January-February 2020
ISSN: 0193-4120 Page No. 8741 - 8746

A Cognitive Approach to Improve the Quality of Service in NB-IoT

Madiraju.Sirisha, PhD Scholar, Dept. Of ECE Jawaharlal Nehru Technological University, Ananthapuramu, madiraju.sirisha@gmail.com

Dr. P.Abdul Khayum, Professor, Dept. Of ECE, G.Pulla Reddy Engineering College, Kurnool, A.P., India, PIN: 518007, abdkhayum@rediffmail.com

Joseph Rajiv Kantheti, Assistant Professor of ECE, Nalla Malla Reddy Engineering College, Hyderabad, josephrajivk@gmail.com

Article Info
Volume 82
Page Number: 8741 - 8746
Publication Issue:
January-February 2020

Article History
Article Received: *5 April 2019*
Revised: *18 Jun 2019*
Accepted: *24 October 2019*
Publication: *08 February 2020*

Abstract:
Narrow Band Internet of Things (NB-IoT), a 3GPP Release-13 proposed technology is well known for its low power consumption and wide area coverage. These are the most urging requirements of current scenarios of industrial, research and also social. To enhance the coverage of NB-IoT, redundant data is transmitted. This redundant data transmission improves the area coverage in NB-IoT when compared with Long Term Evolution (LTE). But a large number of repetitions of the data leads to a reduction in the throughput and a raise in the delay. The battery lifetime of the IoT devices gets reduced and the cost of maintenance increases. In this paper, an efficient routing (Q-AODV routing algorithm) using Reinforcement algorithm is suggested to avoid repetition of data for an extent. A Q-learning algorithm is used for decision making in an Ad hoc On demand Distant Vector (AODV) routing algorithm. This improves the throughput and decreases the delay. Simulation of a network with Q-AODV routing algorithm is performed and compared with the traditional AODV routing algorithm.

I. Introduction

Narrowband in NB-IoT refers to its bandwidth of 200 kHz. To meet the global requirements like quality, speed, coverage and low power consumption , a narrow band Internet of Things (NB-IoT) standard was introduced by 3GPP release 13. The major benefits of NB-IoT are its wider coverage and low power consumption. Because of the low power consumption the battery life of the device increases. The coverage area is increased by transmitting of data repeatedly. But this reduces the throughput of the network and also increases the end to end delay. There will be reduction in Quality of Service (QoS). Several efforts are made by many researchers to increase the quality of service in NB-IoT.

NarrowBand IoT is similar to the mobile communication where communication is done between two things or devices. Backbone of any network is its routing. Proactive and Reactive types of routing algorithms provide routing protocols. In proactive algorithms bandwidth requirement and power consumption are high when compared to reactive routing algorithms. Due the advantage of having low bandwidth requirement and low power consumption, reactive routing algorithms are on demand. Adhoc On Demand Vector Routing (AODV) is a reactive routing algorithm. In this a modified version of AODV, Q-AODV is implemented to increase the Quality of Service in a NB-IoT network. Q-learning a reinforcement algorithm is used with AODV to make it intelligent routing algorithm.

II. Background

In this section AODV and Q-learning algorithms are discussed. Their characteristics and the methodology are analysed. In the next section i.e., in section III motivation towards this approach is given, in section IV proposed algorithm is discussed, in section V results and in section VI conclusion is given.

(a) AODV (Adhoc On Demand Distance Vector):

In this AODV distance vector routing protocol route to the destination is determined only on demand [11]. To perform routing forwarding tables are used at each node. A route request packet (RREQ) is broadcasted by the node that wants to send a packet. This packet is sent to the neighbour nodes. There after the neighbour node broadcast this packet to other neighbor nodes. This process continues until the packet reaches the destination. A reverse path is established while forwarding the request and the destination node replies back by sending RREP through this path. If there is any route breakage then it is informed with an error, RERR (route error). Fig. I shows a network that uses AODV routing algorithm[6].

