

## **Sleeping Multi Armed learning For Fast Uplink Grant Allocation Using SWUCB In Machine Type Communications**

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**Abstract:** multi-armed bandits (MABs) along with Sliding window UCB is used for fast uplink grant allocation in Machine type communication . The set of active MTDs changes over time due to the knowledge on the set of active MTDs is probabilistic, so that SWUCB is maximize the defined metric parameters like bit rate, signaling over head. Analyse the regret as well as effect of the prediction error of the source traffic prediction algorithm on the performance of the proposed sleeping MAB algorithm is investigated. Moreover, to activate fast uplink allocation for multiple MTDs at each time, so concept of best MTD ordering in the MAB setting. Simulation results show that the proposed framework Sliding window UCB yields good results in terms of regret, maximum tolerable access delay, throughput compared to traditional methods.

**Key words:** < IOT, fast uplink grant, sleeping MAB, Discounted UCB, SWUCB>.

### **I. INTRODUCTION**

The next generation wireless networks support to the internet of things(IOT) applications such as unmanned aerial vehicles, autonomous vehicles. For better implementation of the iot applications, next generation wireless network must support to the machine type communication(MTC)[1][2][3]. In MTC has small data packets transferred between the machine type devices. For using different iot applications , MTC data packets had to satisfy the quality of service parameters like latency, security, reliability for data transmission[4]

In general MTC access has dividing into three types 1)Coordinated transmission, in which MTD can send scheduling request to the base station based on availability it provide resource allocation to that MTD. It is not efficient due to for less data it take more time so it has signaling overhead. To overcome it next one 2)grant free transmission, MTD can allocate any random uplink resource for data transmission without any prior requesting schedule to base station . here signaling overhead reduce but more collisions due to no of MTDs are comparatively greater than number of resources available. Later we go for fast uplink grant here no MTD can send scheduling request instead base station allocate resource for active MTD based on collection of past data related to the MTDs analysis.[5]

In the sleeping MAB with Discounted UCB is good in decision strategy for the sub-band selection by optimizing the discounted factor and exploration bonus. It assign less weight to the past data and more weight to recent data. But it is not match our QOS standards for non stationary data. So in proposed method with sleeping MAB with sliding window upper confidence bound(SWUCB) can get better results in terms of regret, maximum tolerable access delay, throughput[9][11].

In this paper, section II associates with the related research of our method, section III associated with our framework of proposed method, section IV deals with the results and its discussions and conclusion is discussed in the section V.

## II. RELATED WORK

Sleeping MAB is how effectively used with fast uplink resource allocation and importance of the UCB in resource allocation.

Sleeping MAB:

In general problem of MAB is assumed that all the MTDs are active over period of time, but in real in MTC we can send small packets data transfer so that after transmission, they become inactive for some time. So set of active MTDs changes over period of time so sleeping MAB is used. In this method availability of the MTDs are fallows distribution of traffic. It get optimal regret only when it assumed set of active MTD can be known in advance to the decision maker at the base station. Due to MTDS are probabilistic nature due to inactive MTD taken resources are wasted. But it is not correct assumption because due to the error in the source traffic prediction of the MTDs active leads to effect the sleeping MAB[10][13]

To select the MTD at the base station based on  $x(t)$  such that

$$x(t) = \arg \max_{i \in \mathcal{K}_t} (\Lambda_i(t)) \left( \frac{z_i(t)}{n'_i(t)} + \sqrt{\frac{\psi \log t'}{n'_i(t)}} \right)$$

(1)

where  $z_i(t)$  is MTD rewards sum,  $n_i(t)$  is the MTD $_i$  was selected and was active, and  $t_0$  is the total number of the times that the selected MTD was active.  $\mathcal{K}_t$  is defined as the set of active MTDs at time  $t$ . In differs from original method of UCB, here we count only the selected MTD was active in how many number of times. This provides UCB values and statistical average are correctly estimated. The error at the BS about MTD active can be propagate to the sleeping MAB. Good performance in probabilistic sleeping mab only prediction algorithm had less error.

