Computer Networks and Communications
https://ojs.wiserpub.com/index.php/CNC

Article

Mechanism for Efficient Media Propagation in Event-Driven Cyber-Physical Systems

Rolando Herrero

College of Engineering, Northeastern University, Boston, MA, USA
E-mail: rolando.herrero@northeastern.edu

Received: 27 November 2023; **Revised:** 4 January 2024; **Accepted:** 18 January 2024

Abstract: Many key applications in Cyber-Physical Systems require the transmission of speech, audio, or video. These scenarios involve the use of traditional Real-Time Communication (RTC) protocols and technologies, which cannot always be used in the context of core networks. This is particularly critical in the context of Event-Driven Architectures (EDAs), where RTC protocols require the use of complex topologies that rely on costly infrastructure. One way to avoid this is by encapsulating all media traffic in EDA protocols. However, this approach does not come without challenges. Specifically, the nature of the transport protocols causes the media to be heavily affected by application layer impairments that render their usage highly impractical. To prevent this from happening, this paper introduces a unified scheme that supports the efficient encapsulation of media traffic in EDA scenarios. This is accomplished through a mechanism that relies on a Machine Learning (ML) model that is exercised in an experimental framework.

Keywords**:** EDA, RTC, SIP, RTP, MQTT, IoT, media, cyber-physical system

1. Introduction

Cyber-Physical Systems incorporate three main components: (1) a physical side with devices like sensors and actuators, (2) a cyber side with applications and (3) a communication mechanism that connects both. The applications convert the sensor readouts into knowledge that triggers actuation back on the devices. The communication mechanism is typically carried out by means of Internet of Things (IoT) protocols [1].

Figure 1 illustrates a topology that embodies the configuration discussed in this paper. Specifically, it comprises a device (or multiple devices) that generates media readouts, which are transmitted to the network border where a gateway relays them to the application server on the core network. The access network, where the device resides, employs an IEEE 802.15.4-based protocol stack, while the core network, where the application resides, utilizes an IEEE 802.11-based protocol stack. Both protocol stacks leverage IP networking.

Access network communication relies on application-layer protocols such as the Constrained Application Proto-col (CoAP), which supports Representational State Transfer (REST) architectures. In contrast, core network communication utilizes Event Driver Architecture (EDA) mechanisms, such as the Message Queue Telemetry Transport (MQTT) protocol [2]. CoAP is well-suited for access networks due to its minimal latency. However, since it is transported over the User Datagram Protocol (UDP), it is unable to traverse firewalls. Firewalls, which are present in the network core, are compatible with Transport Control Protocol (TCP)-based application-layer technologies like MQTT.

In the aforementioned topology, a broker is positioned between the edge device and the application server. This broker relays packets in both directions between the devices. A major challenge in this scenario arises from the fact that the TCP protocol responds with retransmissions to network packet loss. This results in excessive

DOI: https://doi.org/10.37256/cnc.2120243999

application level latency, which impacts performance and Quality of Service (QoS). This paper attempts to address the research gap associated with improving the performance of TCP based protocols in the context of media transmission in Cyber-Physical systems.

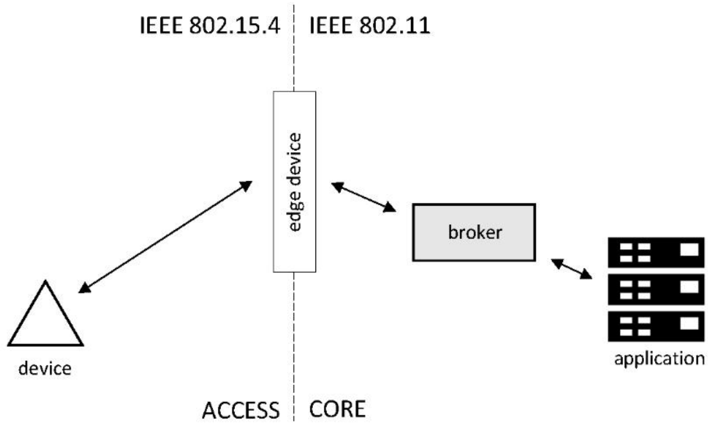

Figure 1. Cyber-Physical System Topology

This paper proposes a mechanism that utilizes a regression Artificial Neural Network (ANN) to estimate the number of MQTT sessions and the transmitted traffic pattern that minimize the measured application-layer latency on the receiver, considering the media frame size and the sampling rate of the coder-decoder (codec) under consideration. The following list formalizes the contributions of this paper:

- It introduces an ANN-based algorithm that optimizes the transmission of media over EDA topologies in Cyber-Physical systems. The algorithm is used to determine the TCP connection multiplexing patterns used by the MQTT EDA protocol.
- It integrates several audio and speech codecs in the context of transmission over IoT protocols.
- It introduces a novel experimental framework that can be used to train and test the ANN.
- It combines multiple different application layer technologies over a unique TCP transport layer.

The remainder of the paper is organized as follows: A detailed discussion of the related work is presented in Section 2. The dynamic EDA session selection algorithm is described in Section 3. Section 4 provides a description of the evaluation framework as well as comparative results. Conclusions and future work are introduced in Section 5.

2. Related Work

This paper presents a novel mechanism that effectively reduces end-to-end latency in IoT EDA architectures. The primary focus is on optimizing system parameters for IoT session layer protocols, particularly MQTT, using ML techniques. In the context of EDA, a significant portion of research has centered on the transmission of non-real-time sensor data, specifically for applications and use cases that rely on such scenarios. For instance, in [3], the authors introduce an indoor localization system that utilizes MQTT over IEEE 802.15.4. Similarly, in [4,5], a traffic light control solution based on MQTT is presented. An air monitoring station incorporating an MQTT stack is proposed in [6]. Furthermore, in [7], MQTT and IPv6 are combined to facilitate home automation scenarios.

