Resource Allocation Strategy for Latency Sensitive IoT Traffic

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Abstract

An efficient resource allocation scheme directly affects the overall system's network utilization, and notably, the wireless resource such as bandwidth is itself an expensive commodity. In this regards, to address the requirement of massively increased IoT traffic at the edge, as a solution approach, a number of small cell base stations (SBSs) have been deployed with certain computational capabilities. However, it is still limited, and any inappropriate resource allocation scheme for the associated nodes with traffic characterized by ultra-reliability and low-latency (URLLC) requirements can impact the system's resource utilization and performance. Considering a reserve resource for such kind of traffic, the resource allocation problem in each time slot behaves as a node selection problem with contention amongst active nodes for the resource. In this paper, we have formulated this as an index problem, and with simulation results have shown that the cumulative reward in terms of network utility is maximized following this approach.

Keywords* – *MAB, Index Theory, IoT, URLLC

I. Introduction

Radio resources such as bandwidth is considered scare, and is therefore an expensive utility whose management has been of a great challenge for the evolution of mobile networks. On the top of that, traffic with strict latency and reliability requirements in 5G networks requires an efficient resource allocation scheme to make it a success [1]. On the other hand, the massive growth of IoT networks has brought up numerous challenges while handling such traffic in an effective way [2].

Wireless Network virtualization has emerged as an promising alternative to manage the wireless resources amongst number of participating users. It invoked the concept of network slicing, and flexible allocation of the slices of network resources, such as bandwidth [3] - [5] to the users. In [6], authors have introduced an online network slice broker to facilitate the network resources for improving the overall network utilization ratio. The problem was formulated as a bandit problem (MAB) corresponding to the mobile traffic forecasting scenario [7]. As with the MAB problem, there exist the dilemma of *exploration* and *exploitation* to attain the cumulative reward, while minimizing the total regret in the system. The solution for this can be found using Bellman's equation [10], however, the solution cost is expensive for the larger systems. In case of IoT systems, with abrupt traffic response and latency sensitive requirements, such approach may appear to be impractical. Thus, there should be a mechanism to efficiently allocate the network resources for addressing these stringent demands of IoT traffic while improving the overall network utility. We formulate this scenario by firstly employing the technique of reserve resources for latency sensitive traffic of IoT nodes in terms of mini-slots, as mentioned in 3GPP standard for 5G networks. We define the network scenario as a family of bandit process, and implement the index theory approach [8] for a family of semi-decision Markov Process to prioritize the nodes that could maximize the overall network utilization upon reserve resource allocation.

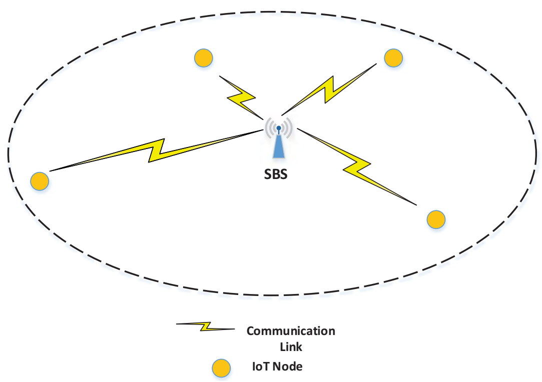

Fig. 1. System Model

The paper is organized as follows. Section II discusses the system model and Section III explains about the problem formulation and proposed solution approach. Section IV shows simulation results. Finally, Section V concludes the paper with future work.

II. System Model

We consider n IoT nodes associated with a single small cell base station (SBS) as in Fig. 1. Each node can collect sensory

Algorithm 1 Index Based Node Association

Input: $\mathcal{B} = \mathcal{F}, \mathbf{r}, a$.
Output: ν, *index*.
$\mathcal{I} = \{\}, i = N$;
while $i > 0$ **do**
  Calculate the index value, $\nu(F_i)$
  $\mathcal{I} = \mathcal{I} \cup \nu(F_i)$;
  $\mathcal{B} = \mathcal{B} \backslash i$;
  $i = i - 1$;
end while
Return maximum value in $\mathcal{I}$ as ν, and its corresponding index as *index*.

