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Delay-Conscious Service Quality Constraint in IoT Sensor Networks for Smart Farming

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Abstract: The Internet of Things (IoT) offers different services for the agriculture industry, such as monitoring and analysing real-time data related to current weather conditions, water level, irrigation requirements, growth of plant disease and health status/temperature/humidity, etc.,). The performance of IoT networks may vary due to environmental conditions and operational areas (rural area/urban area/underwater). These constraints may degrade the transmission quality due to delay factors because the signal propagation may vary in these areas. IoT sensors are low-powered devices designed for long-distance communication. The transmission rate may be degraded due to the delay factor, which may cause packet loss/ congestion/collision, thus resulting in unnecessary re-transmission over the cost of network resources. To resolve the transmission delay issue, there is a need to develop a solution to ensure reliable transmission under the constraint of delay, and this study will introduce a delay-aware scheme to manage the uncertainty over IoT networks in rural and urban areas. Its performance will be analysed using different quality of service constraints (i.e., throughput/delay/residual Energy/Energy Consumption, etc.) using two different IoT-based communication standards, i.e., LoRaWAN and SigFox, with IoT sensor density variation from 100-400 IoT sensors only. For simulation, an NS-3 network simulator will be utilised.

Keywords: IoT, Sensors, LoRaWAN, Delay, Quality of Service, Smart Farming

Introduction

Agriculture land can be developed in urban areas (areas within the city having to build as obstacles) or rural areas (areas outside the town with minimal barriers). IoT networks may be deployed over these areas. Still, it is necessary to use different propagation models per area type to ensure the quality of signal propagation under the constraints of other obstacles. In this study, for IoT-based smart farming, a solution will be introduced to ensure transmission quality by estimating the delay threshold to avoid packet loss.

IoT networks can be used to collect sensitive data on agriculture that can be used to ensure product quality and losses, which can be optimised for historical data. However, the following constraints may hinder IoT-based smart farming in Fig. 1.

Reliability: Network operations under uncertain environmental conditions may cause delays or interruptions in network operations. Fault tolerance capabilities of IoT applications may also suffer due to the hybrid nature of networks.

Deployment: Agriculture land may be deployed in Urban areas or in rural. In the case of Urban areas, the transmission quality may be degraded due to interference/ buildings, rural/remote locations, network deployment/ maintenance /connectivity, etc.

Operational Cost: The setup cost of IoT networks for intelligent farming is quite expensive and thus may also increase the maintenance cost. IoT networks may consume excessive resources, i.e., electricity/batteries/storage space, etc.

Connectivity: In a remote area, connectivity is a significant issue. Interruption in transmission may cause delay/packet loss/re-transmission etc.

Scalability: IoT network expansion over a large-scale coverage area of agricultural land may degrade the network efficiency. IoT applications must be able to process the data under the constraints of scalable network parameters (sensor density/payload variations).

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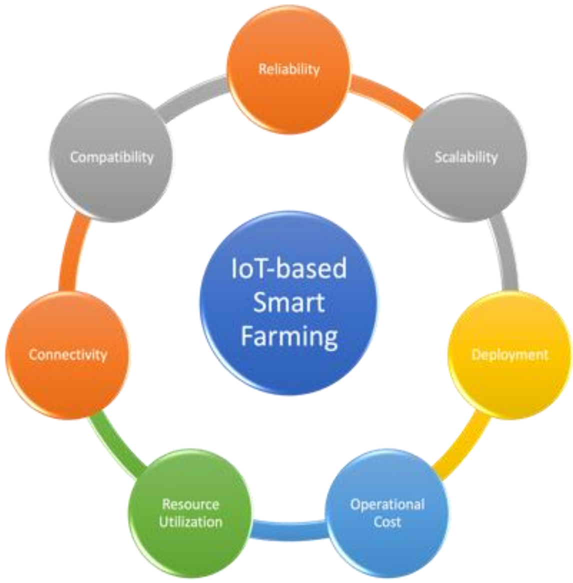

Fig. 1: Challenge for IoT-based smart farming

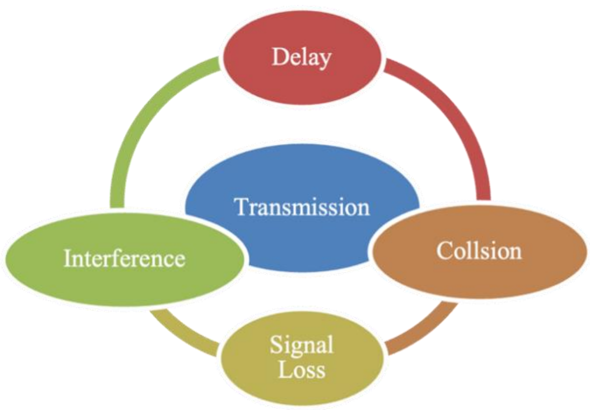

Fig. 2: Wireless communication constraints

Incompatible Hardware Standards: Different vendors have developed various communication standards and hardware incompatibility and transmission over hybrid networks; both are critical issues.

Resource Utilisation: Optimal allocation of sensor density w.r.t. farm size, energy consumption, and maximum bandwidth usage are critical constraints for network performance (Mijwil *et al*., 2023; Sharma *et al*., 2022).

All above-discussed constraints (except operational may degrade the quality of services (quality of service) of the IoT network and thus may cause communication delay/interruption/signal loss etc., (Kassim, 2020; Narwane *et al*., 2022; Maroua *et al*., 2022; Islam *et al*., 2020; Tephila *et al*., 2022) in Fig. 2. Above mentioned factors may consume excessive network resources and reduce network performance.

In this study, experiments following IoT standards are used as explained.

LoRaWAN is a Media Access Control (MAC) protocol developed/maintained by the LoRa alliance and operates over LoRa modulation. It is designed to transmit small size packets over long distances. The following are its features:

(a) Low cost
(b) Easy to deploy and maintain
(c) License-free spectrum (Locatelli *et al*., 2022)

SigFox is designed for long-range transmission using binary phase shift keying, and the following are its features:

(a) Frequently used for remote monitoring
(b) Data security
(c) Pairing is not required
(d) Supports cellular wireless transmission (Elijah *et al*., 2022)

Problem Statement and Contributions

IoT sensors can be deployed in smart farming to collect critical agriculture data for analysis. Agriculture land may be inside the city (urban area) or outside of the town (rural area), and in the case of the metropolitan area, there may be different obstacles (i.e., buildings/bridges/transmission interference, etc.) that can degrade the transmission quality due to delay. In the case of rural areas, there are fewer obstacles as compared to urban areas. So, there is a need to analyse the performance of different IoT standards in these constraints.

This study introduces a delay-aware scheme for smart farming to optimise the transmission delay. Current research includes a simulation-based analysis (using Network Simulator version 3 (NS-3)) to calculate the network performance parameters (delay/throughput/ energy consumption/residual energy etc.). I am using two different IoT communication standards (LoRaWAN and SigFox).

Following section II highlights the recent development related to the relevant domain.

Florita *et al*. (2020) extended the MAC layer of the LoRa network to integrate the delay-tolerant capabilities. It uses multiple gateways to forward the data to the Server. Outcomes show that it offers higher network efficiency with minimal delay. However, the analysis also indicates that signal quality may be reduced due to interference between multiple gateways.

Hakami *et al*. (2020) developed a machine learning method to manage the transmission w.r.t. available network resources (residual energy/buffer capacity). Analysis indicates that it can efficiently regulate the transmission under a resource-constrained network while maintaining higher residual energy with optimal delay factor.

Li *et al*. (2020) developed a secure and delay-tolerant scheme for IoT networks that utilise data caching during computations to avoid transmission delays and uses blockchain to secure data. Experiments indicate that it consumes fewer resources to provide efficient and secure data exchange over IoT networks.

Zhao *et al*. (2020) proposed a UAV-based optimal data processing solution for IoT-based smart farming. It estimates resource availability w.r.t. actual requirement for successful transmission. Analysis shows optimal delay/energy consumption outcomes and is suitable for scalable IoT networks.

Chinnasamy *et al*. (2021) presented a delay-tolerant IoT network that selects relay nodes w.r.t. given coverage area using a genetic algorithm to avoid transmission delay. Analysis shows that optimal placement of relay nodes can reduce the overall uncertainty and improve network throughput.

Naik (2020) integrated edge/fog computing networks with IoT networks and presented a scheduler to distribute traffic load over these networks. Analysis shows that transmission delays over heterogeneous networks can be reduced using this scheduler, and network efficiency can be improved.

Huang *et al*. (2021) proposed a time-constrained data collection method for IoT sensor networks. It estimated the expected/receiving interval for packets to cope with the delay factor. Analysis shows that it can ensure transmission reliability with optimal transmission delay.

Sankayya *et al*. (2021) developed a protocol to utilise network resources efficiently. It estimates the transmission requirements and dynamically allocates the available spectrum. Analysis shows that intermediate transmission delay can be reduced under the quality-of-service constraints using this protocol compared to existing IoT protocols.

Su and Wang (2021) proposed a solution to synchronise data transmission to optimise the transmission delay over IoT networks by estimating the computational load w.r.t. data rate. Analysis shows that it has robust delay-tolerant capabilities and can ensure reliable transmission over IoT-sensor networks.

Su *et al*. (2021) investigated the impact of transmission delay over real-time IoT networks. The study identified that the efficiency/decision-making/accuracy/ convergence rate of automated IoT networks might be degraded due to intermediate transmission delay. Analytical data from this study can be utilised to develop a delay-tolerant scheme for IoT networks.

More and Kale (2022) reviewed the issues related to delay-tolerant networks. The study found some critical factors (i.e., buffer management/data processing by multiple nodes/ queuing algorithms/stable data rate) that can be optimised to reduce delays over different networks (i.e., IoT/ satellite networks, etc.).

Diamanti *et al*. (2022) introduced a delay-tolerant process over IoT-enabled networks. It synchronises the load over different network layers w.r.t. user's preferences. Experiments show that IoT network integration with heterogeneous (edge/fog networks) can reduce the processing delay for end users.

Chakravarty and Acharya (2022) presented a scheduler to regulate the traffic load w.r.t. available energy resources. It can synchronise the data transmission with the harvesting cycle under the delay's constraints. Outcomes show its performance regarding extended network lifetime/higher throughput w.r.t. optimal delay.

Kumar *et al*. (2022) developed a protocol for IoT networks that selects the nearest neighbours for packet forwarding. Acknowledgement is also produced to keep track of all intermediate packets to avoid duplicate packets over the web. Its performance evaluation shows minimal packet forwarding delay compared to existing protocols.

Han *et al*. (2022) emulated the IoT-enabled software-defined networks to investigate the critical factors (packet loss/delay). They offered a delay-aware routing scheme to resolve these issues. Analysis shows that it can efficiently reduce overall uncertainty while maintaining higher network efficiency using hybrid networks.

Nejadhasan *et al*. (2022) introduced a hardware-based solution that can regulate the residual energy at a different level to reduce the transmission delay. Analysis shows that signal amplification at different voltage levels minimises the uncertainty and consumes less computational power, thus extending the overall network lifespan.

Long *et al*. (2022) developed a scheduler for IoT-enabled edge networks. It uses a Q-learning method to compute the traffic load and prepares a load scheduling policy. Simulation shows that it has a fault/ delay tolerance capability to ensure reliable communication and outperforms optimal delay/resource utilisation etc.

Darabkh *et al*. (2022) reviewed the performance of the RPL routing protocol for IoT networks. Study shows that it is an energy-efficient and reliable protocol for IoT networks; however, congestion control/quality of service, routing in highly mobile networks/cross-layer communication/load balancing are still open issues.

Malekijou *et al*. (2023) developed a solution to regulate eh transmission control w.r.t. network resources (buffer/payload). It uses a Q-learning method to estimate the transmission policy under the quality-of-service constraints. Analysis shows that it can reduce the overall transmission delay/energy consumption compared to existing methods.

Wang *et al*. (2022) evaluated the performance of various communication standards developed for IoT networks (LoRa /NB-IoT, Sigfox/ LTE Cat-M1). A comparison study found a few factors (optimal channel utilisation/ energy consumption/ delay/ jitter/ routing/ reliable communication/fault tolerance etc.) that can degrade the performance of these standards. All these factors are open issues for IoT networks.

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Pavithra and Rekha (2022) proposed a MAC-based IoT network scheduler. It uses a genetic algorithm to estimate the number of slots required w.r.t. transmission interval and enforce a schedule for all nodes. Analysis shows that it can schedule the packet transmission with optimal delay, thus improving the network efficiency.

Demiroglou *et al*. (2022) used mobile devices to collect data from the nodes deployed over a large coverage area. After data acquisition, it is forwarded to intermediate gateways. Analysis shows that this scheme can minimise the overall transmission delay and is suitable for scalable IoT networks compared to traditional delay-tolerant methods.

Gupta *et al*. (2023) created a program based on the Internet of Things that can advance smart farming. However, the farm's coverage area, location, environmental conditions, etc., can all impact the performance of IoT networks. If it takes much energy to keep the network running in different conditions, that could cut into the lifespan of an Internet of Things sensor. In this study, we will present a method for energy-efficient smart farming that uses two separate Internet of Things standards, and we will assess its performance using a variety of metrics.

Muthanna *et al*. (2022) developed a tree-based topology for IoT networks that forms multiple clusters for data sharing over the web. A deep learning method schedules duty cycle w.r.t. available network resources (i.e., data rate/frequency/spreading factors, etc.). Simulation results show that it offers higher network efficiency with optimal resource consumption/delay.