IPv6 adaptation to support media transmission and other more general traffic within the IoT domain has been an active area of research. This involves various physical layer technologies, including IEEE 802.15.4 [8–10], NB-IoT [11], BLE [12, 13], and generic ultrasound [14]. In the context of media over MQTT, the authors in [15] analyze the impact of impairments and throughput on audio transmission. Similarly, in [16], the performance of MQTT is compared against other session layer protocols. Additionally, in [17], the authors propose a mechanism that propagates speech using MQTT in an end-to-end solution that integrates embedded devices with cloud-based natural language processing capabilities. In [18], the authors introduce a mechanism that relies on an ANN to qualify metrics relying on several IoT topologies including MQTT based ones. The use of ANNs in the context of MQTT is introduced in [19] for the purpose of intrusion detection. In [20], the authors introduce a mechanism to cluster multiple MQTT brokers into a secure broker service. MQTT in the context of media applications is presented in [21] where multiple sessions are used to improve the overall QoS.

Many papers explore the use of AI techniques to support Cyber-Physical Systems and IoT technologies. Specifically, in [22], the authors present an IoT-based food supply chain system for smart cities that improves food quality, routing, and contamination tracing, outperforming existing methods. In [23], a novel IoT and deep learning-based system for remote health monitoring in smart cities achieves high accuracy (97.6%) and provides immediate intervention for critical patients, surpassing traditional methods. Research that proposes a new highly secure public key encryption system for Industrial IoT, utilizing advanced concepts to protect data privacy and resist quantum attacks, with faster decryption compared to existing solutions is presented in [24]. A hybrid deep learning anomaly detection system for complex Cyber-Physical Systems that combines Convolutional Neural Networks, Kalman Filters, and a Gaussian-Mixture Model to accurately identify suspicious behavior while preserving data privacy is introduced in [25]. In [26], the authors propose novel IoT-based healthcare system with dual-level scheduling

that surpasses existing methods by efficiently utilizing fog and cloud resources and incorporating social media/drug data for optimal task execution. A novel AI-powered intrusion detection system for wireless networks in smart homes and the Internet of Things that outperforms traditional methods by combining reinforcement learning and deep learning, achieving higher accuracy in identifying and classifying cyberattacks is presented in [27]. In [28], the authors introduce data prediction in Wireless Body Area Networks that reduces data transmission by sending anticipated sensor values instead of actual ones, requiring accurate prediction models for efficient energy saving. Finally, a three-stage ML-powered intrusion detection system for ubiquitous networks that leverages edge/fog computing for real-time threat identification, analysis, and model self-improvement for efficient and resource-optimized security is presented in [29].

Table 1 summarizes the content of the references above, including this paper, and describes their features in respect to media, AI, MQTT, and efficient transmission of traffic.

Table 1. Related Work Comparison

reference	MQTT	audio	video	AI	Efficient transmission
[3]	x				
[4,5]	x				
[6]	x				
[7]	x				
[8–10]					x
[11]					x
[12,13]					x
[15]	x				x
[16]	x				x
[17]	x		x		x
[18]	x			x	x
[19]	x				
[20]	x				
[21]	x	x			x
[22]				x	
[23]				x	
[24]				x	
[25]				x	
[26]				x	
[27]				x	
[28]				x	
[29]				x	
this work	x	x	x	x	x

3. Theoretical Background

This section introduces the theoretical background and models that lead to the development of an algorithm that efficiently minimizes the latency measured at the application layer.

3.1 *The Topology*

As indicated in Figure 1, the network core follows an EDA architecture. In this context, the focus of this paper is in the communication between the edge device and the application.

Figure 2 depicts the core topology of a scenario where the edge device relays IoT messages containing sensor readouts and audio frames to an application. Sensor readouts are transmitted using the MQTT protocol, while audio frames necessitate both the Session Initiation Protocol (SIP) and the Real-Time Transport Protocol (RTP) to facilitate session signaling and media transmission, respectively [30,31].

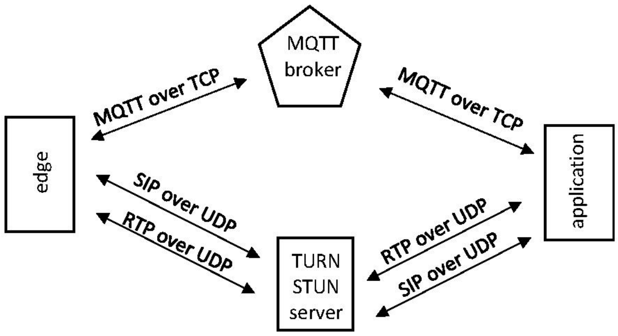

Figure 2. Topology: Sensor Readouts and Audio

Figure 3 illustrates the protocol stacks associated with the transmission of sensor readouts and audio frames. MQTT utilizes TCP transport, whereas both SIP and RTP employ UDP transport. As mentioned in Section 1, MQTT is an EDA protocol that necessitates the presence of a broker. SIP and RTP are REST protocols that are susceptible to Network Address Translation (NAT) complications. Consequently, SIP and RTP are employed in conjunction with media relay servers, namely Traversal Using Relays around NAT (TURN) and Session Traversal Utilities for NAT (STUN), to alleviate these issues. In all instances, both IoT messaging and signaling/media experience additional latency due to multihop transmissions. Furthermore, due to the utilization of two distinct transport layer protocols (UDP and TCP), the communication paths diverge, potentially affecting the synchronization between readouts and audio.