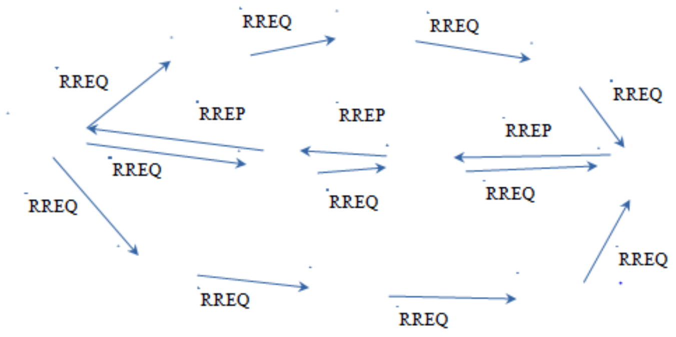

Fig I. Example network using AODV routing protocol

(b) Q-Learning:

Q-Learning is one of the method of reinforcement learning which is a classification of machine learning. Q stands for qulity here. It is an off policy algorithm that decides the next state whrn the current state is known and gets rewarded for the next state. It checks for the next state which has a maximum reward and proceeds with that next state. A Q-table [q (state, action)] is created with states, actions and the rewards [8]. This Q-table is updated until an end of the episode is reached. This table is used by the agent to predict which action to be taken for the current state to get better rewards.

Reaction of an agent with the environment is done in 2 ways, exploiting and exploring. In exploiting, the agent takes the maximum value of reward and does that action. Exploring is where the agent takes the action randomly and decides the next state. Exploring is the best way of taking an action. As the action is chosen randomly, there is a chance of exploring the new states[5].

A q-table is updated at each and every action until the end of an episode is reached. For a network, packet reaching the destination is an end of episode. The agent learns only till the end of episode and gets the optimised values for the q denoted as q*. After reaching the end of episode it stops learning.

The following code shows the creation of the Q-table.

```
import numpy as np
# Initializing  q-table
Q = np.zeros((Size_state, Size_action))
```

Q-learning is the best algorithm in the situations where decision making is crucial at each and every step for a long run goal. Q-learning algorithm implementation in a network improves the throghput of the network as the action of maximum rewards is selected for the next state from the current state.

III. Related Work

NB-IoT is similar to Mobile Adhoc Networks or simple MANET which is basically network of networks[11]. Many routing protocols are proposed to manage these MANETs. There are proactive and reactive protocols which are used to route the data from source to destination. AODV is one such type of protocol. To improve the performance of a network some intelligent component has to be included. AI (Artificial Intelligance) is one which

January-February 2020
ISSN: 0193-4120 Page No. 8741 - 8746

makes the protocol better. So, a modified AODV with AI gives better performance results.

Ali Nauman et. al. specifies a key solution for NB-IoT UE. It is specified that to increase the performance two hops system is proposed instead of direct transmission [2]. Optimization of Expected packet Delivery Ratio (EDR) and End to End Delay is acheived by opportunistic approach. But this gives an additional delay due to lack of intelligent systems. This lead to design an intelligent system called as deterministic D2D (2D2D) relay selection strategy for NB-IoT UE s (User Equipments).

Coverage in NB-IoT can be enhanced by machine learning algortithms. A dynamic spectrum access is proposed to reduce the repeated transmission of data which in turn increases the coberage and reduces the energy consumption. [1]

Md Khalid Hossain Jewel et. al. Proposes a technique to reduce complexity. To reduce the complexity of Linear Minimum Mean Square Error (LMMSE) which is used to reduce the channel condition, [3]Singular Value Decpomposition (SVD) and spliting the channel auto correlation matrices is perofrmed.

Q-learning is one of the reinforcement learning technique. It is used for solving shortest path (STP) problem. The average sum of the rewards is anyway moderate. To address the problem of low average sum, a Multi-Q-Table is proposed [8]. In this method a Q-Table is built at every sub-goal. It helps the agent to know that sub-reward is collected. The proposed modifies algorithm with Multi-Q-Tables collect all rewards and avoids pit in reaching the goal with shortest path.[8]

To improve the Quality of Service (QoS) in NB-IoT, in this paper, a modified AODV routing protocol is used. Q-learning technique is introduced in AODV to make it more efficient. This algorithm improves the throughput of the network and reduces the delay. Section IV gives the complete knowledge of the proposed algorithm.