Chen *et al*. (2023) simulated a positioning algorithm for an IoT network. It uses the Kalman filter to compute the accurate position of intermediate nodes to ensure reliable transmission. Experiments show that mobile nodes/gateways can reduce the transmission delay compared to stationary IoT networks.

Prade *et al*. (2022) developed a data acquisition method for intelligent farming. It uses multi-hop transmission to gather the data from intermediate nodes. Analysis shows that it is more efficient than traditional LoRa-based IoT Networks.

Qos Constrained

Agriculture land may be located in rural areas or urban areas. So, the IoT sensor network's performance (low throughput, delay/energy consumption/excessive packet loss and re-transmission, etc.) may vary w.r.t. in each area. This study introduces a QoS-constrained transmission scheme to overcome this issue.

There are different phases in proposed schemes, i.e., in phase 1, IoT Sensor's Deployment is performed (as explained); in phase 2, IoT Sensor side data is prepared; and in phase 3, IoT Gateway side data is processed:

Phase 1: IoT Sensor's Deployment over Farm:

Step 1: Get the total coverage area of the farm: $\sum cvf$
Step 2: Create Local coverage area $Lcvf = \sum cvf/4$
Step 3: If no. of sensors: $\sum n$, then the required sensor density $sd = \sum n /4$ w.r.t.$\sum Lcvf$
Step 4: If *cvf*-type==RURAL, then
 Set Propagation_Model-Type = LogDistance)
 Else cvf-type==URBAN then
 Set Propagation_Model-Type=Nakagami)
End if
Step 5: Transmission delay factor df can be defined as:
Df = 0: No delay
Df = 1 With delay
Step 6: if pkt-type== control packet then *df* = 0
Step 7: if pkt-type== !control packet then *df* = 1

Control packets must have higher priority over sensed data to ensure connectivity. So there should be a minimum delay for such packets.

Phase 2: IoT Sensor side data preparation

Step 1: Sense data
Step 2: Estimate Delay threshold (*sdTh*) for sensor:
 Sensor- >Current time + (*Sn->d* * *h*)
Where sensor- >distance is d, no. of hops h required to forward a packet p from the sensor to Gateway
Step 3: If the source is any sensor, then it is calculated as *sdTh*. The intermediate Gateway is calculated as *gdTh*, as shown in Table 1 and Figs. 3, 4, and 5.
Step 4: Forward (sensor->*pkt*, *df*, Gateway, TRUE)

Phase 3: IoT Gateway side data processing

Step 1: Collect (data, Sensors)
Step 2: Gateways->Verify (Delay Threshold, Sensor->Data)
Step 3: get expected time = (current time at Gateway - sensor- >*sdTh*) > 0
Step 4: If (Sensor- >*pkt*- >*sdTh*> expected-time)
 If *pkt*- >*df* !=0 then *pkt*- >status = expired
Discard (*pkt*)
Else
Forward (gateway ->*pkts*, *df*, Server)
End if

Phase 4: IoT Server side data processing

Step 1: Collect (data, gateway)
Step 2: Server->Verify (Delay Threshold, Gateway->Data)
Step 3: Get expected-time = (current time at Server-Gateway->*sdTh*) > 0
Step 4: If (Gateway->*pkt*->*gdTh*> expected-time)
If *pkt*->*df*! = 0 then pkt->status = expired
Discard (*pkt*)
Else
Accept (Valid data, Gateway, true)
End if

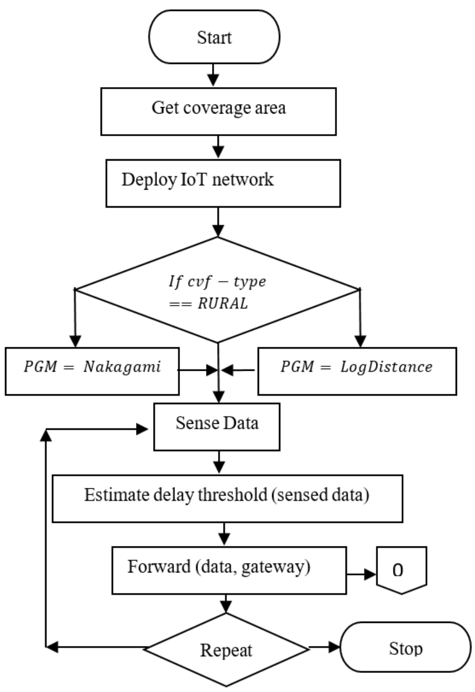
Table 1 shows the source nodes (1-5), having distance (d) (in meters) from gateways with the number of Hops (h), the current time is marked as CT (milliseconds), and dTH is the delay threshold for packets. Table 1 values are obtained from simulation results (in a run-time environment).

Flow chart 1 shows the basic setup of the network as described in phase 1. First of all, in phase 1, the entire coverage area of the farm is calculated as $\sum cvf$ for the IoT sensor deployment. Then it is divided into local coverage area (*Lcvf*) as $\sum cvf/4$ and finally, several sensors $\sum n/4$ are deployed w.r.t. $\sum Lcvf$.

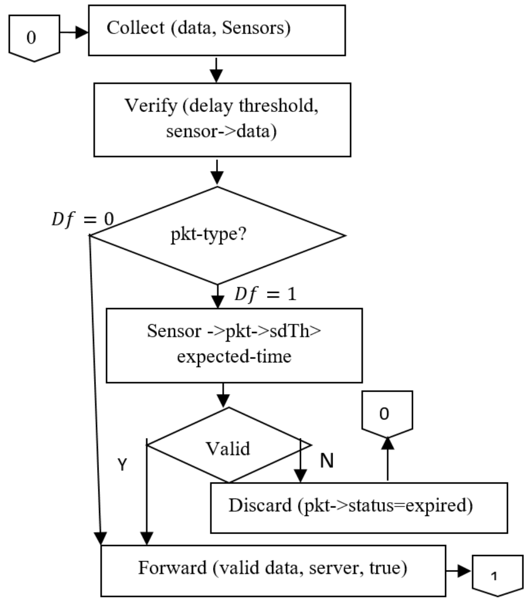
The farm may be located in a rural/urban area, so according to area type, the propagation model is selected (log distance model for rural areas and Nakagami model for urban areas). Transmitted data may contain control packets or ordinary sensed data; the delay factor (0 for control packets and 1 for data packets) is initialised according to its type. According to phase 2, to minimise delay, the delay threshold and expected time are calculated for the packet arrival (based on the number of hops required to forward the packet and the distance between source and destination over a particular interval) between sensors and Gateway as well as it is also estimated for gateways and Server in Table 1. After calculating the above factors, data is forwarded from sensors to intermediate gateways.

Table 1: Delay threshold

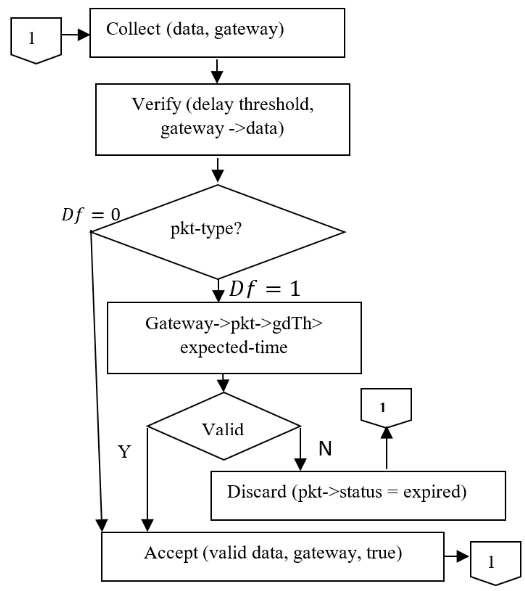
Source	Distance (d)	Hops (h)	Current Time (CT)	dTH
1	9	2	1	19
2	2	1	3	5
3	7	3	7	28
4	5	5	5	30
5	15	8	8	128



Flow Chart 1: Sensor-level data forwarding



Flow Chart 2: Gateway-level data forwarding



Flow Chart 3: Server Level Data processing

Flow chart 2 shows the steps of phase 3; in this, Gateway receives the data from sensors and verifies its expected time (at Gateway), which must be greater than zero. If there is any delay, only control packets are accepted and forwarded to the Server, and all other invalid data packets are marked as expired and discarded.

Flow chart 3 shows steps of phase 4, in which the Server receives the data from the Gateway and verifies its expected time (at the Server), which must be greater than zero; otherwise, all data packets are discarded and marked as expired except control packets. All the above phases may be repeated as required.

Materials and Methods

This study introduces a delay-aware scheme for delay-optimized smart farming using a simulator called NS-3. The simulation-based methodology used in the present study computes the network performance parameters like delay, throughput, energy consumption, residual energy, etc. We have implemented two distinct Internet of Things communication standards (LoRaWAN and SigFox).

Results

For experiments, NS-3 over Linux platform/Intel(R) Core(TM) i7-7600U CPU @ 2.80GHz 2.90 GHz and 32 GB RAM, Packet size 64 bytes were used with different simulation scenarios, i.e., Delay aware Quality of Service constrained scheme (DQS) and Normal method (NDQS) for smart farming using two different IoT standards (LoRaWAN and SigFox) over rural/urban areas. IoT sensor density varies from 100-400 sensors and simulation time is 600 sec, initial energy 10J, Rx/Tx (10), etc., NS-3 flow monitor is used to calculate the network performance parameters, and the NS-3 energy model is used to obtain the energy consumption data over the simulation interval. NS-3 patches integrate the support for LoRaWAN and SigFox standards and IoT sensors.

Performance Analysis of LoRaWAN in Rural Areas

Figure 6 shows the throughput of LoRaWAN in a rural area with 100 IoT-Sensors using NDQS and DQS scenarios. In the case of NDQS, it is 168 Kbps and 198 Kbps for DQS.

Figure 7 shows the throughput of LoRaWAN in a rural area with 100 IoT-Sensors using NDQS and DQS scenarios. In the case of NDQS, it is 314 Kbps and 394 Kbps for DQS.

Figure 8 shows the throughput of LoRaWAN in rural-area with 100 IoT-Sensors using NDQS and DQS scenarios. In the case of NDQS, it is 450 Kbps, and 591 Kbps for DQS.

Figure 9 shows the throughput of LoRaWAN in a rural area with 100 IoT-Sensors using NDQS and DQS scenarios. In the case of NDQS, it is 564 Kbps and 783 Kbps for DQS.

Figure 10 compares the throughput of LoRaWAN using NDQS/DQS in a rural area. It can be analysed that In each scenario, throughput varies as the sensor density increases. However, NDQS delivered less throughput than DQS w.r.t. IoT sensor density, ranging from 100 to 400.

Figure 11 shows the residual energy of LoRaWAN in rural-area with 100 IoT-Sensors. In the case of NDQS, it is 4.01J; in the case of DQS, it is 5.208J.

Figure 12 shows the residual energy of LoRaWAN in rural-area with 200 IoT-Sensors. In the case of NDQS, it is 3.0516 J; in the case of DQS, it is 4.609 J.

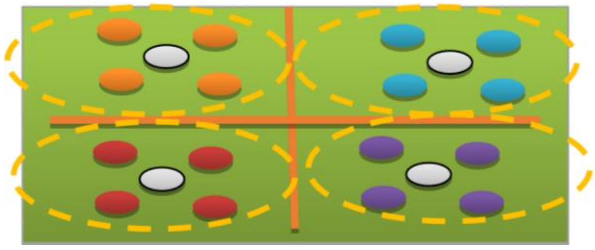


Fig. 3: Distribution of IoT sensors over the coverage area (Tephila *et al*., 2022)