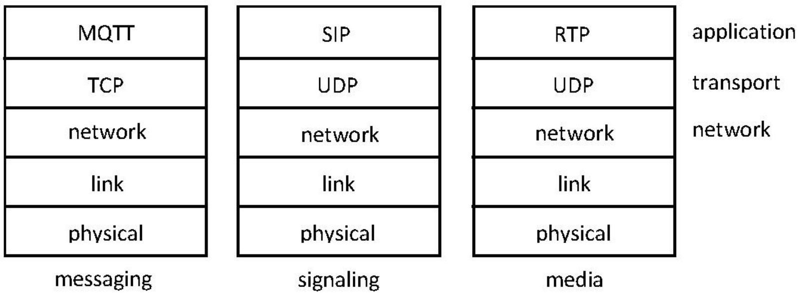

Figure 3. Protocol Stacks: Sensor Readouts and Audio

3.2 *The Proposed Topology*

To prevent the synchronization problems caused by the two transmission paths, this paper introduces a scheme that encapsulates signaling and media over MQTT along with sensor readouts.

Figure 4 shows the proposed topology. Audio is first signaled by means of SIP and then packetized as media frames over RTP. Both SIP and RTP traffic are sent over the MQTT broker from the network edge to the application. In this scenario, audio follows the same path the sensor readouts and synchronization issues are minimized.

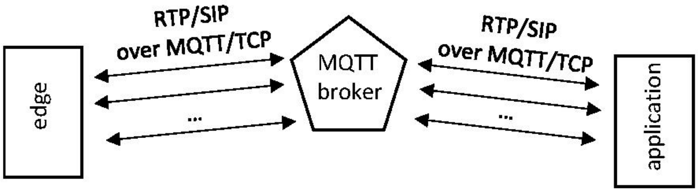

Figure 4. Proposed Topology: Sensor Readouts and Audio

Figure 5 shows the protocol stacks that support the trans-mission of both sensor readouts and audio. A common MQTT session layer enables the encapsulation of SIP and RTP traffic over TCP connections. To prevent the negative effect of TCP in lossy environments, a multi-connection MQTT scheme and algorithm is introduced in the following Section.

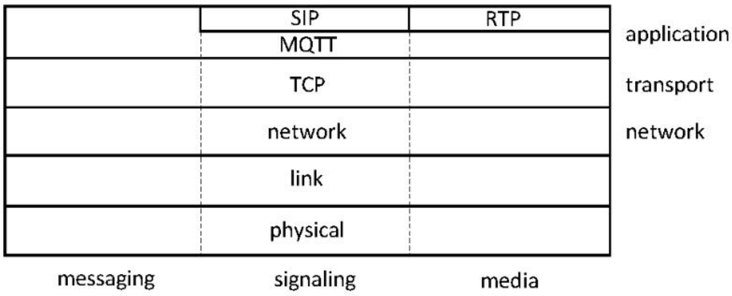

Figure 5. Proposed Protocol Stacks: Sensor Readouts and Audio

3.3 *The Proposed Topology*

The most critical issue with media transmission over MQTT is the excessive latency introduced by TCP retransmissions, even for minimal network packet loss. This stems from Head-of-Line (HOL) blocking issues inherent in TCP transport. By leveraging multiple dynamically maintained TCP connections (rather than a single connection), a behavior akin to UDP transport can be achieved.

Consider the example on Figure 6, two connections are used to transmit five messages from the edge to the broker. Messages 1, 3 and 5 go over one connection while Messages 2 and 4 go over the other. Because HOL blocking prevents the transmissions of subsequent messages when a message is blocked, by reducing the number of messages to be transmitted over each connection, the likelihood of blockage is proportionally reduced. In other words, if for any connection the probability of blockage is given by max $(1, M \times p_M)$ where M is the number of messages per connection and p_M is the probability of blockage per message, then by reducing M, the blockage probability is also reduced. In the Figure, message 4 in the second connection, is lost and retransmitted. This causes a slight latency that affects the timing between message 4 and messages 3 and 5 but that it doesn't the timing of message 5. In Figure 6, it can be seen that message 5 is not delayed.

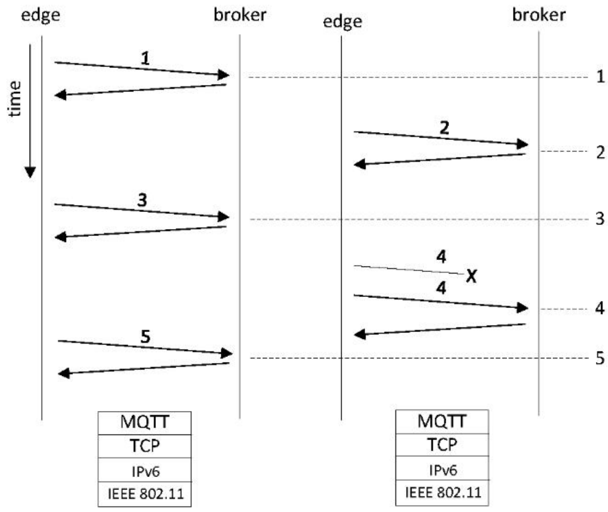

Figure 6. Multi-Connection Approach

Compare Figure 6 to Figure 7. In the latter, because of the inter-relationship between messages 4 and 5, the HOL blockage of message 4 affects the timing of message 5 that is delayed.