we use a Bayesian approach to infer the activity status of each MTD at any given time. For this, let for each MTD  $i$ , we define the following posterior probability of being active as

$$\Lambda_i(t) := P_{i,a}(i \text{ is active} \mid \lambda_i(t)) = \frac{P(\lambda_i(t) \mid \text{active})P(\text{active})}{P(\lambda_i(t))} \quad (2)$$

where the posterior probability  $P(i \text{ is active} | \lambda_i(t))$  gives that active MTD at given time  $t$  based on probability given that the prediction algorithm  $\lambda_i(t)$  provides probability of being active. The marginal likelihood  $P(\lambda_i(t))$  is the probability of providing  $\lambda_i(t)$  for MTD  $i$  by the source traffic posterior probabilities.

Upper Confidence Bound Tuned (UCBT) :

The UCBT algorithm was first proposed. The main characteristic of the UCBT is the use of empirical variance in the bias sequence. Thus, the exploration is reduced for the channels with small reward variance. The UCBT algorithm chooses channel  $s_i(j)$  such that

$$s_i(j) = \arg \max_{i \in \mathcal{N}} \left( z_i(j) + \sqrt{\frac{(z_i(j) - (z_i(j))^2) \sigma \log j}{y_i(j)}} + \frac{c \log j}{y_i(j)} \right) \quad (3)$$

The difference between SWUCB and DUCB is that SWUCB only uses a window of length  $l$  and only consider the average reward within this window. The window length decreases as the dynamic environment changes faster.

### III Proposed methodology

Sleeping MAB with SWUCB has overcome the important challenges that are prediction of the set of MTDs with data to transmit, as well as the optimal scheduling of MTDs, are exposed. To overcome these draw backs, a two-stage approach that includes traffic prediction as well as optimized scheduling is proposed. In specific, different solutions for periodic traffic in MTC for source traffic prediction are analyzed and traffic prediction methods are proposed. The proposed method has potential to activate the cellular networks for support massive MTCs effectively and reduce the throughput and overcome the delay and regret challenges of conventional RA schemes using Sliding window UCB[12]

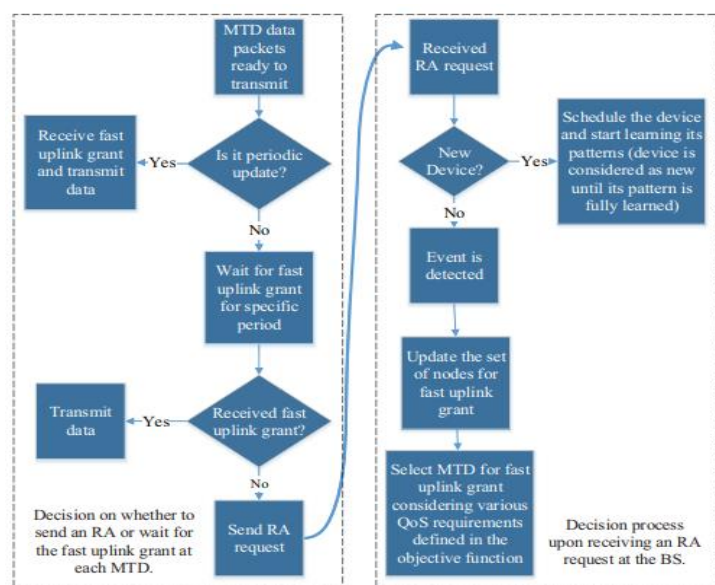


Figure1: Fast uplink grant with SWUCB

MTD can have data packets ready to send if it is periodic update means it receive fast up link grant and transmit the data. if not get the periodic update so wait for specific periodic of time for uplink grant or else send the radio access request to the base station.

So based on that Base station can collection of data related to that MTD for updating the set of nodes in the fast uplink grant and select the MTD for fast uplink grant based on QOS requirements are defined in the objective function.