IV. PROPOSED METHODOLOGY

The proposed methodology is a combination of both the features of AODV routing algorithm and Q-learning algorithm. AODV is used for best routing of the packets from source to destination. Q-learning is a Reinforcement algorithm of machine learning. This is used to make a decision of the next state with the details of the current state. Thus this Q-learning helps AODV for the selection of the best route with smallest distance and with less time.

In AODV protocol the Route discovery overhead is obtained with the two major parameters Route Request (RREQ) overhead and Route Reply (RREP) is mathematically modelled as [4]

$$R_{RREQ}=\sum_{n-1}^{H}(4)3^{(n-1)}\sum_{i=2}^{4}\left[(n-i-1)-\sum_{j=1}^{H-1}Nj\right]pCi \quad (1)$$

Here, H is number hops expected to reach destination

n is the number value of the tier

Nj is the number of neighbours expected at j^{th} hop

Route Reply overhead is given by

$$R_{RREP}= H+(H/2)(n-h-2)p \quad (2)$$

Route discovery overhead is the combination of route request and route reply and it is given by

$$R_{discovery}=R_{RREQ}+R_{RREP} \quad (3)$$

By substituting Eq.(1) and Eq.(2) in Eq.(3)

$$R_{discovery}=\sum_{n-1}^{H}(4)3^{(n-1)}\sum_{i=2}^{4}\left[(n-i-1)-\sum_{j=1}^{H-1}Nj\right]pCi$$

$$+H+(H/2)(n-h-2)p$$

January-February 2020
ISSN: 0193-4120 Page No. 8741 - 8746

The value of H changes with the implementation of Q-learning protocol. With Q-learning protocol the number of hops expected changes to HQ. So, using Q-AODV protocol the throughput increases and the end to end delay decreases. Then the $R_{discovery}$ equation changes to

$$R_{discovery} = \sum_{n-1}^{HQ}(4)3^{(n-1)}\sum_{i=2}^{4}\left[(n-i-1)-\sum_{j=1}^{HQ-1}Nj\right]pCi$$

$$+HQ+(HQ/2)(n-hq-2)p$$

where HQ is the optimal action value function given by

HQ = max(qΠ(s,a)) , qΠ(s,a) is the Bellman equation of the state value function and is given by

$$q\Pi(s,a) = q\,\pi\,(s,a) = R^{a}_{s} + \gamma\sum_{s's} P^{a}\,v\,(s')$$

v(s’) is the state value function that gives the long term value of state s following π policy.

By using optimum value function in the decision making of AODV routing algorithm, the quality of service of the network gets improved. Implementing Q-learning in AODV routing algorithm, makes that routing algorithm cognitive.

V. Result and Discussion

The parameters and its values of the simulated network are given in the Table I. A network of 25 nodes with 10 sinks is used. The data rate is 2kbps, transmitted with 75dBm power. The propagation loss model used is FRIIS propagation loss model. The nodes are moving with random mobility model at a constant speed propagation. The positions of nodes are defined by a random rectangular position allocator. The area of simulation is 300m x 1500m. Nodes are moving at a speed of 0-20ms. The packets sent for second are four packets. Each packet consists of 64 bytes of data.

Traditional AODV and Q-AODV routing protocols are simulated using network simulator with all the specifications given in the Table I.

Table I. List of parameters used in the simulated network and its values

S.No.	**Name of the parameter used in the simulated network**	**Value**
1.	Number of nodes	25
2.	Number of sinks	10
3.	Rate	2.048 kbps
4.	Transmitted Power	75dBm
5.	Propagation loss model	Fri is propagation loss model
6.	Propagation delay model	Constant speed propagation delay model
7.	Node speed	0-20ms
8.	Mobility model	Random way Mobility Model
9.	Protocols	AODV, Q-AODV
10.	Wifi Manager	Constant Rate Wifi Manager
11.	Mac model	802.11b(11 Mbps)
12.	Position allocator	Random Rectangle Position Allocator
13.	Area of simulation	300m x 1500m
14.	Packet size	4 packets per second

January-February 2020
ISSN: 0193-4120 Page No. 8741 - 8746

Fig 2. gives the comparision of end to end delay between traditional AODV and Q-AODV routing protocols. It is observed that delay is reduced when AODV is compared with Q-AODV routing algorithm.