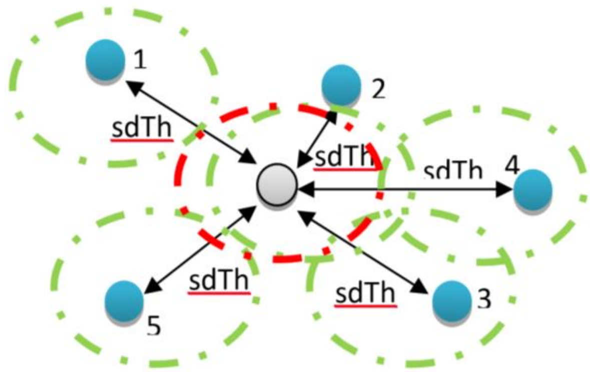


Fig. 4: Delay threshold for sensors and gateway

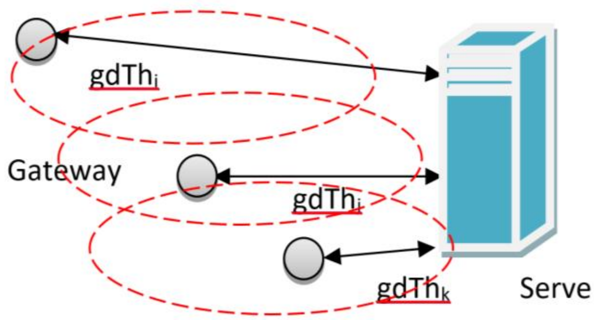


Fig. 5: Delay threshold for gateway and server

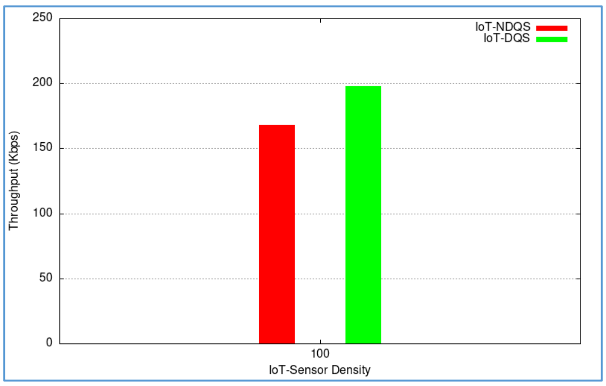


Fig. 6: Throughput-LoRaWAN-rural-area-100-IoT-sensors

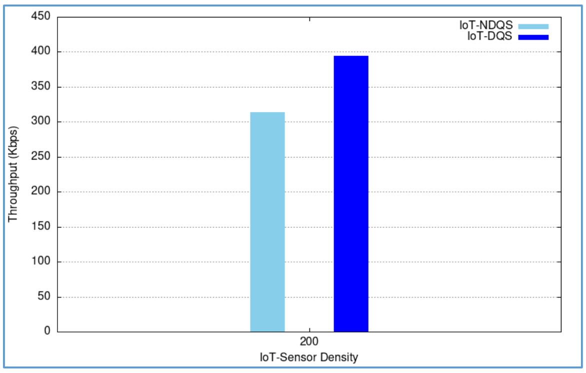


Fig. 7: Throughput-LoRaWAN-rural-area-200-IoT-sensors

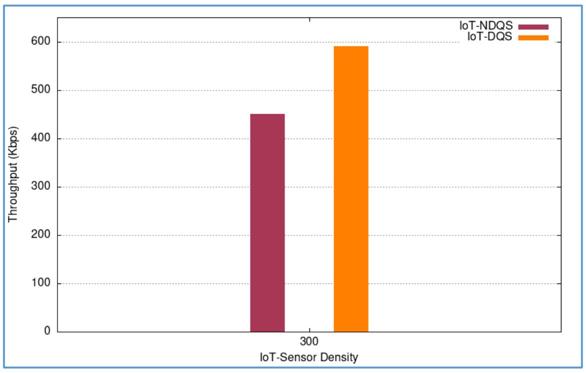


Fig. 8: Throughput-LoRaWAN-rural-area-300-IoT-sensors

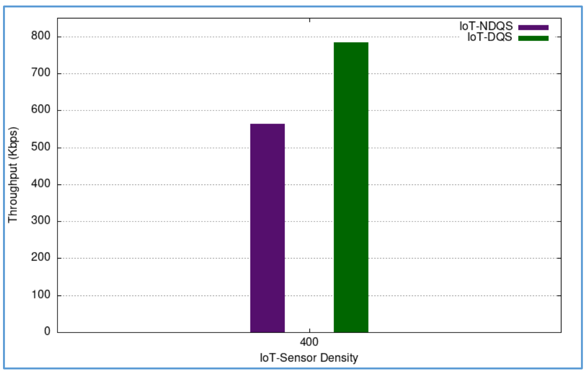


Fig. 9: Throughput-LoRaWAN-rural-area-400-IoT-Sensors

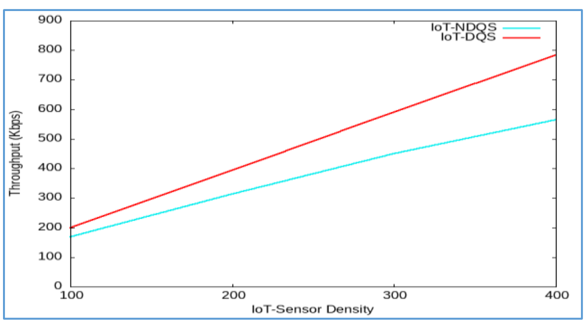


Fig. 10: LoRaWAN-rural-area-comparison-throughput

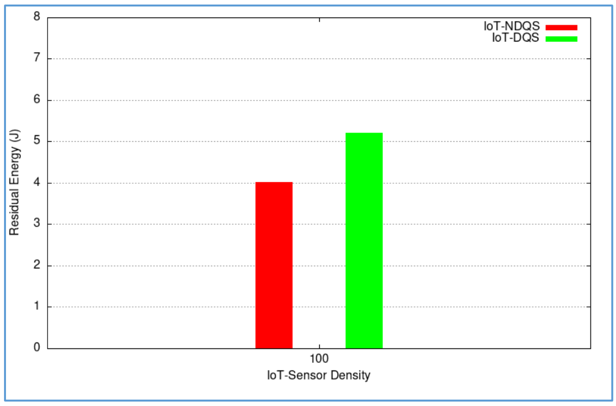


Fig. 11: Residual energy-LoRaWAN-rural-area-100-IoT-sensors

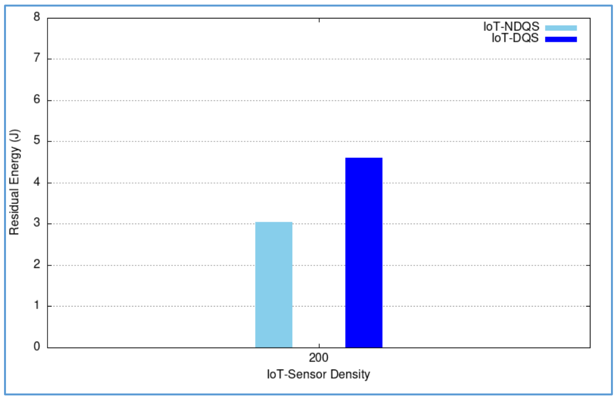


Fig. 12: Residual energy-LoRaWAN-rural-area-200-IoT-sensors

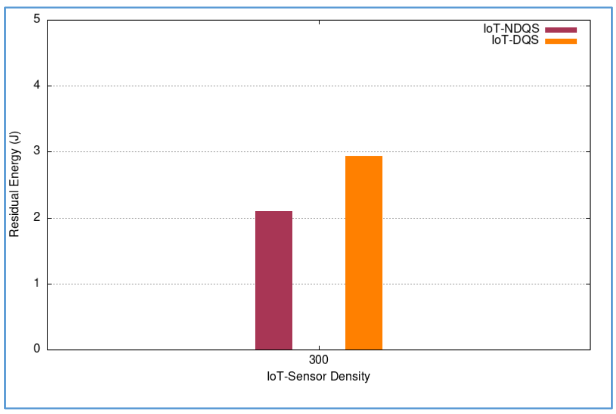


Fig. 13: Residual energy-LoRaWAN-rural-area-300-IoT-sensors

Figure 13 shows the residual energy of LoRaWAN in rural-area with 300 IoT-Sensors. In the case of NDQS, it is 2.0932J, and in the case of DQS, it is 2.9318J.

Figure 14 shows the residual energy of LoRaWAN in rural-area with 400 IoT-Sensors. In the case of NDQS, it is 1.13482 J, and in the case of DQS, it is 1.614 J.

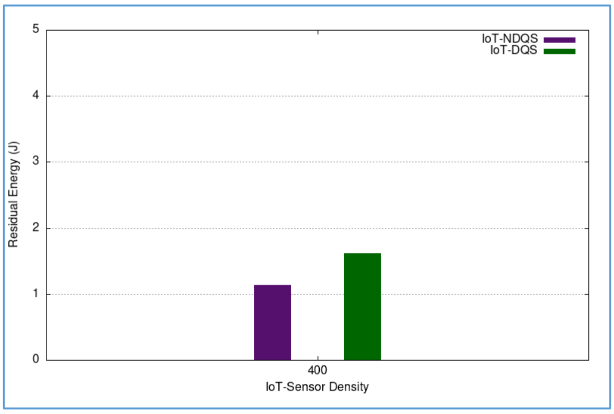


Fig. 14: Residual energy LoRaWAN rural-area-400-IoT-sensors

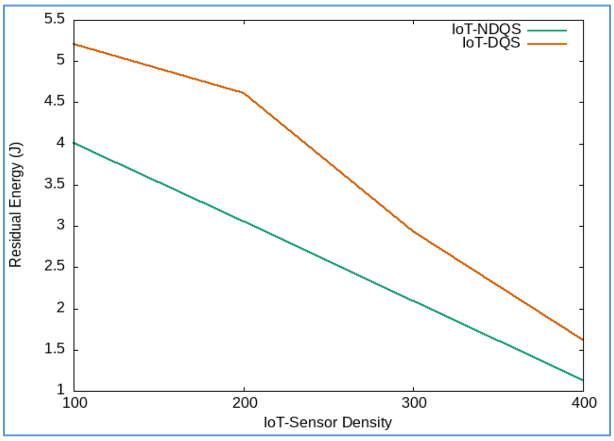


Fig. 15: LoRaWAN rural-area residual energy-comparison

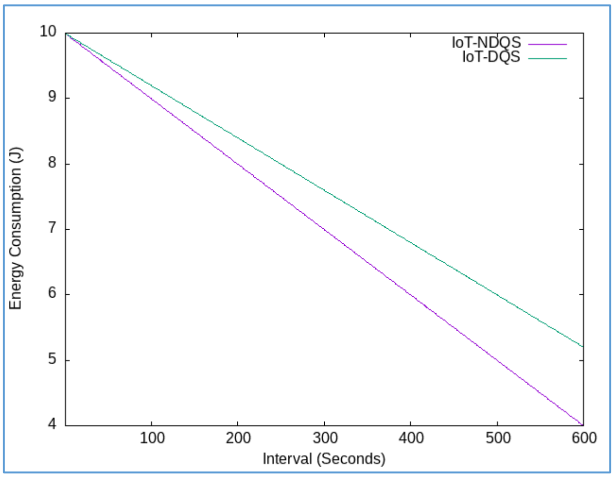


Fig. 16: Energy consumption LoRaWAN rural-area 100-IoT-sensor

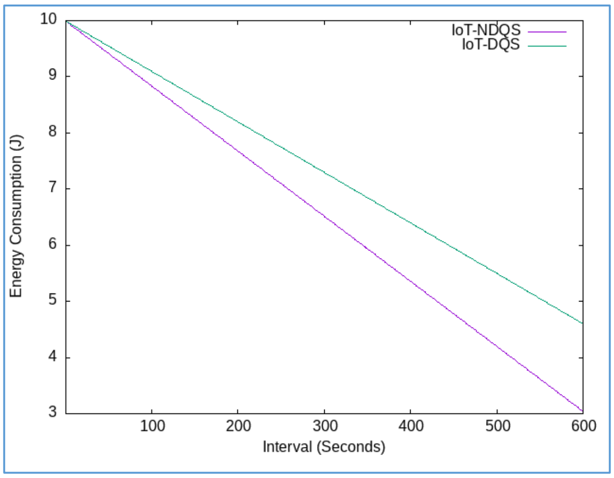


Fig. 17: Energy consumption-LoRaWAN-rural-area-200-IoT-sensors

Figure 15 shows the comparison of residual energy of NDQS and DQS using LoRaWAN in rural-area under the constraints of sensor density. As the sensor density increases, the network consumes more power and with the peak sensor density, it reaches its lowest level. DQS retained a higher residual energy level than NDQS w.r.t. sensor density.

Energy Consumption Analysis-LoRaWAN-Rural Area

Figure 16 shows the energy consumption of DQS and NDQS using LoRaWAN in a rural area with 100-IoT sensors. It can be observed that the energy depletion of NDQS is relatively higher as compared to DQS over the simulation interval, and it reaches up to its lowest level w.r.t. each scheme. However, DQS retained a higher energy level as compared to NDQS.

Figure 17 shows the energy consumption of DQS and NDQS using LoRaWAN in a rural area with 200 IoT sensors. It can be observed that energy depletion of DQS is less than NDQS. NDQS consumed higher energy in contrast to DQS till the end of the simulation interval.

Figure 18 shows the energy consumption of DQS and NDQS using LoRaWAN in a rural area with 300 IoT sensors. It can be observed that the residual energy level of NDQS is relatively less as compared to DQS. However, it becomes constant till the end of the simulation interval.

Figure 19.1 shows the energy consumption of DQS and NDQS using LoRaWAN in a rural area with 400-IoT sensors. It can be observed that in the case of both schemes, there is a sharp decline in energy level over the simulation interval of up to 600 sec. However, DQS consumed slightly less energy as compared to NDQS.

Figure 19.2 shows the variations in delay using NQDS/DQS with LoRaWAN standard in rural-area. It can be analysed that it varies with NQDS/DQS under the constraints of sensor density. Results show that DQS maintained an acceptable delay value as compared to NDQS.

