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Enhancing transmission of data packet in a congested network

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Abstract
The Internet of Things (IoT) connects various areas by connecting millions of devices to meet a wide range of human needs. A huge amount of data has to be transmitted for these services. In this transmission, Internet of Things (IoT) networks do not provide any special priority for emergency data packets while routing. Using conventional QoS processes, these data packets flow through routers. This transmission does not guarantee that an emergency data packet traveling through a congested IoT network will reach the control room in time. One of the major challenges in packet scheduling is the unpredictable behavior of traffic classes, which change dynamically. For this reason, to overcome prioritization problems in IoT networks, innovative packet prioritization techniques, such as a queue management approach, need to be developed. To provide the required transmission priority for emergency data, this paper proposes an AI packet priority queuing model (PPQM) based on P^2 queue-based emergency data packet classification with a prioritization algorithm. In this paper, LSTM is used to classify the emergency data packet, and the Deep Q Network (DQN) algorithm is proposed to make scheduling decisions for communication. Simulation results confirmed that the machine learning modules achieved 91.5% accuracy while identifying the emergency data and assigning them the expected priority.

Keywords: Deep Q Network (DQN), QoS, Internet of Things (IoT), Long Short-Term Memory (LSTM), emergency data packet, Packet Priority Queueing Model (PPQM)

1. Introduction
The Internet of Things (IOT) making the world around us more responsive and smarter, by merging the digital and physical universes. The Internet of Things (IOT), refers to the billions of devices which is connected to the internet, for collecting and sharing data. For dumb devices, connecting these different objects and sensor makes it intelligent and enables it to communicate in real-time data without involving a human being.

We can use IOT devices even in the places which we can't be physically there. Iot devices will capture the data which we can see, hear and/or sense by using sensors, other devices. The captured data is transformed as directed. The data can be used for analysis to inform, automate our continuous actions and/or decisions. Stages of IOT process: IoT devices capture data from their environments using sensors. By the help of available network connections, IoT devices make this data accessible through a private or public cloud, as instructed. Then software is programmed to do something based on that data – such as turn on a fan or send a warning. For analysis data gathered from different devices in IOT networks are used. To take confident actions and decisions on business the informations are provided to the consumers.

IoT devices communicate from their different technical communication models. An effective communication model shows the process workflow and helps one to understand communication. In Request-Response model, client will request the server and the server will respond to those requests. Publisher-Subscriber Model includes Publishers, brokers, and consumers. The broker forwards data for a topic from publisher to all subscribed consumers. Push-Pull communication model involves data producers and data consumers. Data producer will push into the queues, data consumers will pull the required data from the queues.

Exclusive-pair model is full-duplex, bidirectional communication model developed for constant/continuous connections between a client and server. When connection is established, clients and servers can exchange messages/requests.
The expansion of network scale and applications, the data in network become so large or complex that traditional data scheduling schemes are inadequate to deal with them. In some cases, network will receive a data packets that have to be sent to the target node as soon as they arrived, called emergency packets, such as the alarm information in medical rescue service, the fire information in forest fire monitoring service, etc. Thus, emergency data packets response has become a serious challenge, mainly in the disaster recovery system. First Come First Serve algorithm is normally used for multilevel priority queues (PQs). The impact between different nodes will not be considered by these algorithms, so some extra time will taken when the emergency data packets are sent to the sink node. So, we need an efficient packet scheduling algorithms which can allocate network resources intelligently. The objective of the paper is to proposes an Artificial Intelligence based Packet Priority Queuing model for emergency data packet classification with a prioritization algorithm to provide a required transmission priority for emergency data.

