameworks must be designed to adapt dynamically to changing states while tolerating uncertainty. Stochasticity also arises from device mobility and human activity patterns. Wearable sensors and implantable devices attached to patients move unpredictably, thus making deterministic assumptions impractical. Moreover, the pattern of the MC-BAMS traffic flow validates the importance of accounting for stochasticity. Traffic flow competes for resources that must be shared fairly and optimally.

B. Network Objectives function (QoS Metrics)

The primary goal of HIoT D2D network is to ensure connectivity by guaranteeing QoS requirements of traffic flows generated for healthcare service delivery. Latency and jitter are among the most vital metrics. The transmission of ECG data during cardiac arrest must occur timely with strict bounds on delay variation. Data rate and data loss are equally important, as compromised arrival rate and integrity of medical data can lead to unintended consequences. Data rate becomes very critical when devices are streaming medical data in images and videos format. The network must balance the requirements from all traffic flows simultaneously without sacrificing any traffic demand. In summary, connectivity is achieved by simultaneously meeting multiple QoS objectives in HIoT D2D networks, which extend beyond conventional communication goals. Meeting these combined stringent performance metrics' objectives, which are imperative for timeliness and accuracy of healthcare services demands tailored frameworks.

C. Network Constraints (Device and Environmental)

While objectives define "what" should be achieved, constraints determine "how" or "if" such objectives are possible. In other words, in HIoT D2D networks, QoS metrics establish performance targets, however, they can only be achieved within the bounds of multiple layers of constraints. The first set of constraints are device-level constraints, which are due to the limitations of medical devices' hardware. These devices are miniature, and resource constrained. Limited operating power creates tension between sustaining QoS metrics and preserving device lifetime. Continuous and frequent high data rate transmissions can drain power. Furthermore, computational and memory limitations restrict the complexity of algorithms and the size of data buffers that can be deployed on these devices. Environmental constraints also influence performance. HIoT D2D networks function in NFW medical environments where unpredictable channel conditions, multipath fading and interference impact the stability of network connectivity. Therefore, these constraints must be appropriately modelled.

D. Formulation of Optimal Connectivity

To achieve optimal D2D connectivity, the conflicting goal is to minimize and maximize multiple objective functions simultaneously. Thus, the connectivity problem can be defined as a stochastic MO-MF-MC optimization problem. The objectives functions are the QoS performance metrics that capture the QoS goals, which are to minimize latency, jitter, loss and maximize data rate simultaneously. Constraints functions, which are either deterministic or stochastic, model the limitations imposed by devices and the NFW environmental factors. The stochastic MO-MF-MC problem that can be framed from two perspectives. These perspectives, which are discussed in this section are the Constraint Based (CB) and Pareto Optimal Vector (POV) perspectives. Note that in this paper, these perspectives are QoS-based or QoS-focused. The modeling for each of these perspectives involves six steps, which are the formulation of: 1) QoS metrics as objective functions, 2) QoS bounds, 3) one liner connectivity, 4) compact max connectivity, 5) connectivity indicator (for one liner and compact max form) and 6) the optimal connectivity. The notations used in the formulation, and their definitions are outlined in Table I.

TABLE I. FORMULATION NOTATIONS AND DEFINITIONS

NOTATION	DEFINITION
i	Index of a QoS metric
k	Total number of QoS metrics
x	Decision variable
b	QoS bounds
f(x)	Objective function
g(x)	Inequality constraint
h(x)	Equality constraint
$g_j(x,\omega)$ $h_t(x,\omega)$	Stochastic constraint, (device/environmental)
ω	Randomness/uncertainty
∂	Weight
β	set of all x that fulfills the QoS bounds for POV perspective
P	Probability of occurrence
α	Probabilistic threshold/reliability level
σ	POV directions. σ_i=+1: metric is minimized and -1: metric is maximized
1	Binary indicator

1) Constraint Based (CB) perspective

The CB perspectives for optimal connectivity, their formulation steps and how they are interrelated are presented in this subsection. CB perspective treats connectivity as a feasibility question on a strict binary bound or a chance bound.

The outcome for connectivity is either binary (feasible or not) or based on the chance of achieving a given probabilistic threshold. The former case is termed constraint-based binary (CBB) while the latter is constraint based stochastic (CBS). From CBB perspective, connectivity exists if the specified QoS targets are satisfied; otherwise, it does not. CBS states that connectivity exists when the QoS metric bounds are met with a probability.