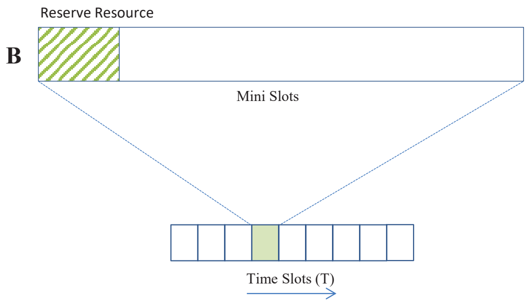

Fig. 2. Resource Reservation

data, perform certain amount of computation upon it and forward it to the SBS for diverse service oriented applications. We further categorize the traffic generated by the IoT nodes in terms of low-latency and ultra-reliability requirements. Here, for each node i, we will define its state at time t, $x_i(t)$ with the fraction of reserve resource, bandwidth B demanded from the SBS, by quantizing the reserved resource into N levels denoted by a set $\mathcal{N} = \{1, 2, \dots, N\}$, where $x_i(t) \in \mathcal{N}$. If node i in state $x_i(t)$ is chosen for the reserved resource in the time slot t, the reward value obtained by the SBS in terms of resource utilization is defined as $r_i(x_i(t))$. This way a sequential node selection scenario exist for the SBS to allocate reserve resource to one of the requesting node. Because the reward distribution is unknown, the SBS can allocate the reserve resource following the solution approach for the multi-armed bandit problem, to maximize its cumulative reward over the time. Alternatively, if we can prioritize a node i, given its state $x_i(t)$ and corresponding reward $r_i(x_i(t))$, the SBS can sequentially resolve the node selection problem in an efficient way. In the following section, we will formulate our problem for this scenario.

III. Problem Formulation

The defined problem can be represented as a n-arm bandit and a single player (SBS) scenario, where at each time t, the player (SBS) chooses one arm (IoT node) to play (allocate its reserve resource as illustrated in Fig. 2). The process can be extended in reference with the sequence of time t_i and states of the nodes, $x_i(t), \forall i$, and be consider a family of bandit process $\mathcal{F} = \{F_1, F_2, \dots, F_n\}$ as in [8]. Here, the bandit process $F_i, \forall i$ is defined with the state $x_i(t)$, and reward at the state $r_i(x_i(t)) > 0$, and is considered to be an exponentially discounted semi-Markov decision process with a constant duration between the decision times. For convenience, we keep it as 1.

We adapt the control set $u = \{0, 1\}$, where the control 0 freezes the process. That means, there is no change in state and no reward is obtained from the process. Similarly, control 1 is defined as the continuation control that returns an immediate reward $a^t r_i(x_i(t)) = e^{-\gamma t} r_i(x_i(t))$. Here, the parameters $a (0 < a < 1)$ and $\gamma(\gamma > 0)$ are defined to be the discount factor and the discount parameter respectively for obtaining a bounded reward value. This way, the presented problem resembles with a discounted- reward Markov decision process which solution can be found using dynamic programming equations [10]. However, the solution becomes difficult to solve for a $n-$bandit process where the problem grows exponentially. Therefore, using these definitions, we refer [9] which states that for a discrete time Markov decision process, there exists an optimal policy defined as index policy, which is characterized by a real-valued index, $\nu(F_i, x_i(t))$, and it is to continue the bandit process having greatest index. With this definition, for a given stopping time τ we have,

$$\nu(F_i) = \max_{\tau > 0} \nu_\tau(F_i) \tag{1}$$

where, τ defines the decision time to stop applying the control $u = \{1\}$.

For the expected total discounted reward over τ steps: $R_\tau(F_i) = E \sum_{t=0}^{\tau-1} a^t r_i(x_i(t))$, and the expected total discounted time over τ steps: $W_\tau(F_i) = \sum_{t=0}^{\tau-1} a^t = (1 - a)^{-1} E(1 - a^\tau)$, we can formalize the Gittins Index value using definition in (1) as,

$$\begin{aligned} \nu(F_i) &= \max_{\tau > 0} \nu_\tau(F_i) \\ &= \frac{R_\tau(F_i)}{W_\tau(F_i)} \end{aligned} \tag{2}$$

Let's analyze the formulation in (2) with a simple case scenario of two bandit process F_1 and F_2. For a stochastically independent bandit processes F_1 and F_2, having indices as $\nu(F_1)$ and $\nu(F_2)$, with $\nu(F_1) > \nu(F_2)$, and the stopping time τ for the process F_1, and φ as an arbitrary stopping time for F_2, we can derive the following relation as,

$$\begin{aligned} \nu(F_1) > \nu(F_2) \Leftrightarrow R_\tau(F_1) + E a^\tau R_\varphi(F_2) \\ > R_\varphi(F_2) + E a^\varphi R_\tau(F_1) \end{aligned} \tag{3}$$

From (3), we can analyze that the return of reward with the choice of control u applied for the bandit process will be improved by selecting continuation control on the bandit with the greatest index. Therefore, for the node selection problem at time t, we can evaluate the index values at the bandit processes given state $x_i(t), \forall i$. Then after, we can choose to apply the continuation control to the bandit with highest index value, as (3) guarantees for better discounted cumulative reward. The detail implementation for this scenario is presented in Algorithm.1.