2. Related Work

In this study, we design a queuing theory- based data traffic model for a scalable IoT system. To the best of our knowledge, only a few works consider scalability and queuing theory for the IoT data traffic management domain. Shreya Khisa, Sangman Moh *et al* [1]. proposed a hybrid MAC protocol named priority-aware fast mac (pf-mac) for UAV-based IIoT networks to achieve the QoS requirements of the target system. they evaluated the average transmission delay, throughput, normalized control overhead, energy consumption and network lifetime to show the performance of our proposed PF-MAC protocol in comparison to the existing protocols. The performance study makes it apparent that the IoT devices can transfer emergency traffic to the UAV with less delay and the transmission of normal monitoring traffics achieves higher throughput. Hafsa Bibi, Farrukh Zeeshan Khan *et al* [2]. proposed and analysed an advanced technique Dynamic Wavelength Grouping (DWG) for absolute QoS in an Optimal Packet Switching, which makes dynamic and most appropriate partitions of available wavelength resources and allocate them to traffic of each class of service in rapidly varying traffic loads by tracking the current link load status. The results are obtained with assumption of just two service classes, describe that DWG is equally efficient even when the number of priority classes increases, and load fluctuations get relatively more complicated.
Jaehwoon Lee *et al* [3]. presented a reservation MAC protocol was presented for transmitting data packet having traffic with multiple classes of priorities in a slotted multi-channel distributed Cognitive radio network (CRN). Number of result shows that we can transmit the high priority data packet faster than low priority data packet. Notwithstanding the above, the maximum sum of the throughput of secondary users (SUs) with different classes of priorities is almost equal to the available capacity, and therefore the proposed protocol can use the most of the available portion in all of the primary channel. Bashir A. Muzakkari, Mohamad. A *et al* [4]. presented a dynamic method to adapt the duty cycle to regulate device sleep and wake-up time of sensor nodes to maximize the network lifetime, but at the same time keeping end- to-end delay at the minimum possible level with reasonable queue length. Their simulation results show that the Energy Efficient and QoS-aware (EEQ) algorithm tends to scale up to meet the growing demands of the network.
JianfangXin, QiZhu, Guangjun Liang *et al* [6]. develop a spatiotemporal mathematical model for the performance study of device-to-device (D2D) underlay cellular network. Results of simulation shows that the validity of analysis of theories. Moreover, by comparing the dropping probability of priority queuing model with and without jump strategy, the rationality of the introduced model is confirmed. Imad Benacer, Francois-Raymond Boyer *et al* [7]. This paper proposed and evaluated a hybrid priority queue architecture intended to support the requirements of todays high-speed networking devices.

3. Architectural Design

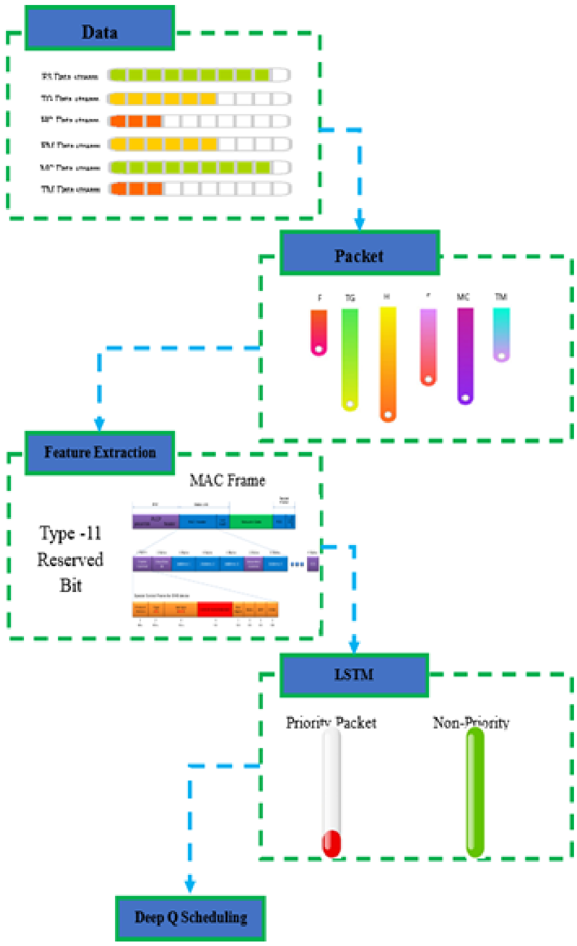

Fig 1: Emergency Packet Classification

Data Buffering: PAS will receive the MAC address packet from the sender node.

Clustering: Received Packet are clustered according to their applications.

Feature Extraction: The incoming packets not only have data packets, but also have emergency information packets and MAC-address packets. Extracted features of Type 11 – reserved bit feature can distinguish the incoming packets from MAC frame.

Classification: Based on the extracted type 11 in the data packet header mac frame the LSTM classifier classified as Emergency and Non- Emergency.

In this phase, the data packets are processed, scheduled, and forwarded based on their emergency information. The data packets are divided into three types according to their priorities and deadlines.

Types of data packets

1. Emergency data packets (PP). This type of packets needs the quickest response. Thus, these packets' end-to-end delays must be reduced as much as possible.
2. Normal data packets (NP). In network most of the data packets will fall under this type. The emergency data packets can pre-empt this type of data packets.
3. Nonemergency data packets (NPP). They have the lowest requirement on delay. Compared with other data packets. Their deadlines are longer.