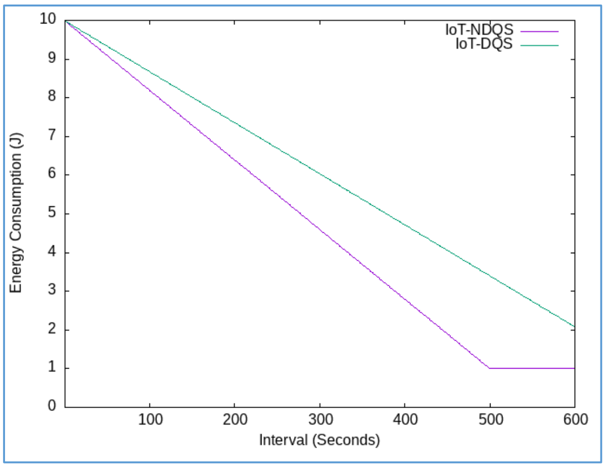


Fig. 18: Energy consumption-LoRaWAN-rural-area-300-IoT-sensors

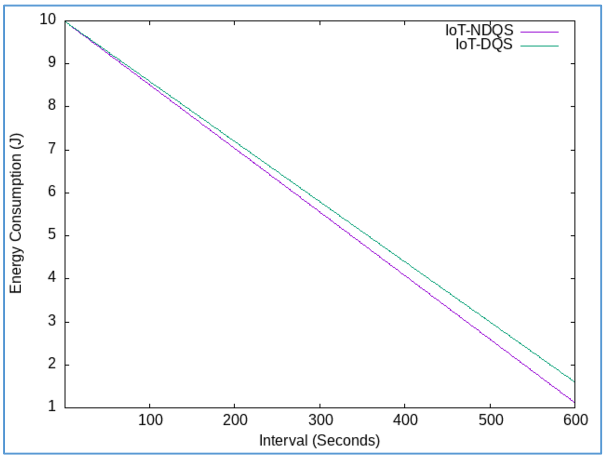


Fig. 19.1: Energy consumption-LoRaWAN-rural-area-400-IoT-sensors

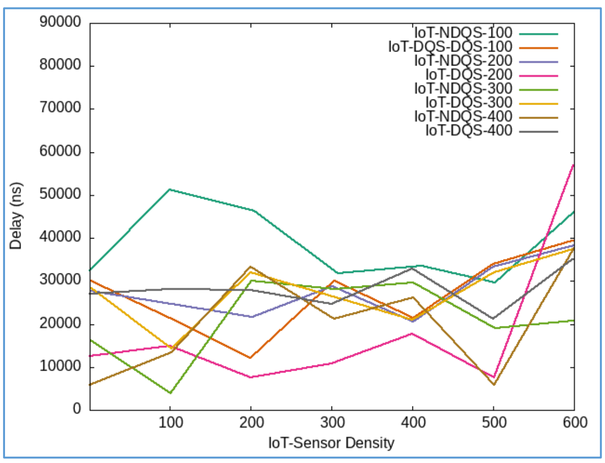


Fig. 19.2: Delay-LoRaWAN-rural-area

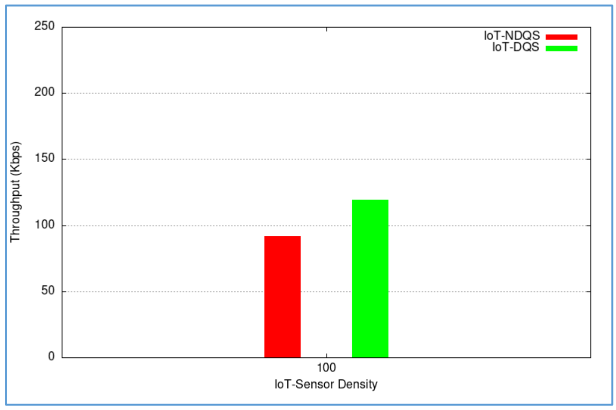


Fig. 20: Throughput-LoRaWAN-urban-area-100-IoT-sensors

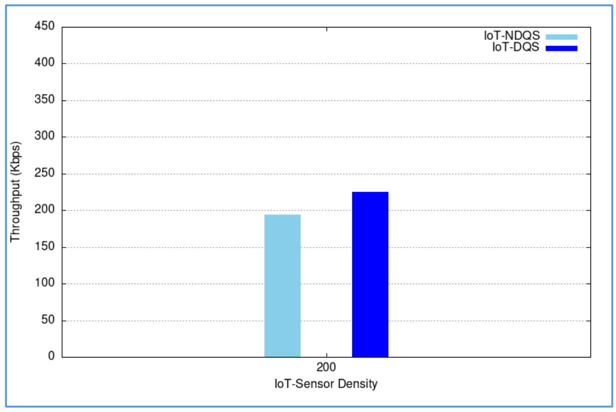


Fig. 21: Throughput-LoRaWAN-urban-area-200-IoT-Sensors

Performance Analysis of LoRaWAN in an Urban Area

Figure 20 shows the throughput of LoRaWAN in an urban area with 100 IoT sensors using DQS and NDQS schemes. For NDQS, it is 92 Kbps and 119 Kbps for DQS.

Figure 21 shows the throughput of LoRaWAN in an urban area with 200 IoT sensors using DQS and NDQS schemes. For NDQS, it is 194 Kbps and 225 Kbps for DQS.

Figure 22 shows the throughput of LoRaWAN in urban areas with 300 IoT sensors using DQS and NDQS schemes. For NDQS, it is 291 Kbps, and 332 Kbps for DQS.

Figure 23 shows the throughput of LoRaWAN in an urban area with 400-IoT sensors using DQS and NDQS schemes. For NDQS, it is 368 Kbps and 460 Kbps for DQS.

Figure 24 shows the throughput Comparison of DQS and NDQS schemes using LoRaWAN standards in urban areas. It indicates that DQS delivered a higher throughput under the constraints of IoT sensor density (100-400) in contrast to NDQS.

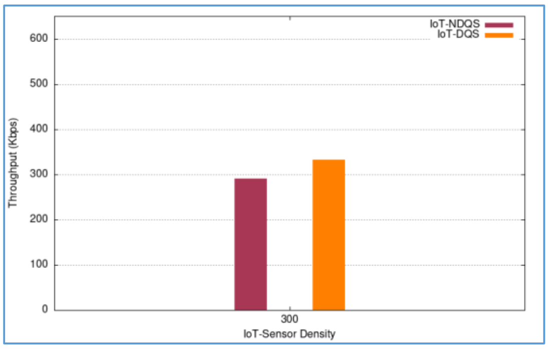


Fig. 22: Throughput-LoRaWAN-urban-area-300-IoT-sensors

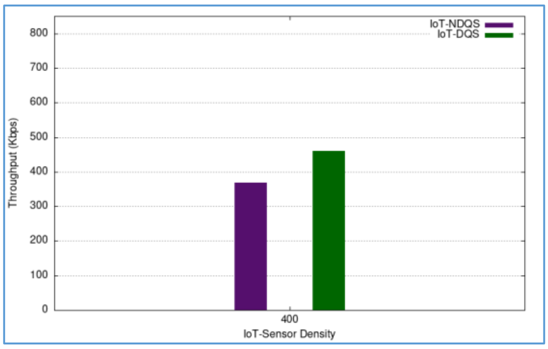


Fig. 23: Throughput-LoRaWAN-urban-area-400-IoT-sensors

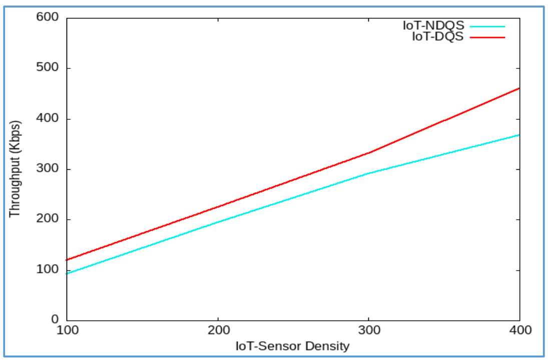


Fig. 24: LoRaWAN-urban-area-comparison-throughput

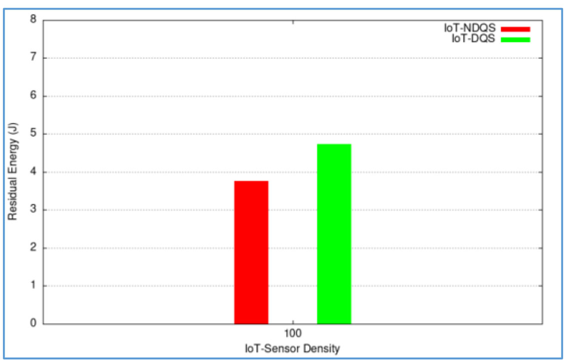


Fig. 25: Residual energy-LoRaWAN- urban -area-100-IoT-sensors

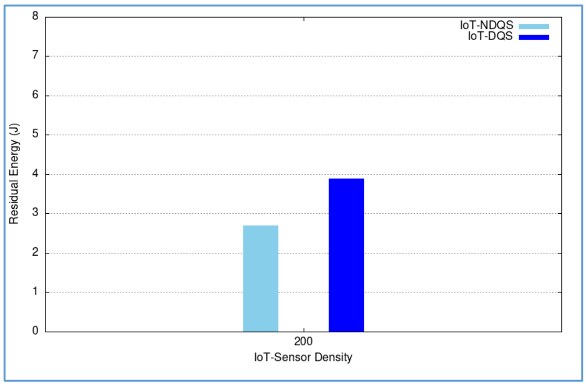


Fig. 26: Residual energy-LoRaWAN-urban-area-200-IoT-sensors

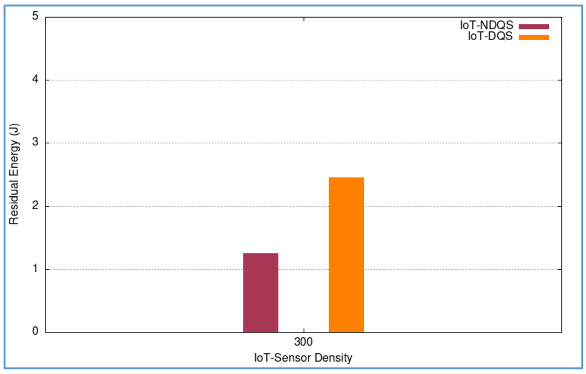


Fig. 27: Residual energy-LoRaWAN-urban-area-300-IoT-sensors

Residual Energy Comparison Analysis-LoRaWAN-Urban Area

Figure 25 shows the residual energy of DQS and NDQS using the LoRaWAN standard in an urban area with 100 IoT Sensors. It is 3.7704 J for NDQS and 4.7288 J for DQS.

Figure 26 shows the residual energy of DQS and NDQS using the LoRaWAN standard in urban areas with 200 IoT Sensors. It is 2.6922 J for NDQS and 3.8902 J for DQS.

Figure 27 shows the residual energy of DQS and NDQS using the LoRaWAN standard in an urban area with 300 IoT Sensors. It is 1.2546 J for NDQS and 2.4526 J for DQS.

Figure 28 shows the residual energy of DQS and NDQS using the LoRaWAN standard in urban areas with 400 IoT Sensors. It is 0.985909 J for NDQS and 1.7338 J for DQS.

Figure 29 compares the residual energy of DQS and NDQS using the LoRaWAN standard in an urban area. It indicates that DQS managed a higher level of residual energy w.r.t. IoT sensor density (100-400). In contrast, NDQS consumed higher resources and could not maintain optimal residual energy compared to the DQS scheme.

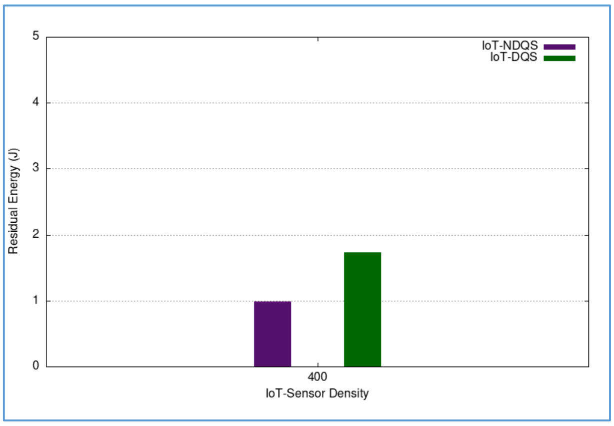


Fig. 28: Residual energy-LoRaWAN-urban-area-400-IoT-sensors

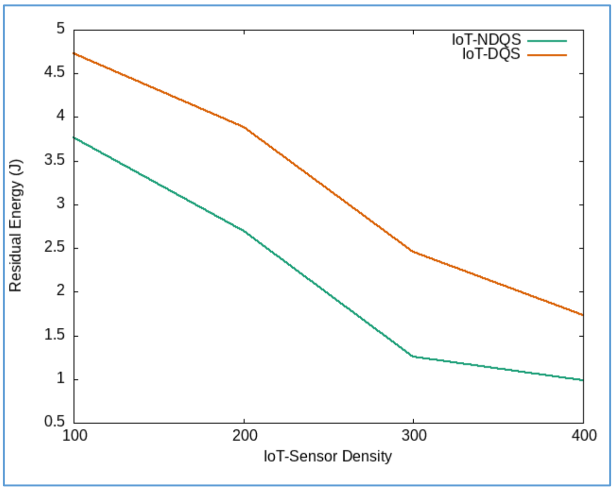


Fig. 29: LoRaWAN-urban-area-residual energy-comparison

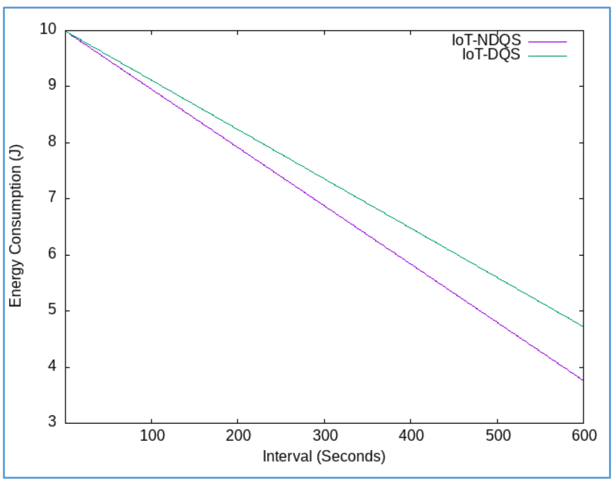


Fig. 30: Energy consumption-LoRaWAN-urban-area-100-IoT-sensors

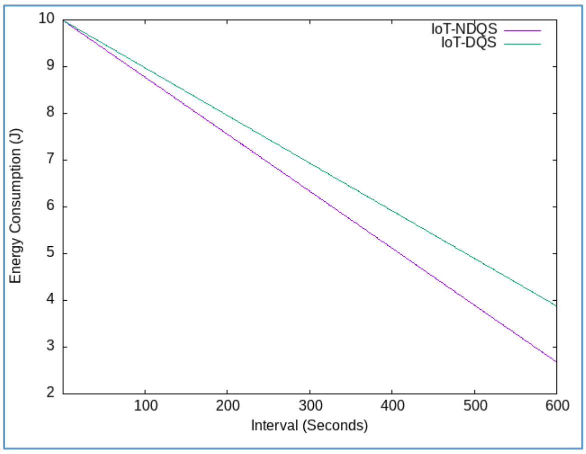


Fig. 31: Energy consumption-LoRaWAN-urban-area-200-IoT-sensors

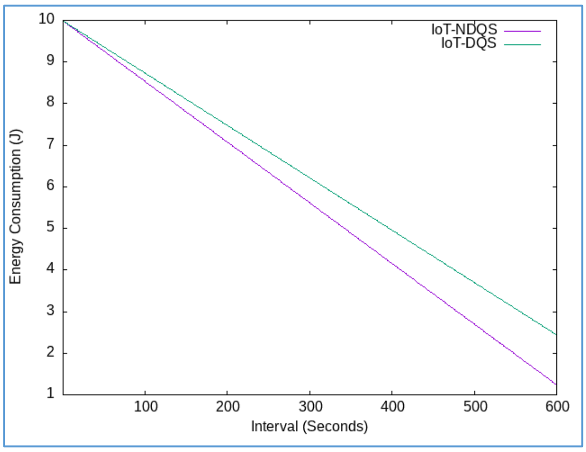


Fig. 32: Energy consumption-LoRaWAN-urban-area-300-IoT-sensors

Analysis of Energy Consumption in an Urban Area Using LoRaWAN Standard

Figure 30 shows the energy consumption of the LoRaWAN standard in an urban area with 100 IoT sensors for DQS and NDQS schemes. It can be observed that energy depletion is relatively higher for the NDQS scheme than the DQS scheme over the simulation interval (600 sec).