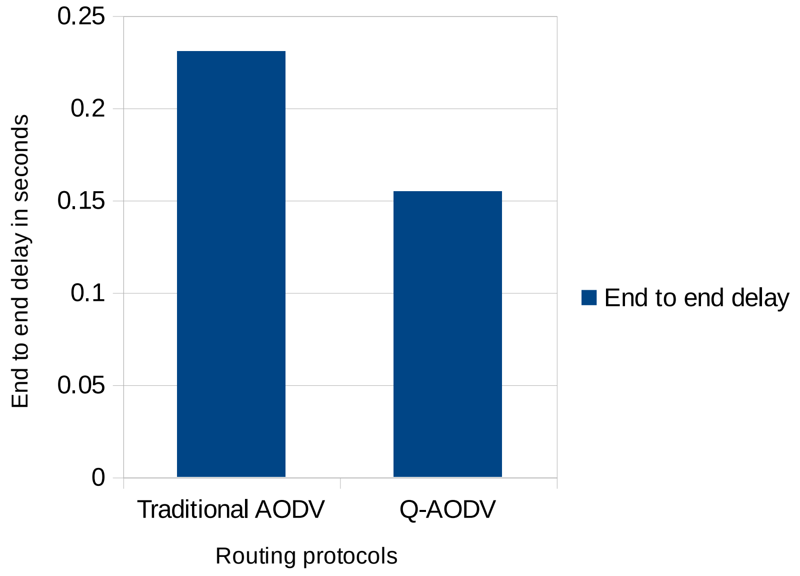

Fig 2. Comparision of End to End delay between traditional AODV and Q-AODV routing protocols

In the Fig. 3 it is very clear that the throughput of the NB-IoT is more with Q-AODV routing rather than traditional AODV routing.

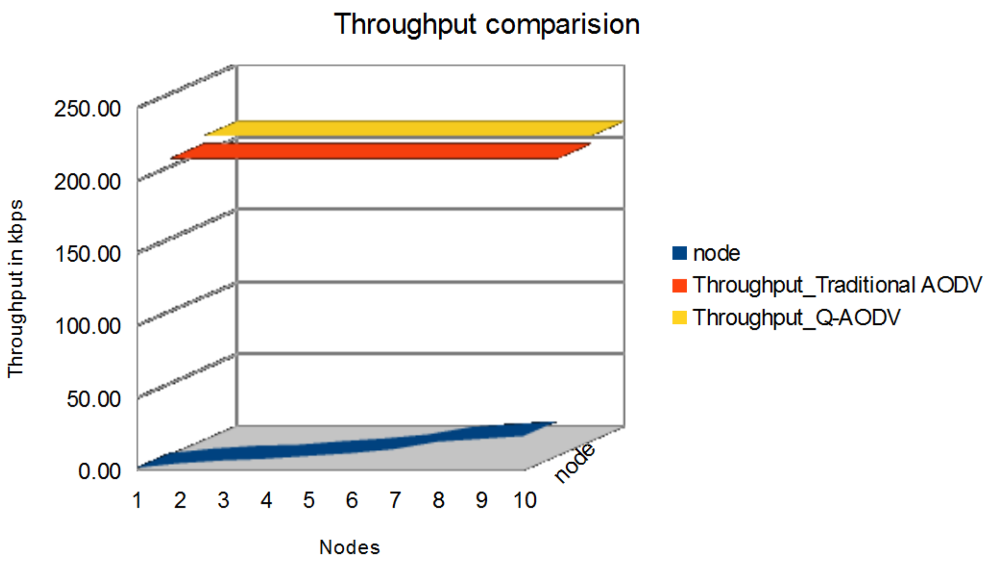

Fig 3. Comparison of throughput between traditional AODV and Q-AODV routing protocols

VI. Conclusion

In this paper an intelligent/ cognitive approach is choosen to improve the Quality of Service. Q-learning algorithm made AODV more intellectual. Thus, with this proposed new cognitive approach algorithm increases the throughput and reduces the end to end delay.