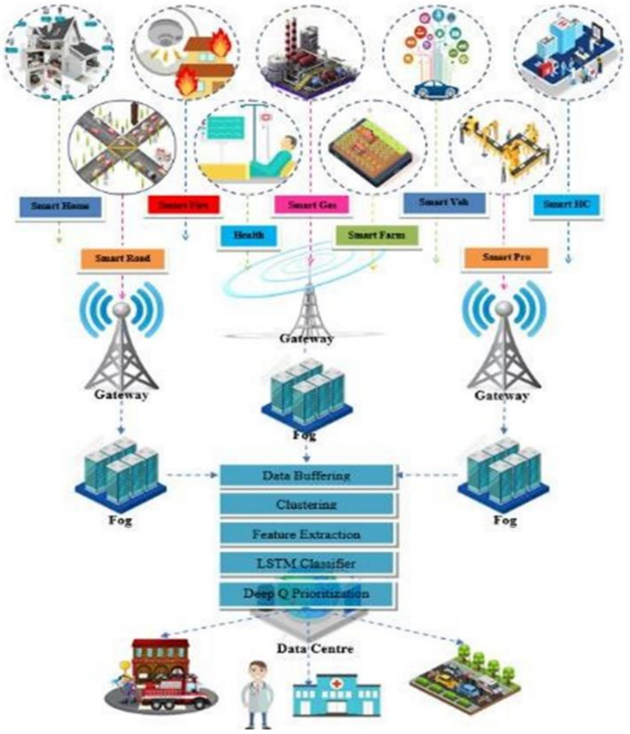

Fig 2: System Architecture

4. System Implementation

Data Packet Description

For test purposes, we chose to insert the identifier within the MAC layer. Any packet data has two major parts, the header and the information. We are focusing on the packet headers. All packet headers contain the same features in the IEEE 802.15.4 standard. The headers are described in the MAC frame format (refer to Table 1). This format consists of the reserved bits that can be used for any specific application. We are using this specific reserved bit to save an identifier at the sensor level. An identifier is only two bits which means it will not take a lot of memory space. Hence, the identifier is included in the header part rather than taking up space in the memory of the application defined information.

Modules Description

1. IoT Network Simulator

In this module, construct a hierarchical form to generalize all the contents in the IoT network. There are three layers in this form: the device layer, the fog intelligence layer, and the centralized intelligence layer. The device layer is consist of all aims, IoT Device, users, and astute terminals that can collect sensed data from live environments. The fog intelligence layer offers distributed, low-latency, and limited computing resources between the device layer and the higher layer. The centralized intelligence layer composed of cloud data centers that add up data from lower layers.

2. Fog Application and service layer

This layer applies services for IoT data analytics and periodically processes sensor data to make IoT based decisions using Publish/Subscribe Machines (PSMs). The output of this layer is the data packets containing decisions. In a scalable fog architecture, multiple PSMs may perform simultaneous operations and generate a low-rate periodic IoT decision traffic pattern independently Context Broker (CB), PAS - A Publish/Subscribe Machine (PSM), Fog Connector (FC).

3. Priority Aware Scheduling

The purpose of this module is to recognize the received information packets and process them according to their priority.

3.1. LSTM packet priority classification

The LSTM based deep learning model is trained on the fog server in advance before the first time slot begins. The proposed system considers the prediction of future real-time spatial information as a regression task. Regression, in general, is a type of task that estimates a numerical value given some input. To solve the task, the learning algorithm is asked to learn a function that maps an input variable to an output variable. The proposed system uses a supervised machine learning model to solve the task. Supervised learning algorithms, in general, deal with a training dataset that contains a set of data and a label or target associated with each of the data.

In the proposed system, the LSTM model for prediction receives the aggregated past sensor data collected from IoT devices in each block as an input and calculates the future real-time spatial information as output. The deep learning model for prediction receives an input variable X, which consists of aggregated sensing data collected in the last few time slots, and predict output variable y, which is the real-time spatial information of each block in the next time slot. The input variable X of the machine learning model for prediction is a $T \times NB$ matrix, where T is the number of time slots used in one prediction and NB is the number of blocks. Each row in the input matrix defines the accrued sensor data collected in NB blocks at T , $T - 1, \ldots,$

1 slots ago, respectively. The output y of the machine learning model for prediction is a vector of NB elements. Each element of the output vector represents the real-time spatial information of each block in the next time slot.

Calculation of importance of blocks

The importance of a block is calculated from the pre-trained machine learning model for prediction on the edge server using a feature selection method. The importance of block Ib is defined as $I_b = \sum^{T} F_{t,b}$, where $F_{t,b}$ is the feature importance of the (t, b) element of the input matrix. $F_{t,b}$ is calculated from the pre-trained model using the feature selection method.