- In the method we can provide the transmitter setting and receiver setting for effective use of channel . Path loss calculation for reducing the power density attenuation
- Later we can calculate the noise figure in base station and MTD. Next Slot quantization size calculated for dividing the channel for effective data transmission. In simulation we consider the MAB setting, based on data base whether MTD is active or not. We consider highest reward arm based on iteration data.
- Later Uplink Data Initialization , channel generation for data transmission, Uplink Resource Block creation Packet assignment with different QOS Requirement (base station & transmission devices)
- If we are getting the regret it should be updated for the next step it is iteration process .
- Calculate the bf probability distributions Discounted UCB for reward calculation Sleeping MTD index prediction multiple MTD device selection end update rules check if the probability distribution for each action does not change, then convergence Maximum power uplink grant transmission
- In Sleeping MAB with discounted UCB has give average past rewards with addition of the discounted factor gives more weight to the recent observation
- In sleeping MAB with SWUCB has local empirical average of observed rewards used only for t seconds. If window size is varies based on random change environment. If window size is small when random change in environment changes rapidly.
- If the MTD bit rate should be greater than threshold bit rate, signal to noise ratio is greater than minimum requirement, access delay should be less than the maximum tolerable delay for that particular application
- Based on signal to noise ratio, maximum power allocation, channel quantization size, path loss, with high efficiency we can calculate the channel parameters like regret, maximum tolerable access delay ,throughput

#### IV RESULTS ANALYSIS

Our main aim is to maximize a cumulative reward or minimize a cumulative regret. Regret is defined as the difference between the reward of the best possible arm at each game instant, and the generated reward of the arm that is played. Let  $\theta(t)$  be the reward of playing an arm from the set of arms  $K$  at time  $t$ , and let  $\theta^*(t) = \max_{i \in K} \theta_i(t)$  [12]

$$R(T) = \mathbb{E} \left[ \sum_{t=1}^T \theta^*(t) - \sum_{t=1}^T \theta(t) \right] \tag{4}$$

the plot show that if no of iterations increases how regret varies. In maximum probability allocation regret increases linearly so in MTC failure of data transmission is high because we can access MTD randomly without considering the QOS parameters. In the use of sleeping MAB with SWUCB we can reduce the regret in the four fold compared to existing method.