Moreover, the binary outcome in CBB can be specified as being deterministic (CBB-D) or as stochastic (CBB-S). In CBB-D, QoS objective functions are set to be achieved in a deterministic "ideal" environmental condition in which there no uncertainty or randomness. The objective function takes the form f(x) in equation (2). In addition, with reference to equation (1), these functions may be constrained with equality or inequality and expressed as fi(x)=bi, fi(x)<bi or fi(x)>bi, if no randomness exists. Equations (2) – (7) express the formulation steps for CBB-D.

STEP 1: QoS metrics	$f_i(x), \quad i = 1 \ldots.. k$	(2)
STEP 2: QoS bounds	$f_i(x) \le b_i \quad i = 1 \ldots. k$ and $f_i(x) \ge b_i \quad i = 1 \ldots. k$	(3)
STEP 3: One liner Connectivity	$Connectivity \Leftrightarrow \forall i,\ f_i(x) \le b_i$	(4)
STEP 4: Compact max form	$Connectivity \Leftrightarrow \max (f_i(x) - b_i), \le 0$	(5)
STEP 5: Connectivity Indicator	*One liner:* $\Phi_{det}(x) = \mathbf{1}\{\forall i:\ f_i(x) \le b_i\} \in \{0,1\}$	(6a)
	Compact max form: $\Phi_{det}(x) = \mathbf{1}\left\{\forall i:\ \max_{i=1\ldots k} (f_i(x) - b_i), \le 0\right\} \in \{0,1\}$	(6b)
STEP 6: Optimal Connectivity	$Optimal\ Connectivity \Leftrightarrow \Phi_{det}(x) = 1$	(7)

The QoS objective functions in CBB-S are set with "realistic conditions", that reflects the existence of randomness within the network. The functions take the form f(x,ω), in equation (8) where ω indicates the uncertainty influencing the QoS objective. If randomness exists, the objective functions may also be constrained with equality or inequality and can expressed as fi(x,ω)=bi, fi(x,ω)<bi or fi(x,ω)>bi). Equations (8) – (13) express the formulation steps for CBB-S.

STEP 1: QoS metrics	$f_i(x,\omega), \quad i = 1 \ldots.. k$	(8)
STEP 2: QoS bounds	$f_i(x,\omega) \le b_i \quad i = 1 \ldots. k$	(9a)
	$f_i(x,\omega) \ge b_i \quad i = 1 \ldots. k$	(9b)
STEP 3: One liner Connectivity	$Connectivity \Leftrightarrow \forall i,\ f_i(x,\omega) \le b_i$	(10)
STEP 4: Compact max form	$Connectivity \Leftrightarrow \max_{i=1\ldots k} (f_i(x,\omega) - b_i), \le 0$	(11)
STEP 5: Connectivity Indicator	*One liner:* $\Phi_{stoch}(x,\omega) = \mathbf{1}\{\forall i:\ f_i(x,\omega) \le b_i\} \in \{0,1\} \quad for\ each\ \omega$	
	Compact max form: $\Phi_{stoch}(x,\omega) = \mathbf{1}\left\{\forall i:\ \max_{i=1\ldots k} (f_i(x,\omega) - b_i), \le 0\right\} \in \{0,1\}\ for\ each\ \omega$	(12)
STEP 6: Optimal Connectivity	$Optimal\ Connectivity \Leftrightarrow \Phi_{stoch}(x,\omega) = 1$	(13)

In CBS, connectivity is stochastic, and objective functions are chance (stochastically) constrained and takes the form P(fi(x, ω) ⩽bi) ∈ [α 1]). Objectives must satisfy at least a target probability threshold. Connectivity holds when the probabilistic QoS requirements modeled by the objective functions are all satisfied in other words, each QoS bound, bi is met with probability of at least a target α. (i.e. within threshold [α 1] and under bounded device and environmental constraints

A QoS metric is satisfied if there is a probability of ⩾ α of its value being within the required bound. CBS builds upon the CBB-S notion by requiring that connectivity is established at a probability of at least some target level (e.g., 95%). Connectivity is defined in terms of the reliability of the network given uncertain conditions. This means that the network is "connected" when the QoS bounds are achieved with at least the likelihood threshold that is specified, thus reflecting randomness and variation in channel and traffic conditions. This captures real-world variability in the NFW environment while still being constraint-based. The requirements are stated in probabilistic terms. So, CBS is a decision-level formalization that uses the CBB-S and then controls it via a probabilistic threshold, in order to gauge the networks' reliability in the presence of uncertainty A reliability threshold is a common way to certify connectivity under uncertainty in wireless QoS contexts [21][22].