Figure 31 shows the energy consumption of the LoRaWAN standard in an urban area with 200 IoT Sensors for DQS and NDQS schemes. It can be analysed that the scheme consumed more energy than the DQS scheme until the simulation's end.

Figure 32 shows the energy consumption of the LoRaWAN standard in an urban area with 300 IoT Sensors for DQS and NDQS schemes. It shows that for both scenarios, there is a steep decline in energy level till the end of the simulation.

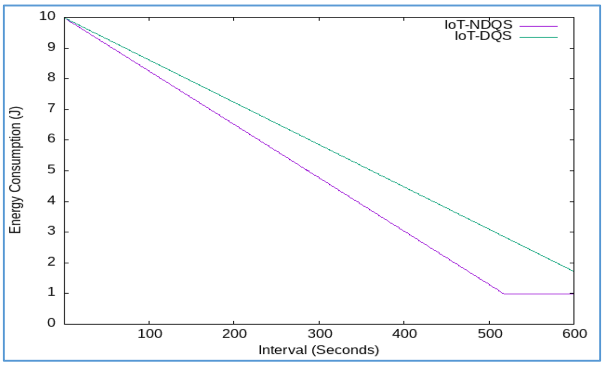


Fig. 33.1: Energy consumption-LoRaWAN- urban -area-400-IoT-sensors

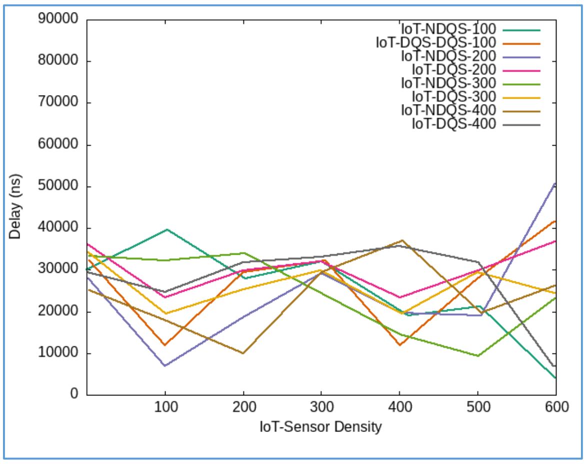


Fig. 33.2: Delay-LoRaWAN-urban-area

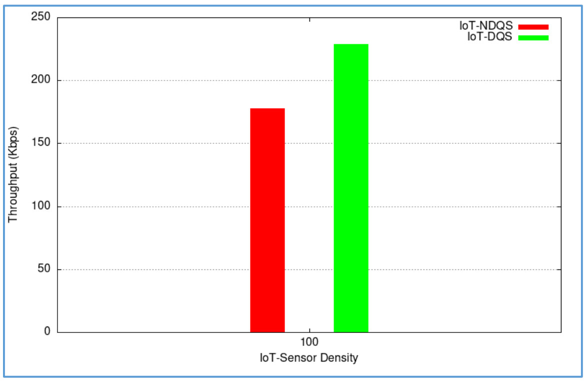


Fig. 34: throughput-SigFox-rural-area-100-IoT-sensors

Figure 33.1 shows the energy consumption of the LoRaWAN standard in an urban area with 400 IoT Sensors for DQS and NDQS schemes. It can be observed that the energy level declined for the NDQS scheme and at the end of the simulation, it became constant as compared to the DQS scheme over the simulation interval 600 sec.

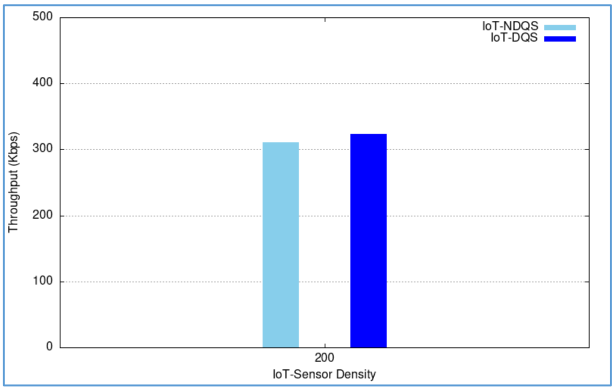


Fig. 35: Throughput-SigFox-rural -area-200-IoT-sensors

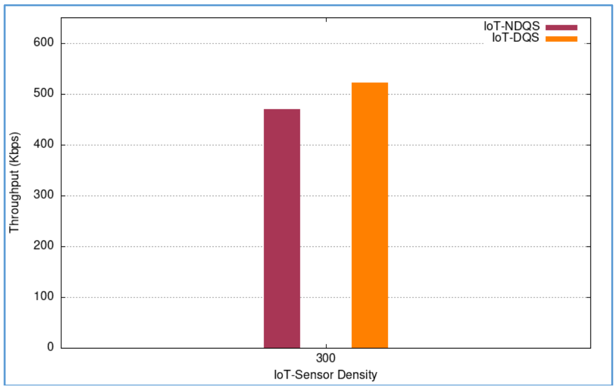


Fig. 36: Throughput-SigFox-rural-area-300-IoT-sensors

Figure 33.2 shows the variations in delay using NQDS/DQS with LoRaWAN standard in urban areas. It can be analysed that it varies with NQDS/DQS under the constraints of sensor density for both schemes. As per the results, DQS has an optimal delay value compared to NDQS.

Performance Analysis of SigFox in the Rural Area

Figure 34 shows the throughput of SigFox in a rural area with 100 IoT-Sensors using DQS and NDQS schemes. In the case of NDQS, it is 177.777778 Kbps and 228.571429 Kbps for the DQS scheme.

Figure 35 shows the throughput of SigFox in a rural area with 200 IoT Sensors using DQS and NDQS schemes. In the case of NDQS, it is 411.428571 Kbps and 442.532268 Kbps for the DQS scheme.

Figure 36 shows the throughput of SigFox in a rural area with 300 IoT Sensors using DQS and NDQS schemes. In the case of NDQS, it is 469.565217 Kbps and 521.73913 Kbps for the DQS scheme.

Figure 37 shows the throughput of SigFox in a rural area with 400 IoT Sensors using DQS and NDQS schemes. In the case of NDQS, it is 528.813559 Kbps and 589.79206 Kbps for the DQS scheme.

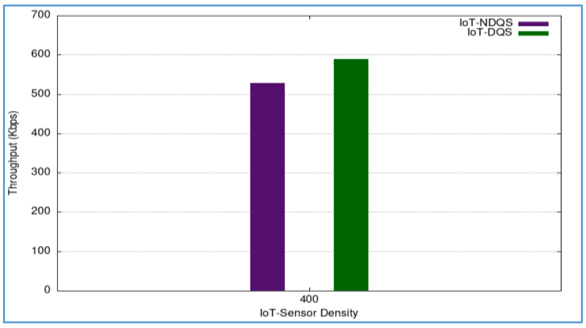


Fig. 37: Throughput-SigFox-rural-area-400-IoT-sensors

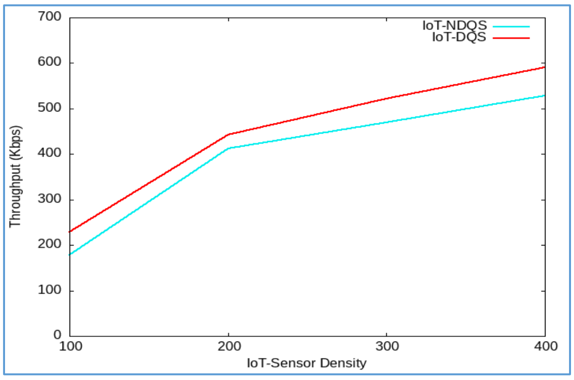


Fig. 38: SigFox-rural-area-comparison-throughput

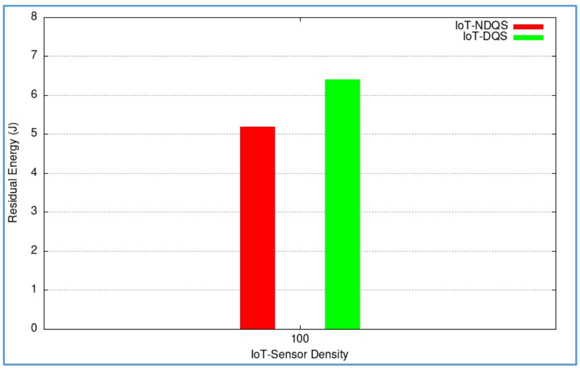


Fig. 39: Residual energy-SigFox-rural-area-100-IoT-sensors

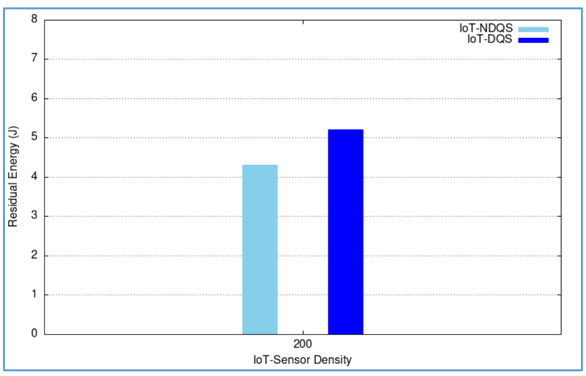


Fig. 40: Residual energy-SigFox-rural-area-200-IoT-sensors

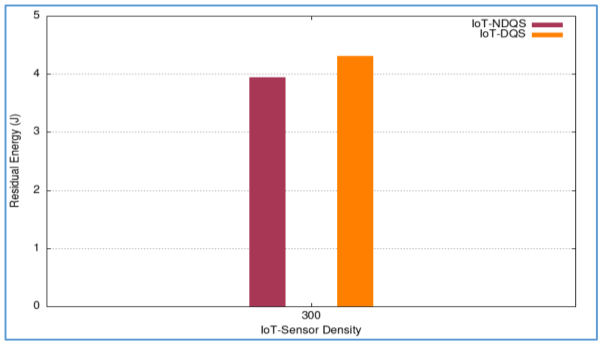


Fig. 41: Residual energy-SigFox-rural-area-300-IoT-sensors

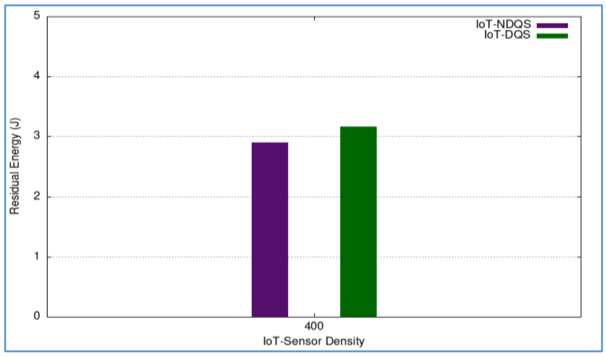


Fig. 42: Residual energy-SigFox-rural-area-400-IoT-sensors

Figure 38 compares the throughput of DQS and NDQS schemes using SigFox standard in rural-area under the constraints of IoT sensor density (100-400). It can be observed that the DQS scheme has a higher throughput as compared to the NDQS scheme w.r.t. IoT sensor density.

Residual Energy Comparison of SigFox Standard in the Rural Area

Figure 39 shows the residual energy of DQS and NDQS using SigFox standard in urban areas with 100 IoT Sensors. It is 5.194 J for NDQS and 6.406 J for DQS.

Figure 40 shows the residual energy of DQS and NDQS using the SigFox standard in an urban area with 200 IoT Sensors. It is 4.3095 J for NDQS and 5.208 J for DQS.

Figure 41 shows the residual energy of DQS and NDQS using the SigFox standard in an urban area with 300 IoT Sensors. It is 3.9501J for NDQS and 4.3095J for DQS.