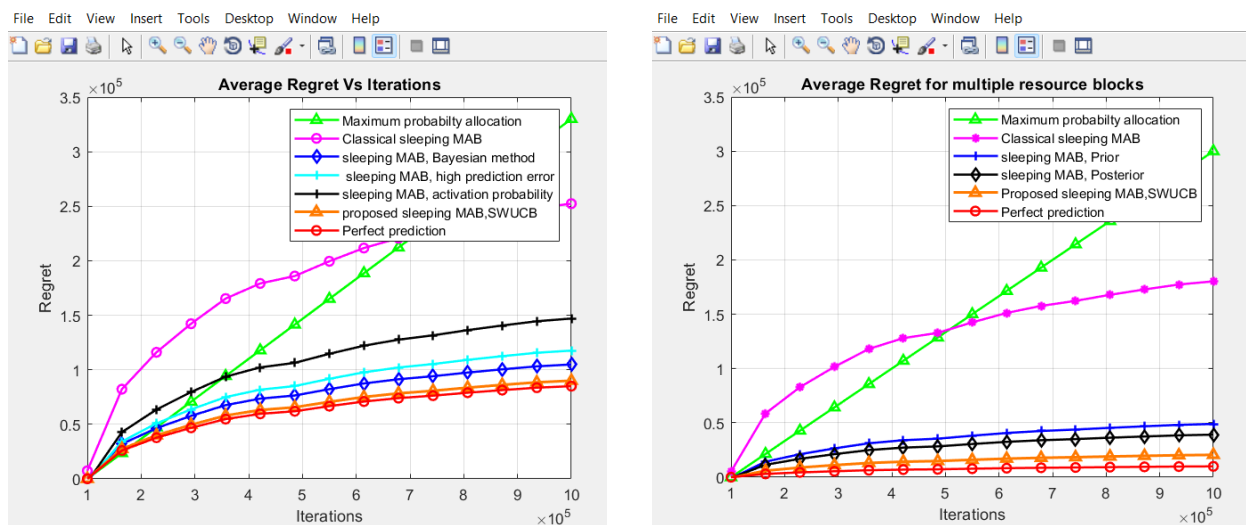


Figure2:regret vs iteration with single and multiple resource blocks are selected

TABLE1:COMPARISON OF REGRET WITH SWUCB& EXISTING METHODS

no of iterations	maximum probability allocation	sleeping MAB bayesian method	sleeping MAB SWUCB	perfect prediction
3*10 <sup>5</sup>	0.7*10 <sup>5</sup>	0.6*10 <sup>5</sup>	0.5*10 <sup>5</sup>	0.5*10 <sup>5</sup>
7*10 <sup>5</sup>	2.5*10 <sup>5</sup>	1*10 <sup>5</sup>	0.8*10 <sup>5</sup>	0.65*10 <sup>5</sup>
10*10 <sup>5</sup>	3.3*10 <sup>5</sup>	1.3*10 <sup>5</sup>	0.8*10 <sup>5</sup>	0.75*10 <sup>5</sup>

maximum tolerable access delay defined as the total delay that can be tolerated from the time instance  $t_s$  at which the data packet is ready to be transmitted at the MTD queue until it is scheduled to be sent

$$T_a = T_{total} - T_t - T_p. \tag{5}$$

Delay in a wireless communication network consists of different components: Processing

delay  $T_p$  which is a function of hardware and software used by the MTDs, queuing delay  $T_q$ , and transmission delay  $T_t$ . Once the data is transmitted and received at the BS, the time required for the packet to travel to the final destination through a network of wireless, wired, or fiber link is called routing delay  $T_r$ . Finally, the access delay  $T_a$  is the time duration from the moment that the packet is ready for transmission, until the MTD receives the uplink resource blocks to transmit the packet.

In the plot shown that if you consider the system delay with selected MTD for data communication. We try to reduce the tolerable access delay for fast uplink data transmission. In maximum probability allocation access delay is more due to randomly selected MTD so not considered the probability sleeping MAB.