Generally, from CB perspective, optimal connectivity exists if all QoS objective function are simultaneously met within acceptable bound, if one bound cannot be guaranteed, then connectivity does not exist. The connectivity feasibility indicator is either {0,1} or it is feasible with a probability α ∈ [α 1]. All quantities f(x, ω) and constraints g(x,ω) or h(x,ω) have fixed performance expectations, which may be deterministic or stochastic. Equations (14) ‒ (19) give the formulation steps for CBS.

STEP 1: QoS metrics	$f_i(x,\omega), \quad i = 1 \ldots.. k$	(14)
STEP 2: QoS bounds	$f_i(x,\omega) \le b_i \quad i = 1 \ldots. k$	
	$f_i(x,\omega) \ge b_i \quad i = 1 \ldots. k$	(15)
STEP 3: One liner Connectivity	$Connectivity \Leftrightarrow P(\forall i,\ f_i(x,\omega) \le b_i)$	(16)
STEP 4: Compact max form	$Connectivity \Leftrightarrow P(\max_{i=1\ldots k} (f_i(x,\omega) - b_i), \le 0$	(17)
STEP 5: Connectivity Indicator	$\Phi_{stoch}(x,\omega) = \mathbf{1}\{\forall i:\ f_i(x,\omega) \le b_i\} \in \{0,1\}$	
	$\Phi_{stoch}(x,\omega) = \mathbf{1}\left\{\forall i:\ \max_{i=1\ldots k} (f_i(x,\omega) - b_i), \le 0\right\} \in \{0,1\}$	
	For both online and compact max, probability of being connected	
	$\Phi_{CBS}(x,\omega) = \mathbf{1}\ (P(\Phi_{stoch}(x,\omega) = 1)) \in [0,1]$	(18)
STEP 6: Optimal Connectivity	*Chance constraint declaration of optimal connectivity at level alpha*	
	$Optimal\ Connectivity \Leftrightarrow \Phi_{CBS}(x,\omega) \ \ge \alpha$	(19)

2) *Pareto Optimal Vector (POV) perspective*

The constraint-based perspective strictly defines a binary feasible region which shows that all QoS metric bounds are being met. This does not require Pareto optimization because connectivity is bound by hard constraints. However, in optimization practice, especially under stochastic and resource-constrained environments, it is rarely possible to meet all objectives' strict thresholds simultaneously. Thus, Pareto optimality becomes important. Instead of absolute satisfaction, connectivity can be interpreted as being Pareto efficient, which means that no objective (e.g., latency) can be improved without worsening another (e.g., data rate). Thus, the connectivity indicator can be expressed as belonging to the Pareto frontier of feasible solutions. Pareto-based modeling is highly suitable for HIoT D2D where traffic flows are of MC-BAMS types, the environment is NFW with stochastic conditions and devices introduce constraints. The QoS performance objectives take the form σi $fi(x, \omega) \leqslant bi$ where $\sigma i \in \{+1, -1\}$ encodes direction ($\sigma i = +1$ for "minimize," $\sigma i = -1$ for "maximize," so all objectives are cast as $\leqslant$). The QoS bounds bi are hardbound ceilings for QoS performance of cost type metrics, where upper limits is b^{max} and hardbound floors for QoS performance of benefit-type metrics with lower limits b^{min}. A Pareto efficient point (PEP) is any feasible decision, which no other feasible decision dominates under the Pareto dominance condition. A Pareto efficient vector (PEV) is the space vector of the objectives induced by a set of PEPs that reflects the combination of QoS metrics to be met simultaneously. The set of all PEVs form the Pareto front and naturally exhibits trade-offs among metrics. In Pareto perspective, connectivity means there exists at least one feasible PEV; which is expressed with the usual one-liner feasibility condition. Alternatively, the compact max form generates PEPs and thus PEVs using weighted sum scalarization. Pareto Optimal Vectors (POVs) denote the subset of PEVs that satisfy the floors/ceilings bound for the objective functions. Thus, the connectivity indicator specifies the binary existence of at least one POV. Optimal connectivity exists if there is at least one POV that can provide an acceptable optimal operational trade-off for the network QoS performance required by an application. The parameters of that POV are then used to configure D2D links. A PEV is the objective-space performance vector on the Pareto front while a POV is a PEV that satisfies the specified floors/ceilings. Equations (20) – (25) gives the optimal connectivity formulation steps for the POV perspectives.

