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PPQM an Emergency Packet Scheduling in IoT Network Using Reinforcement Learning

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ABSTRACT

The Internet of Things (IoT) connect millions of devices in diverse areas such as smart cities, e-health, transportation and defence to meet a wide range of human needs. To provide these services, a large amount of data needs to be transmitted to the IoT network servers. Currently emergency data packets do not get any special priority while routing through the Internet of Things (IoT) networks. These data packets flow through routers using conventional QoS process which does not guarantee that an emergency data packet traveling in congested IoT network will actually be routed to control room on time. A major challenge in packet scheduling is that the behaviour of each traffic class may not be known in advance, and can vary dynamically.

INTRODUCTION

The Internet of Things, or IoT, refers to the billions of physical devices around the world that are now connected to the internet, all collecting and sharing data. Thanks to the arrival of super-cheap computer chips and the ubiquity of wireless networks, it's possible to turn anything, from something as small as a pill to something as big as an aeroplane, into a part of the IoT. Connecting up all these different objects and adding sensors to them adds a level of digital intelligence to devices that would be otherwise dumb, enabling them to communicate real-time data without involving a human being. The Internet of Things is making the fabric of the world around us smarter and more responsive, merging the digital and physical universes.

LITERATURE SURVEY:

1:Priority-Aware Fast MAC Protocol for UAV-Assisted Industrial IoT Systems

Author: Shreya Khisa; Sangman Moh

Year: 2021

Objective:

This article proposes a priority-aware fast mac (pf-mac) protocol for uav-assisted IOT systems, ensuring fast and robust data delivery.

2.Dynamic Wavelength Grouping for Quality of Service in Optical Packet Switching

Author: Hafsa Bibi; Farrukh Zeeshan Khan

Year: 2021

Objective:

This article aimed to analyse DWG with more functions like plr, pdv, bit error rate and response time.

OBJECTIVE OF THE PROJECT:

The objective of the project is to proposes an Artificial Intelligence based Packet Priority Queuing model for emergency data packet classification with a prioritisation algorithm to provide a required transmission priority for emergency data.

SYSTEM REQUIREMENTS

Hardware Specification

- Processors: Intel® Core™ i5 processor 4300M at 2.60 GHz or 2.59 GHz (1 socket, 2 cores, 2 threads per core), 8 GB of DRAM
- Disk space: 320 GB
- Operating systems: Windows® 10, macOS*, and Linux*

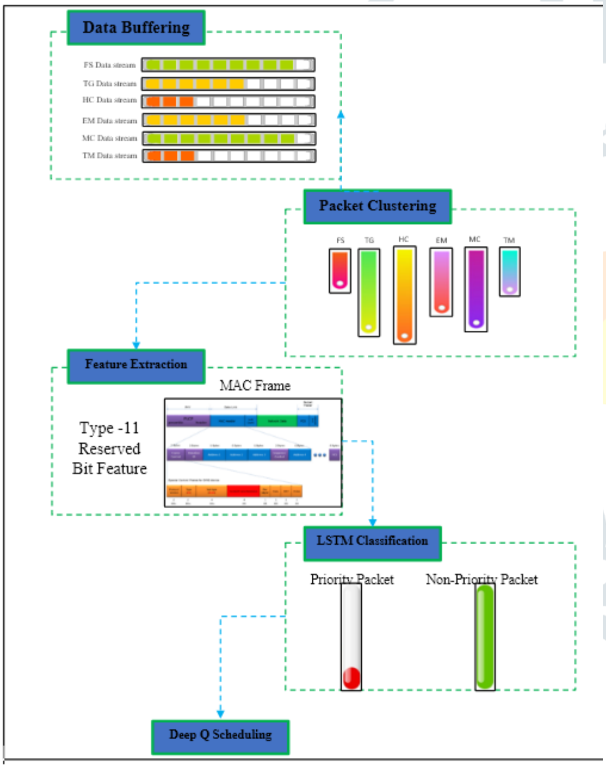
Software specification

- Server Side: Python 3.7.4(64-bit) or (32-bit)
- Client Side : HTML, CSS, Bootstrap
- IDE: Flask 1.1.1
- Back end : MySQL 5.
- Server : WampServer 2i
- BC DLL :pyBlock, pyenv, pyFHE