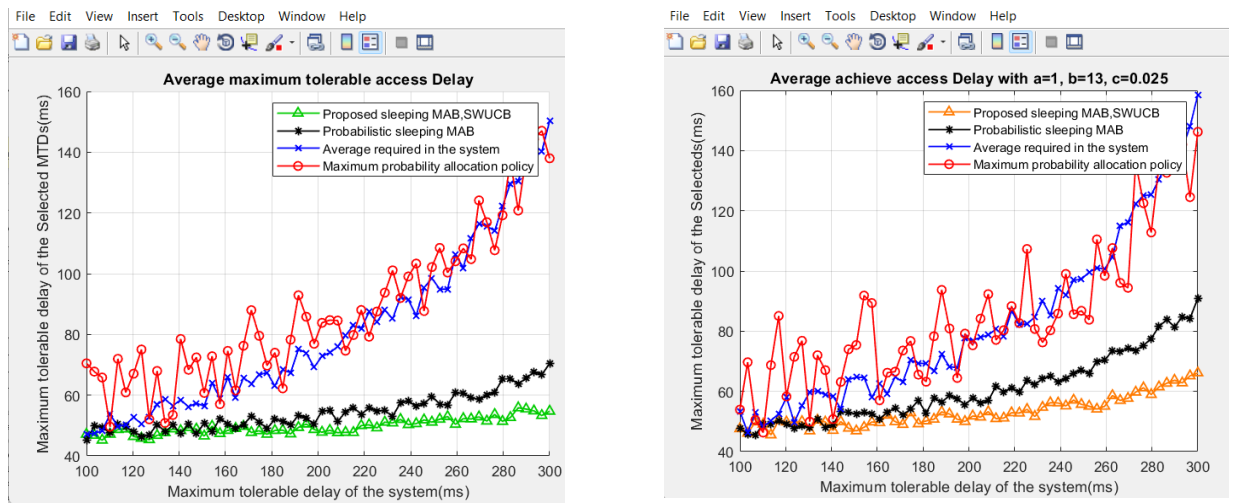


Figure3 :tolerable Access delay in single MTD and multiple resource block with multiple MTDs transmission

in the tabular form shown the comparison of different methods for better understanding of maximum tolerable access delay

TABLE II :MAXIMUM TOLERABLE ACCESS DELAY COMPARISON BETWEEN SWUCB AND DISCOUNTED UCB

Maximum tolerable access delay of the system(ms)	Maximum probability allocation delay(ms)	Probabilistic sleeping MAB delay(ms)	Sleeping MAB with SWUCB Delay(ms)
100	60	50	50
200	80	53	52
300	145	70	55

Access delay for single MTD resource allocation is given in the plot shown below

The access delay in discounted UCB maximum is 100ms, in SWUCB has maximum access delay of 55ms only so reduced access delay by 2 folds compared to traditional methods.

In the multiple resource blocks are considered for satisfying the particular IOT application because for some important application with complicated circuits requires more MTDs at a time to communicate. We try to reduce the delay in SWUCB compared to Discounted UCB can be understood based on the plot