Figure 42 shows the residual energy of DQS and NDQS using the SigFox standard in an urban area with 400 IoT Sensors. It is 2.90185 J for NDQS and 3.16 J for DQS.

Figure 43 shows the comparison residual energy of SigFox standard in rural areas using DQS and NDQS schemes. It can be analysed that more energy is consumed w.r.t. IoT sensor density and DQS retained its optimal level compared to NDQS, and with the peak sensor density (400), it reached its lowest level for both schemes.

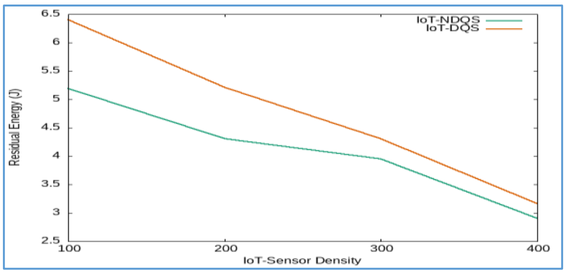


Fig. 43: SigFox-rural-area-residual energy-comparison

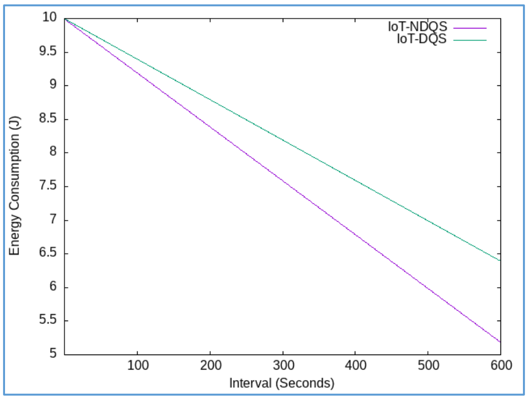


Fig. 44: Energy consumption-SigFox-rural-area-100-IoT-sensors

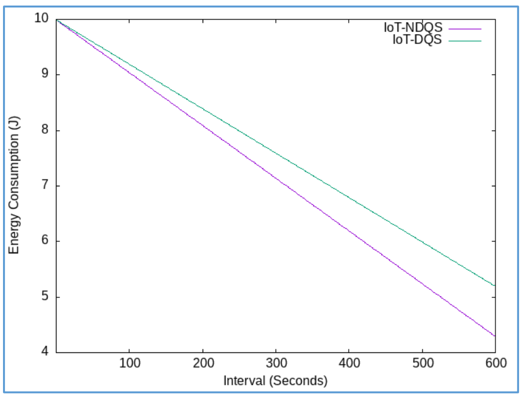


Fig. 45: Energy consumption-SigFox-rural-area-200-IoT-sensors

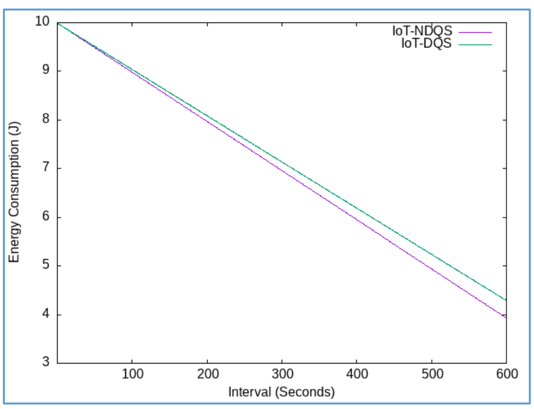


Fig. 46: Energy consumption-SigFox-rural-area-300-IoT-sensors

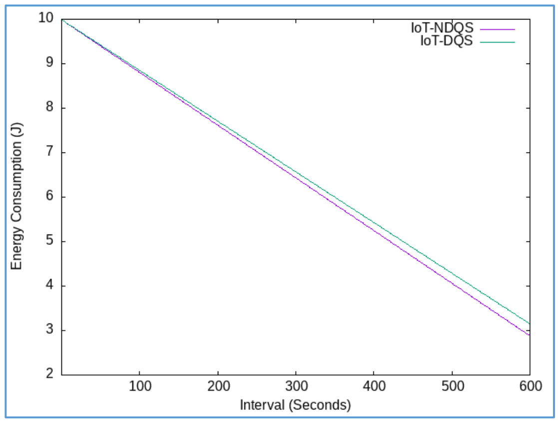


Fig. 47. 1: Energy consumption-SigFox-rural-area-400-IoT-sensors

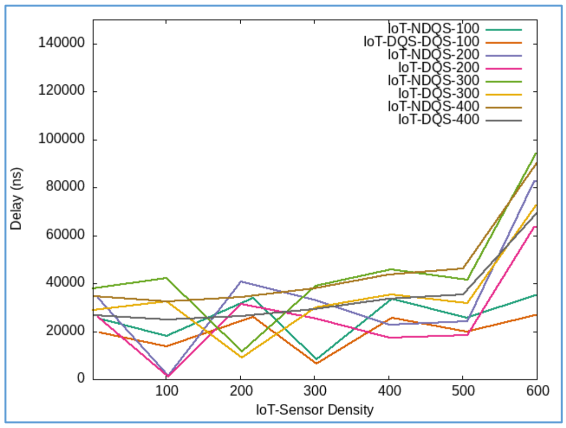


Fig. 47. 2: Delay-SigFox-rural-area

Energy Consumption Comparison for SigFox Standard in a Rural Area

Figure 44 shows that DQS and NDQS energy consumption using Sigfox standard in rural areas with 100 IoT-Sensors. It can be analysed that NDQS has higher energy depletion over the simulation interval as compared to DQS.

Figure 45 shows DQS and NDQS energy consumption using Sigfox standard in rural areas with 200 IoT-Sensors. It can be analysed that NDQS consumed more energy over the simulation interval than DQS w.r.t. sensor density.

Figures 46-47.1 shows the energy consumption-SigFox standard over the rural area using NDQS and DQS with 300-IoT-Sensors. In both schemes, there is a marginal difference in energy consumption, increasing until the end of the simulation interval.

Figure 47.2 shows the variations in delay using NDQS/DQS with SigFox standard in rural-area. Results indicate that it varies w.r.t. sensor density using both schemes (NDQS/DQS). However, it is slightly less using DQS than NDQS over simulation intervals.

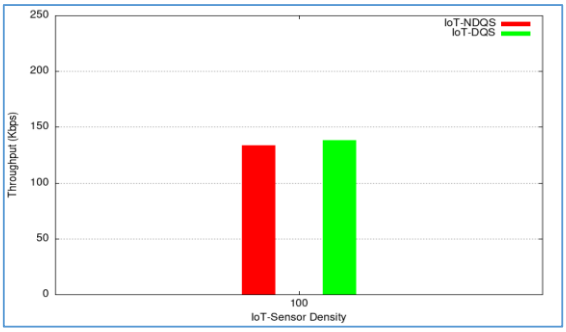


Fig. 48: Throughput-SigFox-urban-area-100-IoT-sensors

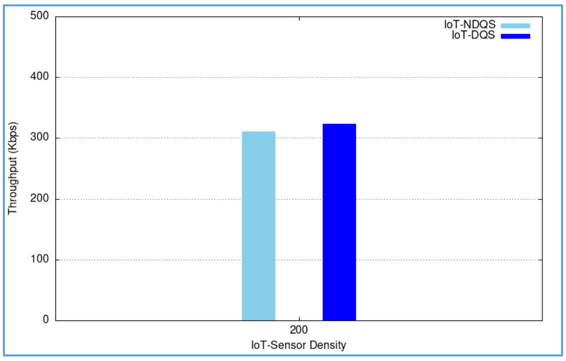


Fig. 49: Throughput-SigFox-urban-area-200-IoT-sensors

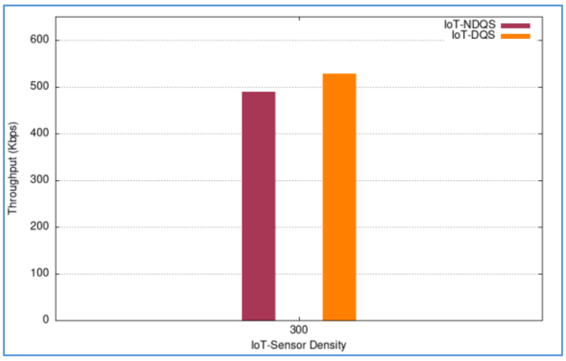


Fig. 50: Throughput-SigFox-urban-area-300-IoT-sensors

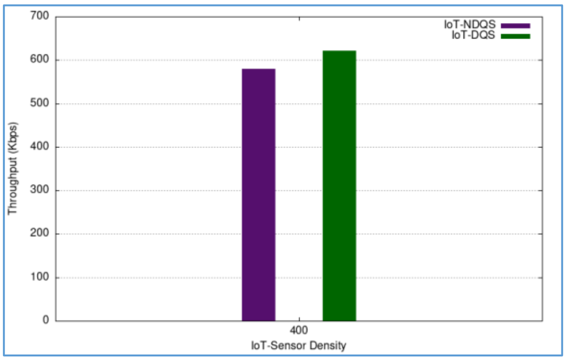


Fig. 51: Throughput-SigFox-urban-area-400-IoT-sensors

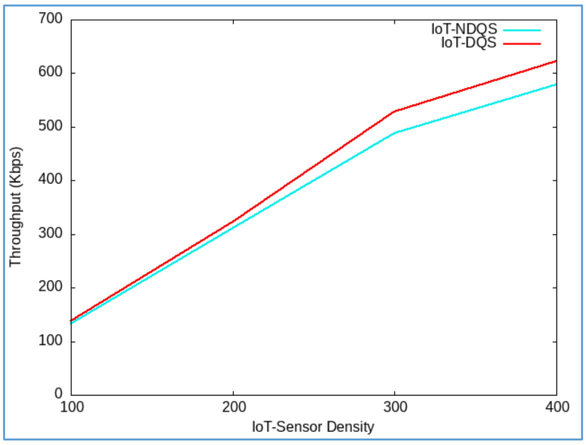


Fig. 52: SigFox-urban-area-comparison-throughput

Performance Analysis of SigFox in an Urban Area

Figure 48 shows the throughput of SigFox in a rural area with 100 IoT-Sensors using DQS and NDQS schemes. In the case of NDQS, it is 133.3333 Kbps and 138.355111 Kbps for the DQS scheme.

Figure 49 shows the throughput of SigFox in an urban area with 200 IoT-Sensors using DQS and NDQS schemes. In the case of NDQS, it is 310.995927 Kbps and 322.828593 Kbps for the DQS scheme.

Figure 50 shows the throughput of SigFox in urban areas with 300 IoT-Sensors using DQS and NDQS schemes. In the case of NDQS, it is 488.707886 Kbps and 527.788884 Kbps for the DQS scheme.

Figure 51 shows the throughput of SigFox in urban areas with 400 IoT-Sensors using DQS and NDQS schemes. In the case of NDQS, it is 579.110651 Kbps and 621.991855 Kbps for the DQS scheme.

Figure 52 compares the throughput of DQS and NDQS using SigFox standard in urban areas w.r.t. IoT sensor density (100-400). Results indicate that with minimal sensor density, it is the lowest for both schemes.

It increases as the sensor density varies and reaches its peak value with the highest sensor density. However, DQS offered higher throughput as compared to NDQS under the constraints of sensor density.

Energy Consumption of SigFox Standard Under Urban Area

Figure 53 shows the residual energy of DQS and NDQS using SigFox standard in urban areas with 100 IoT Sensors. It is 3.412 J for NDQS and 4.132 J for DQS.

Figure 54 shows the residual energy of DQS and NDQS using the SigFox standard in an urban area with 200 IoT Sensors. It is 2.818 J for NDQS and 3.115 J for DQS.

Figure 55 shows the residual energy of DQS and NDQS using the SigFox standard in an urban area with 300 IoT Sensors. It is 1.984 J for NDQS and 2.521 J for DQS.