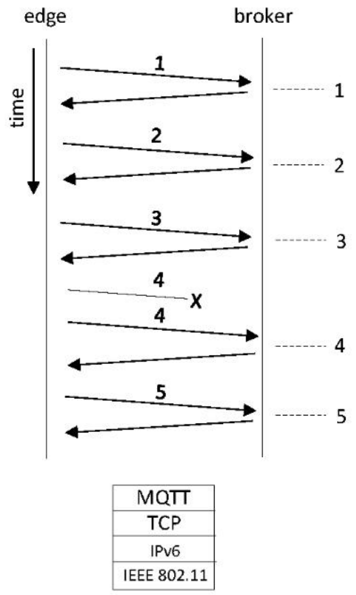

Figure 7. Single-Connection Approach

Figure 8 shows the block diagram with the all the components involved in the proposed mechanism. The mechanism dynamically adjusts two system parameters based on three features that include sensed network layer impairments (i.e., packet latency). This list summarizes these two system parameters:

1) Number of underlying TCP connections (n) that carry the MQTT session: This prevents the HOL issues associated with TCP retransmissions. The number of connections, however, must be kept small enough to minimize resource consumption.
2) Number of underlying TCP connection combinations (k) that specify the combination of connections that are used for the transmission of each media frame from sender to receiver: To prevent HOL issues, frames must be forwarded over different combination of connections following a pattern that is known to both receiver and sender.

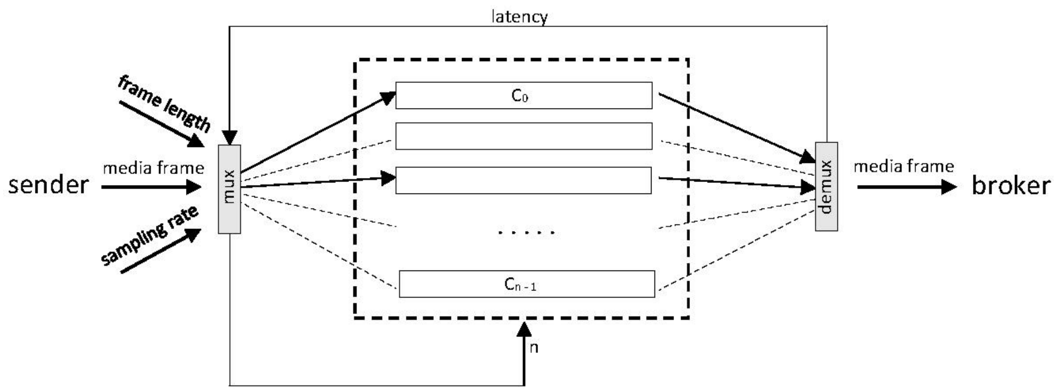

Figure 8. Proposed Mechanism

The multiplexing mechanism, that is depicted in Figure 9, relies on selecting k out of n connections to establish an MQTT session between the device and the broker. The algorithm for multiplexing is the following:

- Set *a* counter $c = 0$
- For each packet to be transmitted from the panel to the broker:
  a. Make k copies (i) of the packet where $0 \leq i < n$
  b. Send i packet over the (c mod k) + 2 × i connection
  c. Increment c as $c = c + 1$
  d. Repeat step for each packet to be sent

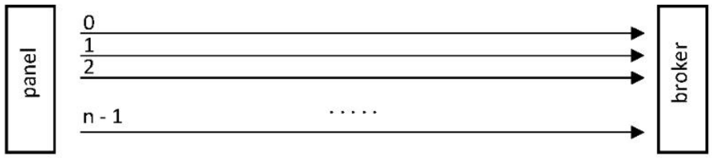

Figure 9. Multiplexing Mechanisms

The initial values of n and k are set to one by default. For the block diagram in Figure 8, the mechanism performs the following steps:

1) A media frame is generated by the sender (in direction to the broker).
2) If available at the sender, based on input features, the number of connections is adjusted to n.
3) If available at the sender, based on input features, the number of connection combinations is adjusted to k. This number is used to determine the combination pattern that specifies the connections that are used for the transmission of the media frame. Other combinations may be possible to reduce the overall system latency.
4) The frame is multiplexed by generating multiple copies that follow the pattern.
5) The copies are de-multiplexed to obtain the copy that arrives the fastest. This copy becomes the received frame.
6) The latency of the received frame is used to update the estimated latency using a moving average.
7) Repeat step 1 if another frame is to be transmitted.

As indicated in Section 1, and shown in Figure 8, three input features are taking into account:

- Latency measured in milliseconds at that the receiver.
- Frame size measured in milliseconds.
- Sampling rate associated with the codec under consideration measured in kilo-samples per second (kSPS).

The structure of the ANN is depicted in Figure 10. It comprises a single hidden layer and a 2-node output layer. The samples associated with all three features are fed into the hidden layer. The rectified linear unit (ReLU) function serves as the activation function in the hidden layer. To ensure that the output falls within the range $[1, L]$, where L is a system parameter that specifies the maximum number of supported MQTT sessions, it is rounded up and normalized. It is crucial to note that the ANN topology employed in this research work represents a compromise between capabilities and computational resources.