DESIGN ARCHITECTURE

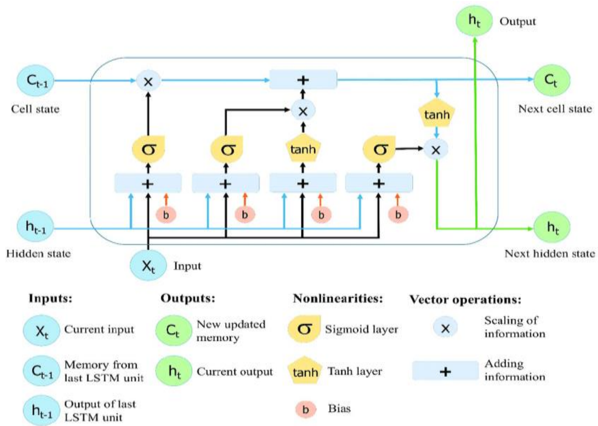
System.Architecture:

Emergency Packet Classification



PROPOSED SYSTEM

The proposed system priorities data on IoT devices on the basis of data importance extracted from the deep learning based LSTM model for prediction, which enables it to reduce the total data traffic for real-time prediction while maintaining prediction accuracy. The proposed system consists of two main components: IoT devices and an edge server. IoT devices (such as probe vehicles, WBAN, smartphones, and UAVs) prioritise collected data and send high importance input data for prediction to the edge server. The edge server aggregates the data received from IoT devices, complements the missing parts of the data, and performs prediction. Predicted packets are then scheduled using Deep Q Learning.



Deep Q-Learning Algorithm

As one of the main reinforcement learning algorithms, Q learning is a model-free learning method which provides the intelligent system with the ability to select the optimal action according to the action sequences from experience in the Markov environment. A key assumption of Q-learning is that the interaction between the agents and the environment can be treated as a Markov decision process (MDP), i.e., the current state and action of the agent will determine the state transfer probability distribution and the next state with an immediate reward.

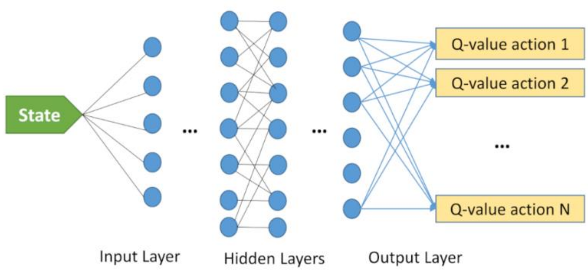


Figure 3.2. Deep Q-Learning

The goal of Q-learning is to find a policy that can maximise the reward. The Q-value is an important parameter in Q-learning. It is defined as the sum of rewards for executing the current related actions and those to be performed subsequently in accordance with a certain strategy. A given state s and action a correspond to a given Qvalue Q(s,a). Q-value is used in the learning process to select the action. If the subsequent actions are performed according to the optimal polices the corresponding Q-value is referred to as the optimal Q value Q*,

$$Q^*(s,a) = r(s,a) + \gamma \sum T(s,a,s') max Q^*(s',a')$$

where T (s, a, s') represents the transfer probability from states to state s' via action a, r(s,a) represents the reward for executing action a from states, γ∈(0,1) is the discount factor, which indicates the degree of farsightedness. If the γ value is small, the system pays attention to only the recent actions. If γ is large the actions during a relatively long period of time are involved. An agent learning process can be viewed as selecting an action from a random state using a strategy. The value of Q(s,a) is updated according to

$$Q_{t+1}(s,a) = (1-a) + Q_t(s,a) + a[\gamma max(s',a')]$$

where α∈ (0,1) is the learning factor used to control the speed of learning: the greater the value of α, the faster the convergence speed. After performing the selected action, the agent observes the new state and the reward obtained, and then updates the Q-value of the state and action based on the maximum Q-value of the new state. In this way the agent continually updates the action according to the new state until it arrives at the terminal state with an optimal Q-value Q*.