STEP 1: QoS metrics

$$\mathbf{f}(x,\omega) = (\sigma_i\, f_i(x,\omega),\ i = 1 \ldots\ldots k) \tag{20}$$

STEP 2: QoS bounds

$$\mathbf{f}(x,\omega) \le \mathbf{b}^{min}\ , \mathbf{f}(x,\omega) \ge \mathbf{b}^{max} \tag{21}$$

STEP 3: One liner Connectivity

Given the Pareto dominance condition.:

$$\forall i\ f_i(x',\omega) \le\ f_i(x,\omega)\ \textit{and}\ \exists j:\ f_j(x',\omega) <\ f_j(x,\omega).$$

$$Connectivity \Leftrightarrow \{(x,\omega) \in PEV := \{ \nexists x' :\ \forall i\ f_i(x',\omega) \le\ f_i(x,\omega)\ \textit{and}\ \exists j:\ f_j(x',\omega) < f_j(x,\omega)\}\} \tag{22}$$

STEP 4; Compact max form

$$Connectivity \Leftrightarrow \{(x,\omega) \in PEV := \{ \exists x: \min_{z} \textstyle\sum_{i=1}^{k} \delta_i\ (f_i(x,\omega)\, , \delta_i \ge,\ \ \sum_i \delta_i = 1\}\} \tag{23}$$

STEP 5; Connectivity Indicator

$$\Phi_{POV}(x,\omega) = \mathbf{1}\{x \in \beta: (x,\omega) \in PEV\} \in \{0,1\} \tag{24}$$

STE 6: Optimal Connectivity

$$Optimal\ Connectivity \Leftrightarrow \{x * \in : \Phi_{POV}(x,\omega) = \{x \in \beta: (x,\omega) \in PEV\} = 1$$

$$\beta = \{x:\ \mathbf{f}(x,\omega) \le \mathbf{b}^{min}\} \text{----------- bound condition} \tag{25}$$

E. *Justification for POV*

In real practice, multi-objective trade-offs are unavoidable. Though strict feasibility defines and models the ideal connectivity, Pareto vectors define and model the realistic operating points where optimal trade-offs are achieved. If strict thresholds are non-negotiable, then connectivity is treated with a hard feasibility. If trade-offs are possible, then connectivity is represented as a Pareto vector solution space. However, when conflicting objectives exist, such as minimizing latency, maximizing throughput, the network does not have a single feasible optimum, instead there is a set of solutions that form the Pareto optimal vectors, which are the feasible regions of connectivity. A set of Pareto optimal vectors indicate connectivity. In addition, the ability to visualize trade-offs through Pareto fronts makes stochastic MO-MF-MC optimization effective in HIoT D2D networks. For instance, a Pareto front might reveal that slightly higher latency can significantly extend device battery life, which is an acceptable trade-off for routine monitoring, but unacceptable in emergency care. Such nuanced decision support is vital for adaptive, real-time systems, where conditions shift unpredictably and human lives may depend on microsecond-level performance [21].

V. CONCLUSION AND FUTURE WORK

This paper studied connectivity in HIoT D2D networks operating in NFW environments and under strict resource limits, which makes connectivity fundamentally stochastic. Therefore, optimal connectivity in HIoT D2D networks has been modelled as a stochastic MO-MF-MC optimization problem, where the network must meet diverse traffic demands while operating within strict device and environmental limitations. The paper identified the unique characteristics of traffic flow in HIoT D2D as MC-BAMS.

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Optimal connectivity was formulated from the CB and POV perspectives. A justification was made for the POV perspective. The constraint-based view defines optimal connectivity as either deterministic or chance constrained for reliability targets, while a Pareto view reveals the trade-off frontier where no QoS metric improves without another worsening within limits. POV is supported because it explicitly manages trade-offs among competing QoS metrics (e.g., latency, jitter, loss, data rate) while respecting device and environmental constraints. This perspective provides a practical foundation for scalable adaptive HIoT device to device systems in dynamic clinical settings. Future work includes a lightweight protocol that instantiates the chance constrained Pareto framework on constrained devices, online learning to tune priorities thresholds and schedules in real time, energy aware orchestration that couples power budgeting harvesting and thermal safety with QoS guarantees, privacy and safety co design aligned with clinical risk, hardware in the loop validation in ICU and home care testbeds with 5G and 6G URLLC, and open benchmarks to support reproducible progress on dependable HIoT connectivity.

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