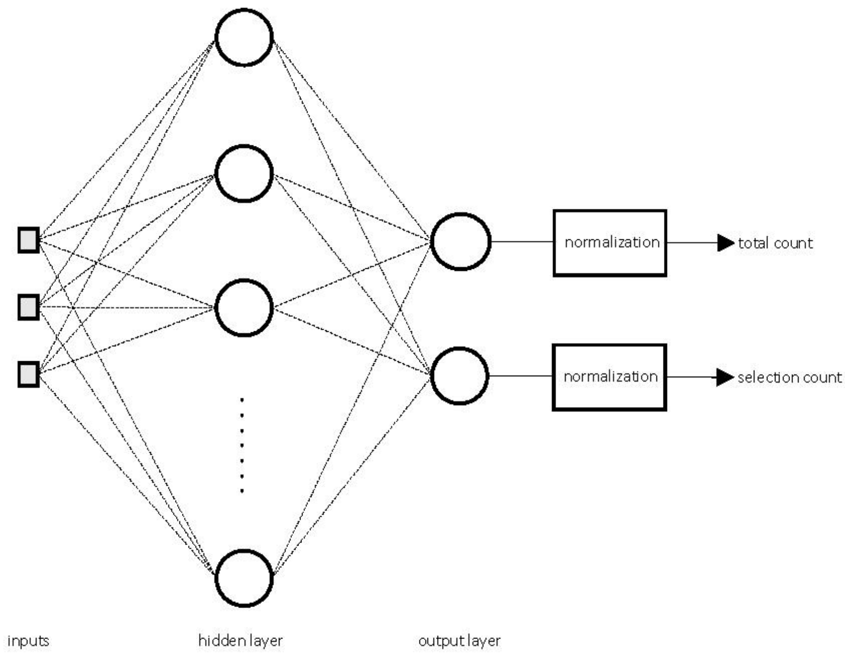

Figure 10. Regression ANN

The ANN is trained with a database that is generated from the system under test shown in Figure 11. The edge, broker and application implement the mechanism in Figure 8. For training, impairments in the form of network layer packet loss probability (p) and network packet loss burstiness (α) in accordance with the Gilbert-Elliot channel model [32] as well as codecs configured with different sampling rates and frame sizes and different values of n and $k \leq n/2$ are used to estimate values of average system latency. Specifically, for each scenario and for N devices streaming audio for 60 seconds, the average RTP latency is obtained. If the latency is below 70 milliseconds, then an entry in added to the training database. This threshold guarantees that decisions in Cyber-Physical System applications fit the requirements of most real time applications. Each entry maps the set of input features (frame size, sampling rate and latency measured for $n = 1$ and $k = 1$) with the optimal values of n and k.

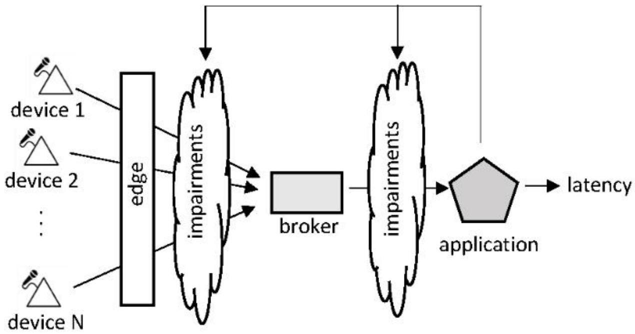

Figure 11. System under Test

Table 2 lists all the parameters that are used to generate the training database. F_s represents the sampling rates associated with the following codecs: ITU-T G.711 μ-Law (8000 KSPS) [33], AMR-NB (8000 KSPS) [34], AMR-WB (16000 KSPS) [35], EVS (32000 KSPS and 48000 KSPS) [36] and s indicates the frame size in milliseconds. These parameters lead to 121968 test cases that are emulated at compressed time using Netualizer. Netualizer is a Protocol Stack Virtualization (PSV) framework that supports the creation of networking scenarios by enabling the emulation of a myriad of IoT protocol stacks [37]. For $N = 12$, the generated database has around 25912 entries.

Table 2. Training Database Generation Parameters

parameter	values
F_s (KSPS)	8000, 16000, 32000, 48000
s (ms)	10, 20, 30
p	0.01–0.12, 0.15, 0.20
α	0.01–0.05, 0.07, 0.10, 0.15, 0.25, 0.5, 0.8
n	1–12
k	1–6

The rationale behind this approach stems from the progressively increasing computational capabilities of smart devices, which render ANNs a pragmatic solution for a vast array of applications. Note that this algorithm has some limitations, specifically, the following is a list of these restrictions:

- The scheme fails to consider the challenges posed by a media fragmentation.
- The current optimization doesn't prioritize minimizing power consumption.
- Video traffic might not perform as well as other media types since video wasn't included in the ANN training data.

4. Evaluation Framework

Once the training database is set generated, the ANN in Figure 10 can be trained by means of Tensorflow. For an accuracy close to 99% in six iterations, the model relies on a 65-node hidden layer that leads to 326 coefficients. This is computationally simple enough that can be run in any low end constrained device. Once the model is defined, it can be tested by relying on the same topology shown in Figure 11.

Figures 12 and 13 show the connection count (n) and the connection selection count (k) as a function of the latency in milliseconds for respective frame sizes of 20 and 30 milliseconds and sampling rates of 8000 and 16000.