Data Buffering: Then PAS will receive the MAC address packet from the sender node.
Clustering: Received Packet are clustered according to their applications.
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3.2. Deep Q Learning - Packet Scheduling
To allocate channels and time slots efficiently, we use the deep Q network (DQN) architecture with experience replay and a greedy policy to solve the reinforcement learning problem. This architecture not only provides more accurate value estimations but also leads to much higher learning stability.

Queuing network model: Based on the traffic mix and flows, a queuing network models are developed for the ingress and egress queues. The queuing model is used to study the effects of changing multiple parameters, such as queuing discipline, drop rates, and priority.

RL agent: For RL model training, on queue configurations the effect of changes are fed into the RL model. It has actions spanning multiple queue configuration parameters. To provide rewards to the agent, observations on latency, throughput, and changes in packet drop are used.

Configuration deployment: The policy generated by the RL agent. Then RL agent is deployed on the router port. This can be directly run on the router operating system or be configured via SDN controllers. Based on the observed traffic mix, the agent's policy is deployed for ingress traffic policing and egress traffic shaping.

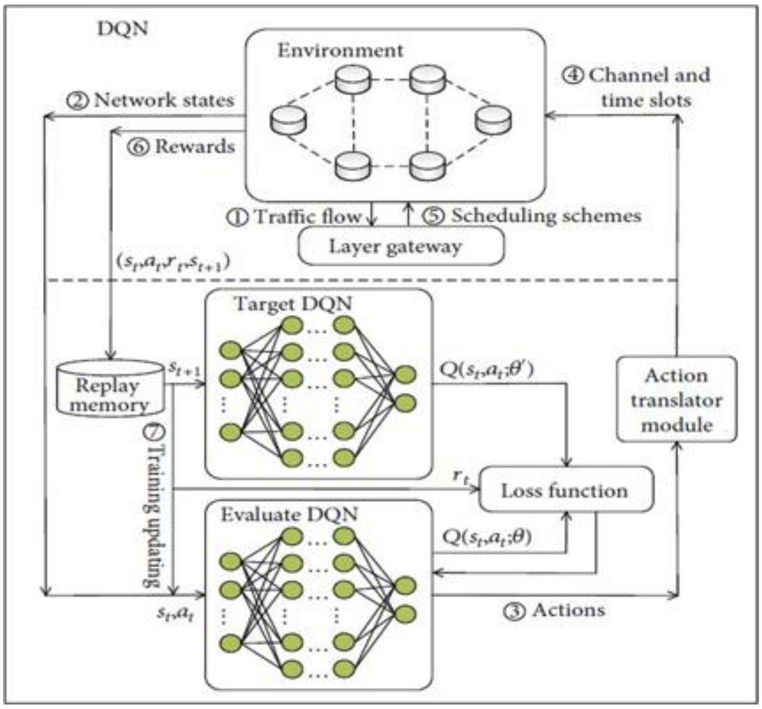

Fig 3: Configuration Development

State- It is collection of the destination node, source node, time slot occupancy and number of transmission time slots.

Action- It is the approach, where the agent decides which time slot and channel combination is available to assign for the current network state.

Reward - The reward is the aim of the algorithm. The agent depends on rewards to examine the effectiveness of the action and improvement of the policies.

4. Packet Forward
Packet entering the router port is assigned an internal priority level and internal drop precedence. This is determined based on a class map linked to the packet header information. As the packet enters the router, it is subjected to a classification

filter. Packets belonging to each class can be rate-limited or marked. The traffic per class can be treated as follows:

(a) The rate limits per class may be set. By default, conforming traffic is marked green; exceeding traffic yellow; and violating traffic red. Violating traffic can be marked red (if the violate red command is configured) or dropped immediately (if the violate drop command is configured).

(b) Packets that are not dropped because of rate limiting can have their drop precedence values modified.

The router transports the packet to the egress port.

Egress scheduling: Based on the destination information from the forwarding table each outgoing packet is assigned to an egress queue. Egress queues also have connected scheduling parameters, such as depths, rates, and relative weights.

4.1. Control plane: This plane maintains a routing table that lists the routes to be taken by a data packet. This may be statically defined or learned based on the traffic mix. The control plane builds the Forwarding Information Base (FIB) that is fed to the forwarding plane.