VII. FUTURE WORK

Instead of using regular NS-3, a NS3-gym-master is suggested to use for the simulation. It will suit well to the Machine Learning algorithms more. Since, here a Q-learning, reinforcement learning along with AODV is used, NS3-gym-master gives good results.

VIII. REFERENCES:

1. M. Chafii, F. Bader and J. Palicot, "Enhancing coverage in narrow band-IoT using machine learning," *2018 IEEE Wireless Communications and Networking Conference (WCNC)*, Barcelona, 2018, pp.1-6. doi: 10.1109/WCNC. 2018.8377263.
2. A.Nauman, M. A. Jamshed, Y. Ahmad, R. Ali, Y. B. Zikria and S. Won Kim, "An Intelligent Deterministic D2D Communication in Narrow-band Internet of Things," *2019 15th International Wireless Communications & Mobile Computing Conference (IWCMC)*, Tangier, Moroco, 2019, pp. 2111-2115. doi: 10.1109/IWCMC.2019.8766786.
3. M. K. Hossain Jewel, R. Sale Zakariyya, O. J. Famoriji, M. S. Ali and F. Lin, "A Low Complexity Channel Estimation Technique for NB-IoT Downlink System," *2019 IEEE MTT-S International Wireless Symposium (IWS)*, Guangzhou, China, 2019, pp. 1-3. doi: 10.1109/IEEE-IWS.2019.8803938.
4. A. Srivastava, D. Kumar and S. C. Gupta, "Geographic and Reactive Routing Protocols for MANET," *2013 European Modelling Symposium*, Manchester, 2013,pp.590-594. doi: 10.1109/ EMS.2013.98.
5. A. Tripathi, A. T S and R. M. R. Guddeti, "A Reinforcement Learning and Recurrent Neural Network Based Dynamic User Modeling System," *2018 IEEE 18th International Conference on Advanced Learning Technologies (ICALT)*, Mumbai, 2018, pp. 411-415. doi: 10.1109/ICALT.2018.00103.
6. A. Singh, T. Singh, M. Mittal and K. Kumar, "Performance improvement in AODV routing protocol with artificial intelligence," *2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom)*, New Delhi, 2016, pp. 45-49.
7. X. Chen, Z. Li, Y. Chen and X. Wang, "Performance Analysis and Uplink Scheduling for QoS-Aware NB-IoT Networks in Mobile Computing," in *IEEE Access*, vol. 7, pp. 44404-44415, 2019. doi: 10.1109/ ACCESS.2019.2908985.
8. N. Kantasewi, S. Marukatat, S. Thainimit and O. Manabu, "Multi Q-Table Q-Learning," *2019 10th International Conference of Information and Communication Technology for Embedded Systems (IC-ICTES)*, Bangkok, Thailand, 2019, pp.1-7. doi: 10.1109/ICTEmSys.2019.8695963.
9. W. Su and K. Feng, "QoS-Guaranteed Power-Saving Configuration Prediction Scheme for 5G IoT," *GLOBECOM 2017 - 2017 IEEE Global Communications Conference*, Singapore, 2017, pp. 1-6. doi: 10.1109/GLOCOM.2017.8254684
10. S. Popli, R. K. Jha and S. Jain, "A Survey on Energy Efficient Narrowband Internet of Things (NBIoT): Architecture, Application and Challenges," in *IEEE Access*, vol. 7, pp. 16739-16776, 2019. doi: 10.1109/ACCESS.2018.2881533
11. J. Xu, J. Yao, L. Wang, Z. Ming, K. Wu and L. Chen, "Narrowband Internet of Things: Evolutions, Technologies, and Open Issues," in *IEEE Internet of Things Journal*, vol. 5, no. 3, pp. 1449-1462, June 2018. doi: 10.1109/JIOT.2017.2783374