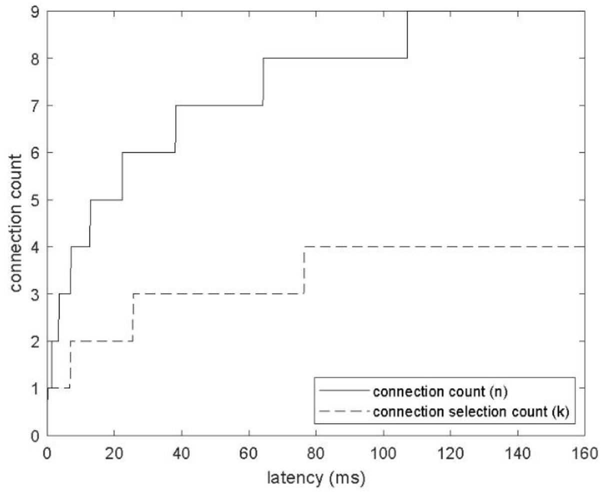

Figure 12. Connection Count vs Connection Selection Count (s = 20, F_s = 8000)

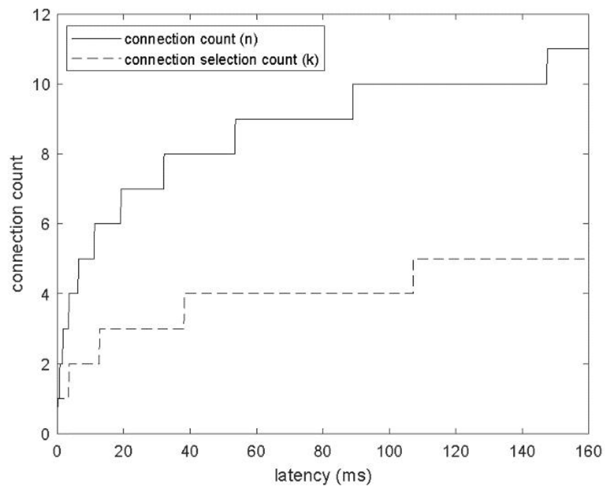

Figure 13. Connection Count vs Connection Selection Count (s = 30, F_s = 16000)

For a subset of the codecs and different network packet loss probability as well as burstiness, the latency of the system is recorded and compared against that of the traditional single-session scenario. For ITU-T G.711 μ-Law generated audio, Figures 14 and 15 show the application layer latencies for the legacy single connection and the proposed multi-connection mechanisms for low (α = 0.1) and high (α = 0.4) packet loss burstiness. The average latency reduction between the legacy and proposed mechanisms for the low and high packet loss burstiness are respectively 51.06 and 73.49 milliseconds.

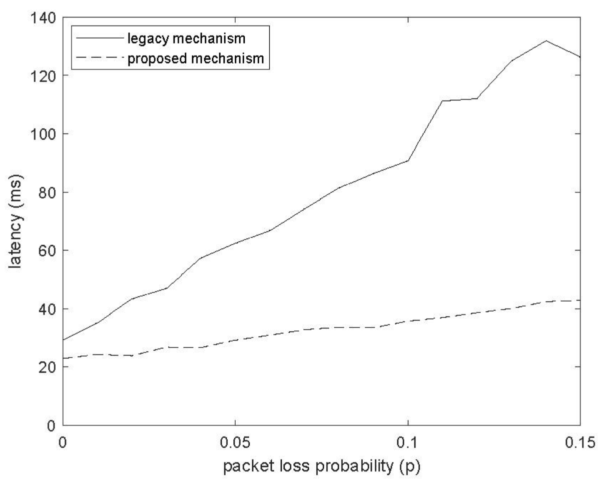

Figure 14. Latency vs Network Loss Probability (α = 0.1)

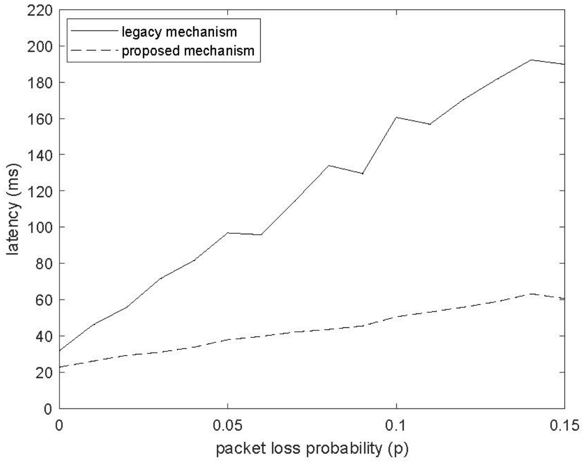

Figure 15. Latency vs Network Loss Probability ($\alpha = 0.4$)

In all cases, it can be seen that the proposed mechanism tends to minimize the overall latency even for high values of packet loss probability (p). Table 3 shows the actual latency reduction for low and high packet loss burstiness for other codecs.

Table 3. Latency Reduction

codec	reduction ($\alpha = 0.1$)	reduction ($\alpha = 0.4$)
ITU-T G.711	51.06	73.49
AMR-NB	65.92	85.29
AMR-WB	71.25	86.73
EVS (32000)	76.12	93.33
EVS (48000)	81.09	98.86

5. Conclusions and Future Work

In this paper, we present a novel algorithm that effectively lowers the end-to-end latency in an EDA scenario where devices and applications interact by means of a broker. This mechanism solves the problem of excessive latency caused by HOL blocking due to TCP retransmissions. The algorithm dynamically allocates MQTT sessions and multiplexes messages to ensure their delivery with minimal latency. Compared to legacy message transmission, the proposed mechanism consistently reduces overall end-to-end latency. This reduction ranges from 60% to 80%, depending on the codec and network packet loss probability and burstiness.