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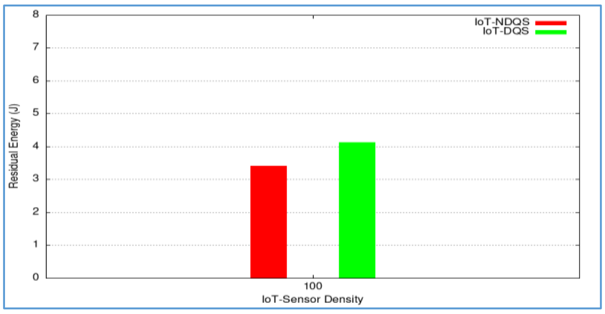

Fig. 53: Residual energy-SigFox-urban-area-100-IoT-sensors

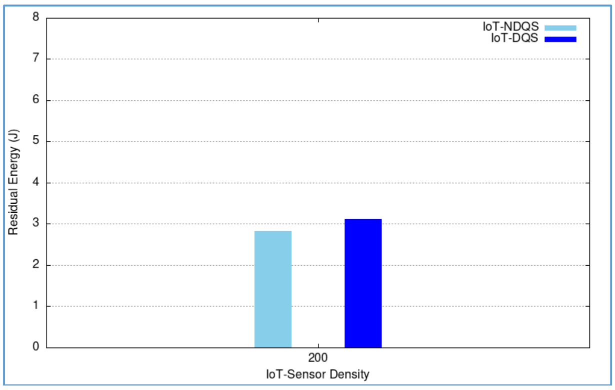

Fig. 54: Residual energy-SigFox-urban -area-200-IoT-sensors

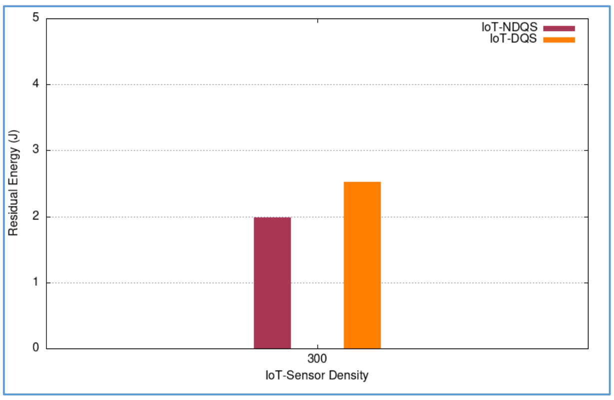

Fig. 55: Residual energy-SigFox-urban-area-300-IoT-sensors

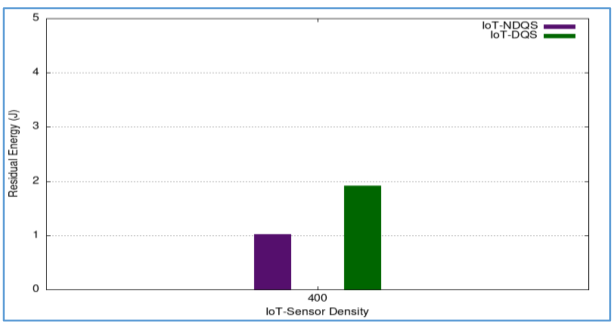

Fig. 56: Residual energy-SigFox-urban-area-400-IoT-sensors

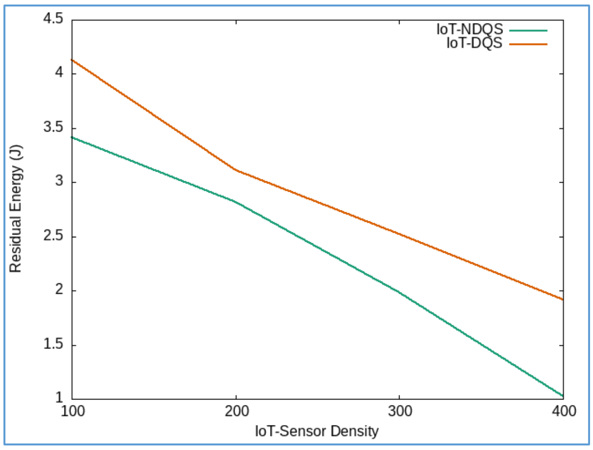

Fig. 57: SigFox-urban-area-comparison-residual energy

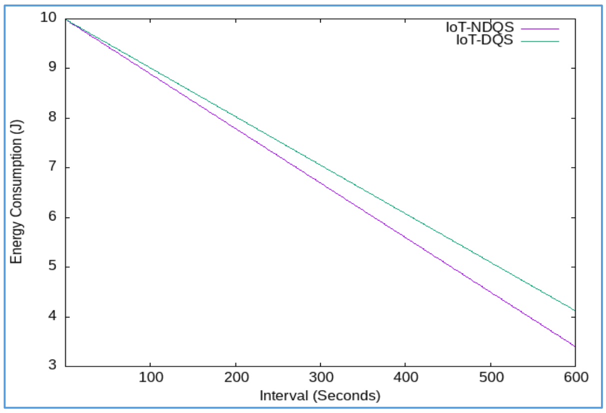

Fig. 58: Energy consumption-Sigfox- urban-area-100-IoT-sensors

Figure 56 shows the residual energy of DQS and NDQS using the SigFox standard in an urban area with 400 IoT Sensors. It is 1.024 J for NDQS and 1.918 J for DQS.

Figure 57 compares the residual energy of DQS and NDQS schemes using the SigFox standard in an urban area. Analysis shows that the lowest sensor density (100) is higher for both scenarios, decreasing w.r.t. sensor density variations and reaching its lowest level with the highest sensor density. However, it is higher for DQS than NDQS under the constraints of sensor density.

Energy Consumption Comparison of SigFox in an Urban Area

Figure 58 shows the energy consumption of DQS and NDQS using Sigfox standard in urban-area with 100-IoT sensors. It shows that the energy level of both schemes is decreasing gradually.

Figure 59 shows the energy consumption of DQS and NDQS using Sigfox standard in urban-area with 200-IoT sensors. It offers a marginal difference between the energy level of DQS and NDQS and decreases until the end of the simulation interval.

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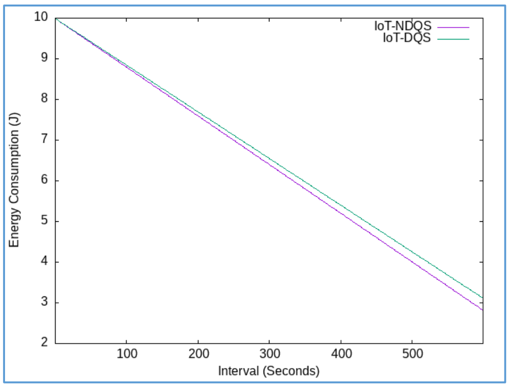

Fig. 59: Energy consumption-Sigfox- urban-area-200-IoT-sensors

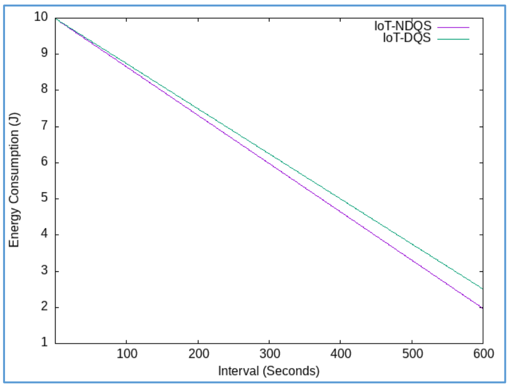

Fig. 60: Energy consumption-Sigfox- urban-area-300-IoT-sensors

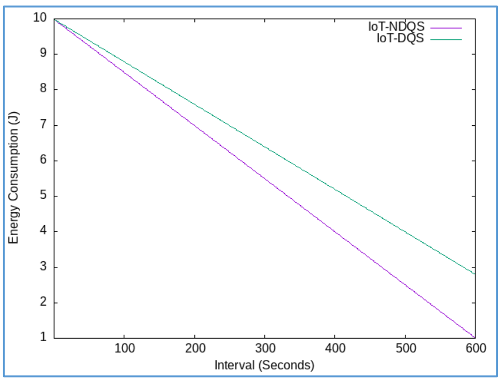

Fig. 61: Energy consumption-Sigfox- urban-area-400-IoT-sensors

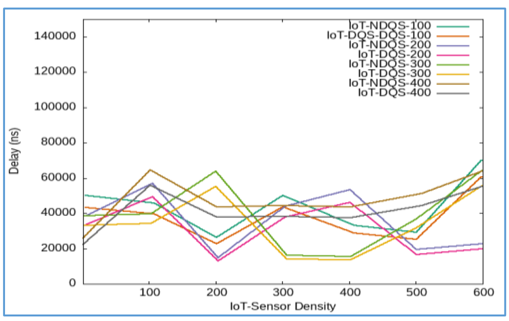

Fig. 62: Delay-SigFox-urban area

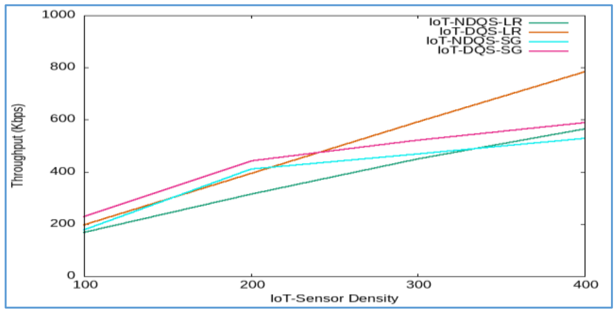

Fig. 63: Throughput comparison-LoRaWAN/SigFox-rural-area

Figure 60 shows the energy consumption of DQS and NDQS using Sigfox standard in urban-area with 300-IoT sensors. It shows that the energy level of DQS and NDQS decreases gradually, with a slight difference between their energy levels.

Figure 61 shows the energy consumption of DQS and NDQS using Sigfox standard in urban-area with 400-IoT sensors. It can be observed that there is a sharp decline in the energy level of NDQS as compared to DQS till the end of the simulation.

Figure 62 shows the variations in delay using NDQS/DQS with SigFox standard in an urban area. As per the results, the delay value varies w.r.t. NDQS/DQS over sensor density. DQS offered optimal delay in contrast to NDQS over the simulation interval.

Comparison of LoRaWAN and SigFox Rural Area

Figure 63 shows the throughput comparison of LoRaWAN and SigFox standards in rural areas using NDQS and DQS schemes. It can be observed that throughput for both scenarios varies w.r.t. sensor density (100-400), and for SigFox, NDQS delivers slightly less throughput than DQS. It can be analysed that DQS enhanced it for both standards (LoRaWAN/SigFox) in contrast to NDQS.

Figure 64 shows the residual energy comparison of LoRaWAN and SigFox standards in rural areas using NDQS and DQS schemes. It varies w.r.t. sensor density and is reduced to its lowest level with the highest sensor density (400) for both systems. However, DQS retained optimal residual energy levels for LoRaWAN and SigFox compared to NDQS.

Figure 65 shows the delay comparison of LoRaWAN and SigFox standards in rural areas using NDQS and DQS schemes over a simulation interval. It can be observed that using NDQS, the performance of LoRaWAN/SigFox is affected due to a higher delay factor w.r.t. sensor density. However, DQS managed the delay up to a significant level for both standards.

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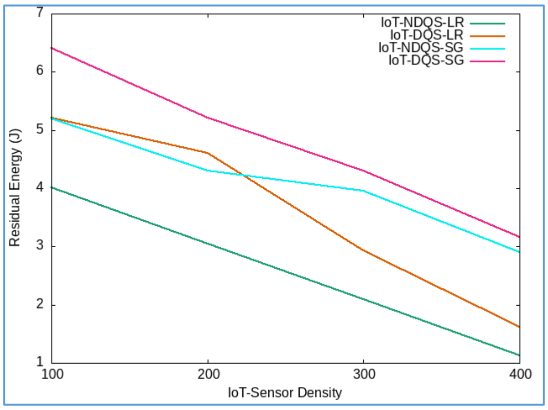

Fig. 64: Residual energy-comparison-LoRaWAN/SigFox-rural-area

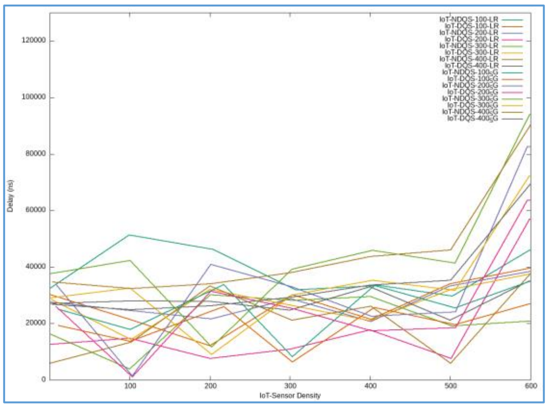

Fig. 65: Delay comparison-LoRaWAN/SigFox-rural-area

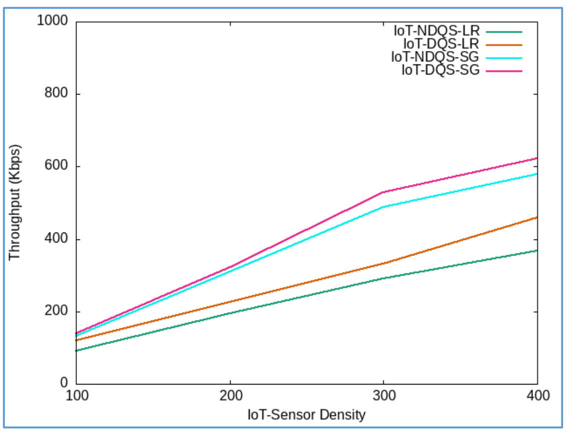

Fig. 66: Throughput comparison-LoRaWAN/SigFox-urban-area

Comparison of LoRaWAN and SigFox Urban Area

Figure 66 shows the throughput comparison of LoRaWAN and SigFox standards in an urban area using NDQS and DQS schemes. It can be observed that there is a marginal difference between its value for the sensor density 100-200 using NDQS and DQS schemes w.r.t. LoRaWAN/SigFox.

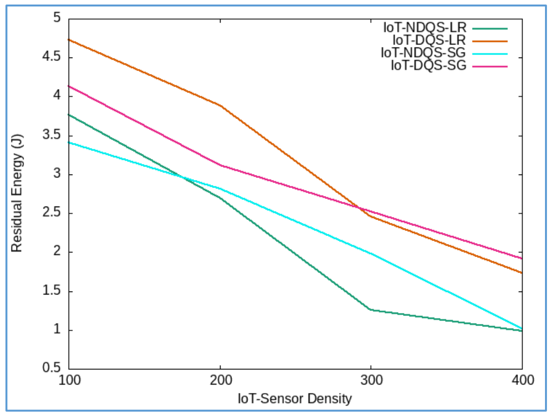

Fig. 67: Residual energy-comparison-LoRaWAN/SigFox-urban-area

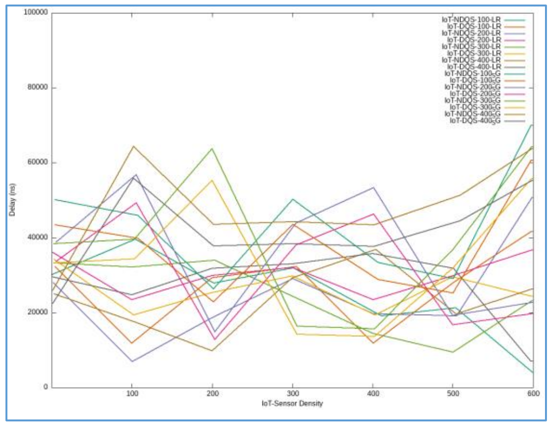

Fig. 68: Delay comparison-LoRaWAN/SigFox-urban-area

However, it varies as the sensor density increases to 300-400 for LoRaWAN/SigFox. DQS delivered the higher throughput for SigFox, followed by LoRaWAN, compared to NDQS.