4.2. Forwarding plane: The router forwards data packets between incoming and outgoing port connections. Using information from the packet header, the accurate FIB is used to map the outgoing packet. Both the switch and router ports have ingress (inbound) queues and egress (outbound) queues. This packet scheduling scheme contain three units:

1. Access Control Unit (ACU), 2. Emergency- Aware Unit (EAU), 3. Packet Forward Unit (PFU). The incoming packets may also have emergency information packets, data packets and MAC-address packets. The packet analysis (PA) can distinguish the incoming packets. Through the analysis of Packet Analysis, the data packets are sent to conditional access control to check whether the deadlines expire or not, then the emergency information packets are forwarded to EAU, and the MAC-address packets are sent to PFU for further processing. Then, the packets within their deadlines are placed into priority queue. Corresponding to three different priorities, each node has three priority queues. In the same priority queue, the packets are sorted based on their deadlines. Among the three priorities, we select the packet with the highest emergency to extract its emergency information. The generated emergency packet will be sent to EAU.

In EAU, emergency information forward (EIF) sends the emergency information packets that get from local's ACU and sibling nodes' ACUs to the destination node in the TDMA method. When there is only an emergency information packet at EIF, we send the data packet directly instead of sending the emergency information packet. EIA mainly analyses the emergency information packets received from the child nodes. It will get the emergency information packet with the highest priority and the shortest deadline among these packets. Then, the MAC address of the node where the most emergency packet is sent can be known. We put the MAC address into the MAC-address packet and broadcast it.

5. Results and Discussion

In this part, we have evaluated our proposed packet Priority queueing model (PPQM) with the end-to-end delay, waiting time, packet loss rate as metrics.

Waiting Time

In the simulation experiments, we control the packet generation rate to simulate the normal network load. In order to improve the accuracy of the simulation, three different experimental situations are set up. The ratio of PP packets, NP packets, and NPP packets is set as {3:5:2, 1:1:1, 5:3:2} corresponding to these three situations. The average value of the experimental results are obtained from the three situations are the final result.

End-to-End Delay

It is the average time from the packet generation to delivery in the network. The emergency packets need to be delivered as fast as possible. Thus, the end-to-end delay is an important metric to evaluate the real-time performance of the scheduling scheme. It can be seen that with the increase of the packet arrival rate, the end-to-end delay of BS scheme first decreases then increases. The reason is that the BS cannot generate enough pressure at the low network load because there is not enough queue backlog difference gradient. BS scheme will explore all possible paths, so the end- to-end delay increases. When the network load increases, the end-to-end delay of BS scheme reduces because the queue backlog difference gradient is formed. Subsequently, the queue backlog starts to increase, which leads to the increase of end- to-end delay.

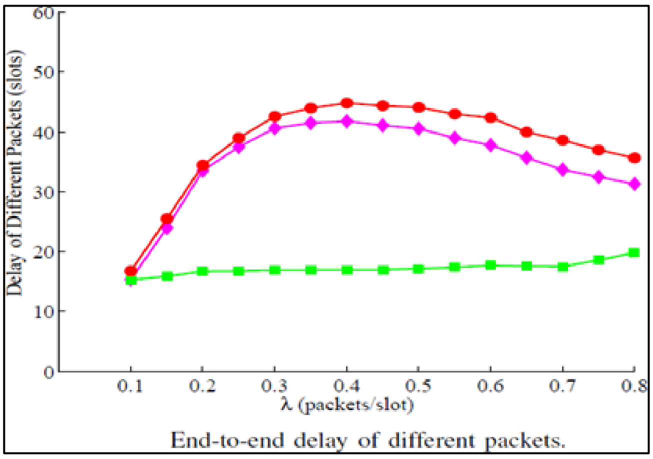

Fig 4: End- to-end delay

6. Conclusion

Packet classification and Scheduling is one of the essential problems in IoT networks. In this paper, we had developed a Packet Prioritization Queueing Model (PPQM) to analyze IoT-Fog data traffic then, proposes a scheduling policy for reducing waiting time gaps observed in the multi- level priority queue design. Driven by this trend, a tremendous amount of attention are received by the combination of deep reinforcement learning and edge computing. In this paper, LSTM Model used to classify the emergency packets, classic deep Q network (DQN) architecture employed in intelligent scheduling. This PPQM model can find time slot combinations, reasonable channel with competitive performance. Extensive simulation experiment was implemented and demonstrating that our packet Priority queueing model (PPQM) can obtain better network performance compared with traditional scheduling schemes.

Future Enhancement

In future we have planned to use genetic algorithm to optimize the transmission of packets. For a more practical evaluation, other deep learning models along with suitable feature selection methods for the models can be considered.

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