Other open research paths include enhancements to improve the algorithm's performance. Specifically, the algorithm can be further refined by considering additional relevant input features, such as Mean Opinion Scores (MOS), packetization schemes, and physical layer characteristics like coverage, power, and modulation schemes. Additionally, the mechanism can be extended to accommodate other media types, such as video. Other open research paths include the fine tuning of the algorithm to optimize power consumption by reducing the complexity of the ANN.

Conflict of Interest

There is no conflict of interest for this study.

References

[1] Herrero, R. *Practical Internet of Things Networking*; Springer: Cham, Switzerland, 2023; ISBN: 978-3-031-28445-8. https://doi.org/10.1007/978-3-031-28443-4.

[2] Fielding, R.T. REST: architectural styles and the design of network-based software architectures. PhD Thesis, University of California: Irvine, CA, USA, 2000.

[3] Puspitaningayu, P.; Funabiki, N.; Huo, Y.; Hamazaki, K.; Kuribayashi, M.; Kao, W.C. Application of fingerprint-based indoor localization system using IEEE 802.15. 4 to two-floors environment. In

Proceedings of 2022 IEEE 4th Global Conference on Life Sciences and Technologies (LifeTech), Osaka, Japan, 7–9 March 2022, https://doi.org/10.1109/LifeTech53646.2022.9754790.
[4] Zitouni, R.; Petit, J.; Djoudi, A.; George, L. IoT-based urban traffic-light control: modelling, prototyping and evaluation of MQTT protocol. In Proceedings of 2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), Atlanta, GA, USA, 14–17 July 2019, https://doi.org/10.1109/iThings/GreenCom/CPSCom/SmartData.2019.00051.
[5] Petit, J.; Zitouni, R.; George, L. Prototyping of urban traffic-light control in iot. In Proceedings of 2018 IEEE International Smart Cities Conference (ISC2), Kansas City, MO, USA, 16–19 September 2018, https://doi.org/10.1109/ISC2.2018.8656717.
[6] Tanyingyong, V.; Olsson, R.; Hidell, M.; Sjödin, P.; Ahlgren, B. Implementation and deployment of an ou tdoor IoT-based air quality monitoring testbed. In Proceedings of 2018 IEEE Global Communications Con ference (GLOBECOM), Abu Dhabi, United Arab Emirates, 9–13 December 2018, https://doi.org/10.1109/ GLOCOM.2018.8647287.
[7] Biju, S.; Shekokar, N.M. Security approach on MQTT based smart home. In Proceedings of 2017 IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI), Chennai, India, 21–22 September 2017, https://doi.org/10.1109/ICPCSI.2017.8391883.
[8] Herrero, R. Mobile shared resources in the context of IoT low power lossy networks. *Internet Things* **2020**, *12*, 100274, https://doi.org/10.1016/j.iot.2020.100274.
[9] Tournier, J.; Lesueur, F.; Le Mouël, F.; Guyon, L.; Ben-Hassine, H. A survey of IoT protocols and their se curity issues through the lens of a generic IoT stack. *Internet Things* **2020**, *16*, 100264, https://doi.org/10.1 016/j.iot.2020.100264.
[10] Higuera, J.; Polo, J. Understanding the IEEE 1451 standard in 6loWPAN sensor networks. In Proceedings of 2010 IEEE Sensors Applications Symposium (SAS), Limerick, Ireland, 23–25 February 2010, https://doi.org/10.1109/SAS.2010.5439427.
[11] Ayoub, W.; Mroue, M.; Nouvel, F.; Samhat, A.E.; Prévotet, J.C. Towards ip over lpwans technologies: Lo rawan, dash7, nb-iot. In Proceedings of 2018 sixth international conference on digital information, networ king, and wireless communications (dinwc), Beirut, Lebanon, 25–27 April 2018, https://doi.org/10.1109/D INWC.2018.8356993.
[12] Tabish, R.; Mnaouer, A.B.; Touati, F.; Ghaleb, A.M. A comparative analysis of BLE and 6LoWPAN for U-HealthCare applications. In Proceedings of 2013 7th IEEE GCC conference and exhibition (GCC), Doha, Qatar, 17–20 November 2013, https://doi.org/10.1109/IEEEGCC.2013.6705791.
[13] Decuir, J. Bluetooth Smart Support for 6LoBTLE: Applications and connection questions. *IEEE Consum. Electron. Mag.* **2015**, *4*, 67–70, https://doi.org/10.1109/mce.2015.2392955.
[14] Herrero, R. Ultrasonic physical layers as building blocks of IoT stacks. *Internet Things* **2022**, *18*, 100489, https://doi.org/10.1016/j.iot.2021.100489.
[15] Chen, Y.; Kunz, T. Performance evaluation of IoT protocols under a constrained wireless access network. In Proceedings of 2016 International Conference on Selected Topics in Mobile & Wireless Networking (MoWNeT), Cairo, Egypt, 11–13 April 2016, https://doi.org/10.1109/MoWNet.2016.7496622.
[16] Herrero, R. MQTT-SN, CoAP, and RTP in wireless IoT real-time communications. *Multimedia Syst.* **2020**, *26*, 643–654, https://doi.org/10.1007/s00530-020-00674-5.
[17] Lai, C.H.; Hwang, Y.S. The voice controlled Internet of Things system. In Proceedings of 2018 7th interna tional symposium on next generation electronics, Taipei, Taiwan, 7–9 May 2018, https://doi.org/10.1109/I SNE.2018.8394641.
[18] Herrero, R. Multifactor QoE scores in IoT topologies. *Internet Things* **2023**, *24*, https://doi.org/10.1016/j.i ot.2023.100892.
[19] Ullah, S.; Ahmad, J.; Khan, M.A.; Alshehri, M.S.; Boulila, W.; Koubaa, A.; Jan, S.U.; Ch, M.M.I. TNN-IDS: Transformer neural network-based intrusion detection system for MQTT-enabled IoT Networks. *Comput. Networks* **2023**, *237*, https://doi.org/10.1016/j.comnet.2023.110072.
[20] Azzedin, F.; Alhazmi, T. Secure Data Distribution Architecture in IoT Using MQTT. *Appl. Sci.* **2023**, *13*, 2515, https://doi.org/10.3390/app13042515.
[21] Herrero, R. RTP transport in IoT MQTT topologies. *Internet Things Cyber-Phys. Syst.* **2023**, *3*, 37–44, https://doi.org/10.1016/j.iotcps.2023.02.001.
[22] Nagarajan, S.M.; Deverajan, G.G.; Chatterjee, P.; Alnumay, W.; Muthukumaran, V. Integration of IoT based routing process for food supply chain management in sustainable smart cities. *Sustain. Cities Soc.* **2021**, *76*, 103448, https://doi.org/10.1016/j.scs.2021.103448.