ADVANTAGES

- Accurately predicting the emergency data packet.
- Emergency data will get higher priority and less delay over normal data;
- Data aggregation will result in less energy consumption and longer network lifetime.
- Minimisation of end to end delay
- Efficient energy consumption
- Reduced waiting
- Time and delivery of data before expiration of deadline

ALGORITHM:

Algorithm 1: LSTM Algorithm for Packet Priority classification

Data: Sequence of raw packets from network

1: *dictionary* = *array* () % Create the mapping Type ii to the index array

2. TranslatedWords = null; %variable to store the values of words to converted to integer format;

3: while true do3: **while** true **do**

4: Parse the packet;

5: Extract 54-byte from each packet

6: **if** packet length < 54 **then**

7: Pad zeros;

8: **end if**

9: Feedforward to the second layer LSTM;

10: Dropout;

11: Feedforward to the third layer LSTM;

12: Dropout;

13: Prepare input for mini-batch (100 packets);

14: Apply RMSProp optimiser;

15: Use softmax to output 0 or 1 to the model;

32: Use binary cross entropy as loss function

33: for epoch = 1; epoch < 200; epoch++ do

15: Evaluate Loss, Validation Loss

17: Evaluate Accuracy and Validation Accuracy

18: end for

Algorithm 2: DQN for Packet Scheduling

1. Input: PKa
2. Output: PA
3. Upon receiving emergency information packets
4. for n ← 1 to Ndo
5. if PKa [n][1] == i then
6. PNi ← PNi + 1
7. Put Hid into Pi
8. end if
9. end for
10. for i ← 1 to 3 do
11. if PNi > 1 then
12. Sort the elements in Pi based on their deadlines;
13. end if
14. end for
15. Get the packet with the highest priority and the
16. shortest deadline to update PA;
17. Broadcast the PA;
18. The node whose MAC address is equal to PA sends the whole packet;

RESULT

In this section, we evaluate our proposed PPQM with the waiting time, the end-to-end delay, and the packet loss rate as metrics.

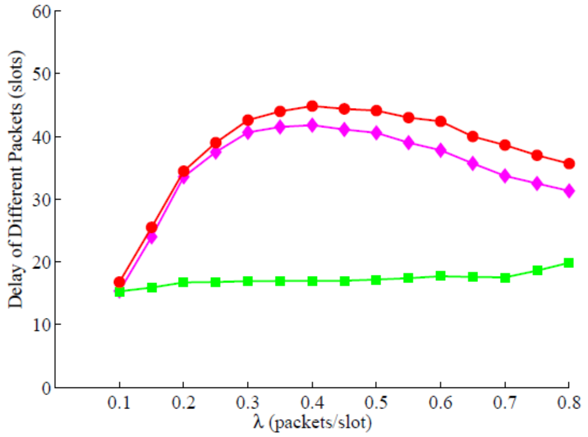
Waiting Time

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 obtained from the three situations is 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.

Output graph:



End-to-end delay of different packets.

CONCLUSION

Packet classification and Scheduling is one of the fundamental problems in IoT networks. In this project, we developed a Packet Prioritisation Queueing for the analysis of IoT-Fog data traffic and propose a scheduling policy for reducing wait time gaps observed in the multi-level priority queue design. Driven by this trend, the combination of edge computing and deep reinforcement learning has received a tremendous amount of attention. In this project, by employing LSTM Model to classify the emergency packets and the classic deep Q network (DQN) architecture in intelligent scheduling, our PPQM can identify reasonable channel and time slot combinations with competitive performance. Extensive simulation experiments were implemented, demonstrating that our PPQM can obtain better network performance than the traditional scheduling schemes.

FUTURE ENHANCEMENT

For a more practical evaluation, in future work, other deep learning models along with suitable feature selection methods for the models should be considered.

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