Figure 67 shows the residual energy comparison of LoRaWAN and SigFox standards in rural areas using NDQS and DQS schemes. It can be observed that NDQS and DQS, both schemes, could not retain it under the constraints of sensor density, and for the highest sensor density, it declined up to its minimal level (for LoRaWAN/SigFox). However, DQS maintained its level for both standards as compared to NDQS.

Figure 68 shows the delay comparison of LoRaWAN and SigFox standards in urban areas using NDQS and DQS schemes over a simulation interval. It can be observed that it varies for NDQS/DQS using LoRaWAN/SigFox w.r.t. sensor density.

Discussion

The study introduces DQS, a delay-aware quality of service-constrained scheme for smart farming, to compare performance in rural and urban areas. The LoRaWAN standard outperforms SigFox regarding throughput, residual energy, and energy consumption, while DQS optimises energy consumption and retains higher residual energy levels. Sensor density also plays a role in the performance.

Conclusion

This study introduces a delay-aware quality of service-constrained scheme for smart farming, DQS. Its performance was compared using various parameters in different constraints, such as throughput, residual energy, and energy consumption. The LoRaWAN standard outperforms the LoRaWAN standard in rural regions with few sensors, while SigFox outperforms it in urban areas with a higher density of sensors. DQS also optimise energy consumption and retains higher residual energy levels. The delay factor varies for NQDS/DQS using LoRaWAN/SigFox based on sensor density and area type, with more variations in delay values in metropolitan areas.

The scope of the DQS is limited to smart farming, and only two IoT communication standards are used for analysis. Future research will analyse its performance in other disciplines, such as healthcare, automotive, and education, where service delivery is affected by delay constraints using other standards.

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Author's Contributions

Zatin Gupta: All Experiments coordination, data collection, implementation, analysis and results.

Amit Kumar Bindal: Manuscript Proofread, edited, correction, grammar and paper flow.

Ethics

It should be noted that the authors have no conflict of interest. All co-authors have read and approved the manuscript, and no competing financial interests exist. We confirm that the submission is not currently being considered for publication anywhere else.

References

Chakravarty, S., & Acharya, T. (2022, December). Sleep Scheduling Based Protocol design for delay tolerant traffic in RF energy harvesting IoT network. *In 2022 IEEE 19th International Conference on Smart Communities: Improving Quality of Life Using ICT, IoT and AI (HONET)* (pp. 157–159). IEEE. https://doi.org/10.1109/HONET56683.2022.10019123

Chen, M., Zhao, H., Shi, C., Chen, X., & Niu, D. (2023). Multi-scene LoRa positioning algorithm based on Kalman filter and its implementation on NS3. *Ad Hoc Networks*, *141*, 103097. https://doi.org/10.1016/j.adhoc.2023.103097

Chinnasamy, P., Udgata, S. K., & K, L. (2021). Multi-objective based deployment of throwboxes in delay tolerant networks for the internet of things environment. *Evolutionary Intelligence*, *14*, 895-907. https://doi.org/10.1007/s12065-020-00474-w

Darabkh, K. A., Al-Akhras, M., Zomot, J. N., & Atiquzzaman, M. (2022). RPL routing protocol over IoT: A comprehensive survey, recent advances, insights, bibliometric analysis, recommendations, and future directions. *Journal of Network and Computer Applications*, *207*, 103476. https://doi.org/10.1016/j.jnca.2022.103476

Demiroglou, V., Sarros, C. A., & Tsaoussidis, V. (2022). NoD: A content retrieval scheme for intermittently-connected IoT networks. *Ad Hoc Networks*, *130*, 102825. https://doi.org/10.1016/j.adhoc.2022.102825

Diamanti, M., Tsiropoulou, E. E., & Papavassiliou, S. (2022, May). An Incentivization Mechanism for Green Computing Continuum of Delay-Tolerant Tasks. In *ICC 2022-IEEE International Conference on Communications* (pp. 3538-3543). IEEE. https://doi.org/10.1109/ICC45855.2022.9838752

Elijah, O., Rahim, S. K., Salihu, Y. O., Bello, M. J., & Sani, M. Y. (2022, April). Development of LoRa-Sigfox IoT Device for Long Distance Applications. In *2022 IEEE Nigeria 4th International Conference on Disruptive Technologies for Sustainable Development (NIGERCON)* (pp. 1-5). IEEE. https://doi.org/10.1109/NIGERCON54645.2022.9803173

Florita, N. J. B., Senatin, A. N. M., Zabala, A. M. A., & Tan, W. M. (2020). Opportunistic LoRa-based gateways for delay-tolerant sensor data collection in urban settings. *Computer Communications*, *154*, 410-432. https://doi.org/10.1016/j.comcom.2020.02.066

Gupta, Z., Bindal, A. K. ., Shukla, S. ., Chopra, I. ., Tiwari, V. ., & Srivastava, S. . (2023). Energy Efficient IoT-Sensors Network for Smart Farming. *International Journal on Recent and Innovation Trends in Computing and Communication*, *11*(5), 255-265. https://doi.org/10.17762/ijritcc.v11i5.6612

Hakami, V., Mostafavi, S., Javan, N. T., & Rashidi, Z. (2020). An optimal policy for joint compression and transmission control in delay-constrained energy harvesting IoT devices. *Computer Communications*, *160*, 554-566. https://doi.org/10.1016/j.comcom.2020.07.005

Han, M. P., Htet, S. Y., & Wuttisttikulkij, L. (2022, July). Hybrid GNS3 and Mininet-WiFi Emulator for SDN Backbone Network Supporting Wireless IoT Traffic. In *2022 37th International Technical Conference on Circuits/Systems, Computers and Communications (ITC-CSCC)* (pp. 768-771). IEEE. https://doi.org/10.1109/ITC-CSCC55581.2022.9895019

Huang, C. C., Chien, Y. C., Zhang, J. C., & Huang, N. F. (2021, January). Reliable and Delay Tolerant Transmission Protocols for LPWAN IoT Sensors. In *2021 International Conference on Information Networking (ICOIN)* (pp. 553-558). IEEE. https://doi.org/10.1109/ICOIN50884.2021.9333934

Islam, N., Ray, B., & Pasandideh, F. (2020, August). IoT based smart farming: Are the LPWAN technologies suitable for remote communication?. In *2020 IEEE International Conference on Smart Internet of Things (SmartIoT)* (pp. 270-276). IEEE. https://doi.org/10.1109/SmartIoT49966.2020.00048

Kassim, M. R. M. (2020, November). Iot applications in smart agriculture: Issues and challenges. In *2020 IEEE conference on open systems (ICOS)* (pp. 19-24). IEEE. https://doi.org/10.1109/ICOS50156.2020.9293672

Kumar, S. A., & Thakur, H. K. (2022, August). Forwarding Factor with Acknowledgement Routing Protocol for Opportunistic IoT Network. In *2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC)* (pp. 1768-1774). IEEE. https://doi.org/10.1109/ICESC54411.2022.9885527

Li, M., Yu, F. R., Si, P., Wu, W., & Zhang, Y. (2020). Resource optimization for delay-tolerant data in blockchain-enabled IoT with edge computing: A deep reinforcement learning approach. *IEEE Internet of Things Journal*, *7*(10), 9399-9412. https://doi.org/10.1109/JIOT.2020.3007869

Locatelli, P., Spadaccino, P., & Cuomo, F. (2022, May). Ruling out IoT devices in LoRaWAN. In *IEEE INFOCOM 2022-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)* (pp. 1-2). IEEE. https://doi.org/10.1109/INFOCOMWKSHPS54753.2022.9798063

Long, T., Ma, Y., Wu, L., Xia, Y., Jiang, N., Li, J., ... & Zhang, B. (2022). A novel fault-tolerant scheduling approach for collaborative workflows in an edge-iot environment. *Digital Communications and Networks*, *8*(6), 911-922. https://doi.org/10.1016/j.dcan.2022.08.010

Malekijou, H., Hakami, V., Javan, N. T., & Malekijoo, A. (2023). Q-learning-based algorithms for dynamic transmission control in IoT equipment. *The Journal of Supercomputing*, *79*(1), 75-108. https://doi.org/10.1007/s11227-022-04643-9

Maroua, B., Rachida, A. A., & Abdelaziz, M. (2022). Smart farming architectures based on IoT review: Comparative study. *Procedia Computer Science*, *203*, 783-788. https://doi.org/10.1016/j.procs.2022.07.117

Mijwil, M. M., Hiran, K. K., Doshi, R., & Unogwu, O. J. (2023). Advancing Construction with IoT and RFID Technology in Civil Engineering: A Technology Review. *Al-Salam Journal for Engineering and Technology*, *2*(2), 54-62. https://doi.org/0000-0002-2884-2504

More, A., & Kale, R. (2022, August). Review on Recent Research Trends and Applications in Delay Tolerant Networks. In *2022 6th International Conference On Computing, Communication, Control and Automation (ICCUBEA* (pp. 1-9). IEEE. https://doi.org/10.1109/ICCUBEA54992.2022.10011041

Muthanna, M. S. A., Muthanna, A., Rafiq, A., Hammoudeh, M., Alkanhel, R., Lynch, S., & Abd El-Latif, A. A. (2022). Deep reinforcement learning based transmission policy enforcement and multi-hop routing in QoS aware LoRa IoT networks. *Computer Communications*, *183*, 33-50. https://doi.org/10.1016/j.comcom.2021.11.010

Naik, K. J. (2020, November). A processing delay tolerant workflow management in cloud-fog computing environment (DTWM_CfS). In *2020 International Conference on Decision Aid Sciences and Application (DASA)* (pp. 908-913). IEEE. https://doi.org/10.1109/DASA51403.2020.9317201

Narwane, V. S., Gunasekaran, A., & Gardas, B. B. (2022). Unlocking adoption challenges of IoT in Indian agricultural and food supply chain. *Smart Agricultural Technology*, *2*, 100035. https://doi.org/10.1016/j.atech.2022.100035

Nejadhasan, S., Mehrabi-Moghadam, Z., Abiri, E., & Salehi, M. R. (2022). Design of a Dynamic ADC Comparator with Low Power and Low Delay Time for IoT Application. *Wireless Personal Communications*, *123*(2), 1573-1591. https://doi.org/10.1007/s11277-021-09201-9

Pavithra, L., & Rekha, D. (2022). Real time scheduling in TSCH for IoT using neurogenetic algorithm. *Wireless Personal Communications*, 1-18. https://doi.org/10.1007/s11277-021-09148-x

Prade, L., Moraes, J., de Albuquerque, E., Rosário, D., & Both, C. B. (2022). Multi-radio and multi-hop LoRa communication architecture for large scale IoT deployment. *Computers and Electrical Engineering*, *102*, 108242. https://doi.org/10.1016/j.compeleceng.2022.108242

DOI: 10.3844/jcssp.2023.1029.1049

Sharma, S., Verma, G. S., & Thakur, K. (2022). Integration of ML and IoT for Healthcare Systems. In *Computational Intelligence and Applications for Pandemics and Healthcare* (pp. 115-138). IGI Global. https://doi.org/10.4018/978-1-7998-9831-3.ch006

Sankayya, M., Sakthivel, R. K., Gayathri, N., & Al-Turjman, F. (2021). Wireless sensor network–based delay minimization framework for IoT applications. *Personal and Ubiquitous Computing*, 1-9. https://doi.org/10.1007/s00779-020-01517-w

Su, B., & Wang, S. (2021). A delay-tolerant distributed optimal control method concerning uncertain information delays in IoT-enabled field control networks of building automation systems. *Applied Energy*, *301*, 117516. https://doi.org/10.1016/j.apenergy.2021.117516

Su, B., Wang, S., & Li, W. (2021). Impacts of uncertain information delays on distributed real-time optimal controls for building HVAC systems deployed on IoT-enabled field control networks. *Applied Energy*, *300*, 117383. https://doi.org/10.1016/j.apenergy.2021.117383

Tephila, M. B., Sri, R. A., Abinaya, R., Lakshmi, J. A., & Divya, V. (2022, March). Automated Smart Irrigation System using IoT with Sensor Parameter. In *2022 International Conference on Electronics and Renewable Systems (ICEARS)* (pp. 543-549). IEEE. https://doi.org/10.1109/ICEARS53579.2022.9751993

Wang, S. Y., Chang, J. E., Fan, H., & Sun, Y. H. (2022). Comparing the performance of NB-IoT, LTE Cat-M1, Sigfox, and LoRa for IoT end devices moving at high speeds in the air. *Journal of Signal Processing Systems*, 1-19. https://doi.org/10.1007/s11265-021-01660-4

Zhao, J., Wang, Y., Fei, Z., & Wang, X. (2020, August). Uav deployment design for maximizing effective data with delay constraint in a smart farm. In *2020 IEEE/CIC International Conference on Communications in China (ICCC)* (pp. 424-429). IEEE. https://doi.org/10.1109/ICCC49849.2020.9238944