[23] Nagarajan, S.M.; Deverajan, G.G.; Chatterjee, P.; Alnumay, W.; Ghosh, U. Effective task scheduling algorithm with deep learning for Internet of Health Things (IoHT) in sustainable smart cities. *Sustain. Cities Soc.* **2021**, *71*, 102945, https://doi.org/10.1016/j.scs.2021.102945.

[24] Deverajan, G.G.; Muthukumaran, V.; Hsu, C.; Karuppiah, M.; Chung, Y.; Chen, Y. Public key encryption with equality test for Industrial Internet of Things system in cloud computing. *Trans. Emerg. Telecommun. Technol.* **2021**, *33*, https://doi.org/10.1002/ett.4202.

[25] Nagarajan, S.M.; Deverajan, G.G.; Bashir, A.K.; Mahapatra, R.P.; Al-Numay, M.S. IADF-CPS: Intelligent Anomaly Detection Framework towards Cyber Physical Systems. *Comput. Commun.* **2022**, *188*, 81–89, https://doi.org/10.1016/j.comcom.2022.02.022.

[26] Nagarajan, S.M.; Devarajan, G.G.; Mohammed, A.S.; Ramana, T.V.; Ghosh, U. Intelligent Task Scheduling Approach for IoT Integrated Healthcare Cyber Physical Systems. *IEEE Trans. Netw. Sci. Eng.* **2022**, *PP*, 1–11, https://doi.org/10.1109/tnse.2022.3223844.

[27] Ramana, T.; Thirunavukkarasan, M.; Mohammed, A.S.; Devarajan, G.G.; Nagarajan, S.M. Ambient intelligence approach: Internet of Things based decision performance analysis for intrusion detection. *Comput. Commun.* **2022**, *195*, 315–322, https://doi.org/10.1016/j.comcom.2022.09.007.

[28] Kaleem, M.; Devarajan, G.G. Wireless Body Area Networks utilizing Data Transmission Techniques based on Prediction. In Proceedings of 2023 10th International Conference on Computing for Sustainable Global Development (INDIACom), New Delhi, India, 15–17 March 2023, pp. 1586–1591.

[29] Karuppiah, M.; Ramana, T.V.; Mohanty, R.; Devarajan, G.G.; Nagarajan, S.M. UIoTN-PMSE: Ubiquitous IoT network - based predictive modeling in smart environment. *Int. J. Commun. Syst.* **2023**, *e5661*, https://doi.org/10.1002/dac.5661.

[30] Rosenberg, J.; Schulzrinne, H.; Camarillo, G.; Johnston, A.; Peterson, J.; Sparks, R.; Schooler, E. SIP: session initiation protocol. Available online: https://www.rfc-editor.org/rfc/rfc3261 (accessed on 17 January 2024).

[31] Schulzrinne, H.; Casner, S.; Frederick, R.; Jacobson, V. RTP: A transport protocol for real-time applications. Available online: https://www.rfc-editor.org/rfc/rfc3550 (accessed on 17 January 2024).

[32] Hohlfeld, O.; Geib, R.; Haßlinger, G. Packet loss in real-time services: Markovian models generating QoE impairments. In Proceedings of 2008 16th Interntional workshop on quality of service, Enschede, Netherlands, 2–4 June 2008, https://doi.org/10.1109/IWQOS.2008.33.

[33] ITU-T. G.711: Pulse code modulation (pcm) of voice frequencies. Available online: https://www.itu.int/rec/T-REC-G.711 (accessed on 17 January 2024).

[34] 3GPP TS 26.071 version 5.0.0 Release 5. Mandatory speech codec speech processing functions. Available online: https://www.etsi.org/deliver/etsi_ts/126000_126099/126071/05.00.00_60/ts_126071v050000p.pdf (accessed on 17 January 2024).

[35] 3GPP TS 26.190 version 7.0.0 Release 7. Speech codec speech processing functions. Available online: https://www.etsi.org/deliver/etsi_ts/126100_126199/126190/07.00.00_60/ts_126190v070000p.pdf (accessed on 17 January 2024).

[36] 3GPP TS 26.445 version 12.1.0 Release 12. Available online: https://www.etsi.org/deliver/etsi_ts/126400_126499/126445/12.01.00_60/ts_126445v120100p.pdf (accessed on 17 January 2024).

[37] L7TR. Netualizer: Network virtualizer. Available online: https://www.l7tr.com (accessed on 17 January 2024).