IV. Simulation

For the simulation scenario, we quantize the fraction of reserve resource as $|\mathcal{N}| = 6$ levels, where each level defines the state of the bandit process. We consider 6 IoT nodes associated with the SBS, and define the transition probability matrix for the family of bandit processes $\mathcal{F} = \{F_1, F_2, F_3, F_4, F_5, F_6\}$. In each round, the reward r was randomly generated for the states. We use the values of discount factor $a = 0.9$. Fig.

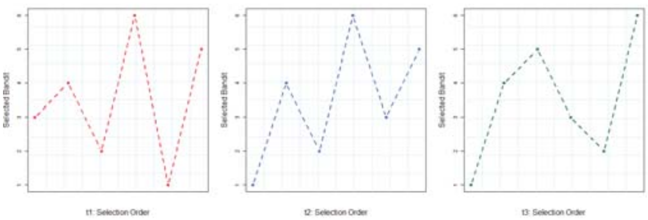

Fig. 3. Sequence of Node Selection via Indexing

3 shows the priority of node selection based upon indexing in each round of decision making. We can observe for three decision time: t1, t2 and t3, the order of node selection based on highest index value should be $\{F_3, F_1, F_1\}$. In this regards, Fig. 4 shows that the index based solution provided better expected reward in terms of reserve resource utilization for the SBS. This is because, and each decision time the SBS applies continuation control to the bandit process (node) with the greater index value. This result complies with the relation derived in (3).

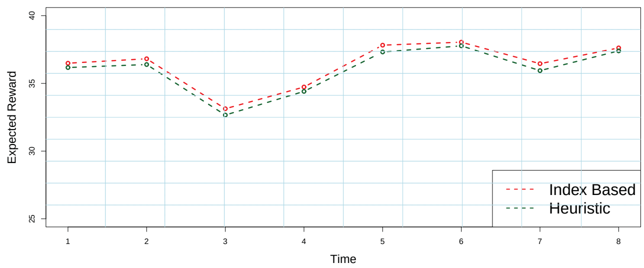

Fig. 4. Comparison of Index Based Node Selection and Heuristic Approach

V. Conclusion

In this paper, we have proposed an index base resource allocation scheme for the latency sensitive IoT traffic to improve the overall network utilization. We have formalized the network utilization in terms of cumulative reward while effectively allocating reserve resource to the family of bandit processes. Our simulation results shows the improvement in cumulative reward while implementing index based node selection approach for allocating the reserved resource.

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References

[1] Bennis, Mehdi and Debbah, Mérouane and Poor, H Vincent, *"Ultra-Reliable and Low-Latency Wireless Communication: Tail, Risk and Scale."*, arXiv:1801.01270 , 2018.

[2] Chen, Shanzhi and Zhao, Jian, *"The requirements, challenges, and technologies for 5G of terrestrial mobile telecommunication."*, IEEE Communications Magazine, vol. 52, no. 5, pp. 36-43, 2014.

[3] Liang, Chengchao and Yu, F Richard, *"Wireless network virtualization: A survey, some research issues and challenges."*, IEEE Communications Surveys & Tutorials, vol. 17, no. 1, pp. 358 -380, 2015.

[4] Nakao, Akihiro and Du, Ping and Kiriha, Yoshiaki and Granelli, Fabrizio and Gebremariam, Anteneh Atumo and Taleb, Tarik and Bagaa, Miloud, *"End-to-end network slicing for 5g mobile networks."*, Journal of Information Processing, vol. 25, pp. 153-163, 2017.

[5] Zhang, Haijun and Liu, Na and Chu, Xiaoli and Long, Keping and Aghvami, Abdol-Hamid and Leung, Victor CM, *"Network slicing based 5G and future mobile networks: mobility, resource management, and challenges."*, IEEE Communications Magazine, vol. 55, no. 8, 138-145, 2017.

[6] Sciancalepore, Vincenzo and Zanzi, Lanfranco and Costa-Perez, Xavier and Capone, Antonio, *"ONETS: Online Network Slice Broker From Theory to Practice"*, arXiv:1801.03484, 2018.

[7] Sciancalepore, Vincenzo and Samdanis, Konstantinos and Costa-Perez, Xavier and Bega, Dario and Gramaglia, Marco and Banchs, Albert, *"Mobile traffic forecasting for maximizing 5G network slicing resource utilization"*, In *INFOCOM 2017-IEEE Conference on Computer Communications, IEEE*, pp. 1-9. IEEE, 2017

[8] Gittins, John and Glazebrook, Kevin and Weber, Richard., 2011 *Multi-armed bandit allocation indices.*

[9] Weber, Richard,1992 *"On the Gittins index for multiarmed bandits"* The Annals of Applied Probability,1024–1033.

[10] Bellman, Richard, 2013 *Dynamic programming.*