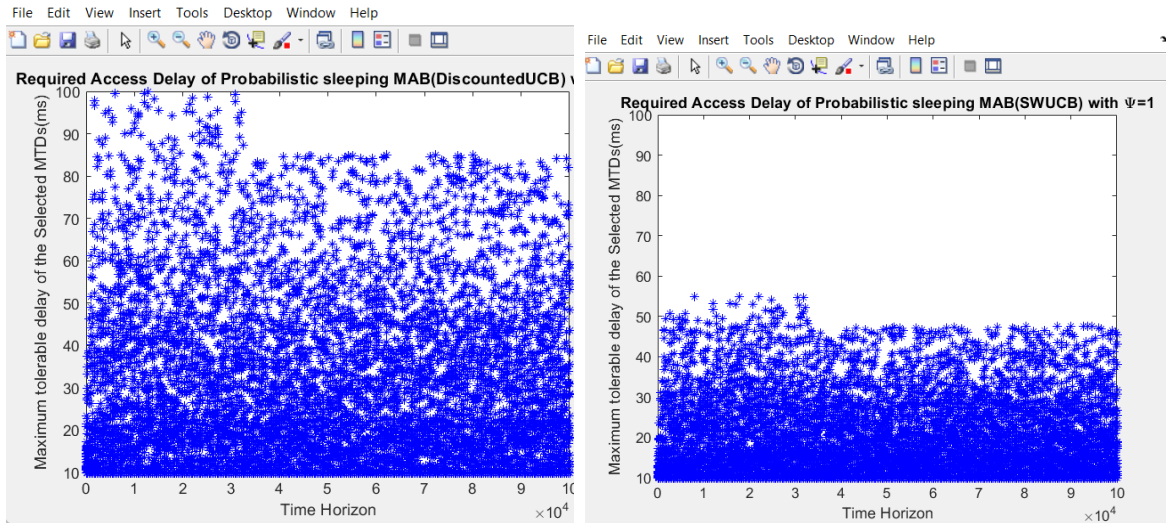


Figure 4: access delay of discounted UCB&SWUCB

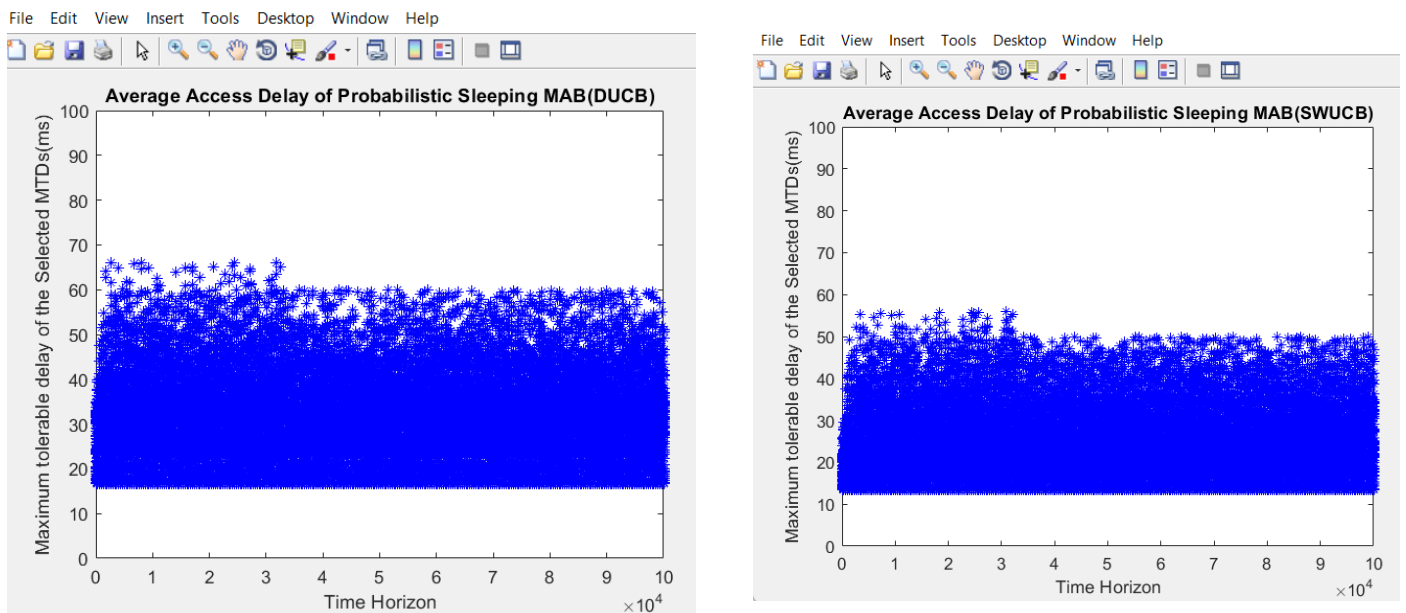


Figure 5 Access delay in multiple resource blocks

TABLE III AVERAGE ACCESS DELAY FOR SWUCB& DISCOUNTED UCB FOR MULTIPLE RESOURCE BLOCKS

<b>Access delay</b>	<b>Probabilistic sleeping MAB with discounted UCB</b>	<b>Probabilistic sleeping MAB (SWUCB)</b>
Minimum avg access delay	15ms	12ms
Maximum avg access delay	60ms	50ms

**THROUGHPUT:**

Once each signal is received at the BS, the signal-to-noise ratio (SNR) is:

$$\gamma_i(t) = \frac{q_i(t)|h_i(t)|^2}{WN_0} \quad (6)$$

Where  $h_i(t)$  represent the channel between MTD node and the BS.  $N_0$  is the power spectral density of the noise,  $W$  is the bandwidth of the transmission channel, and  $q_i(t)$  is the transmit power of MTD .

Where with PLdB denoting the path loss and log-normal shadowing with variance .

$$PLdB=128.1+37.6\log(d) \quad (7)$$

We use the 3GPP path loss model from the BS to MTDs which is given by Subsequently, the rate is given by[14]:

$$C_i(t) = W \log \left( 1 + \frac{q_i(t)|h_i(t)|^2}{WN_0} \right) \quad (8)$$

Table IV: COMPARISON OF THROUGHPUT ON SWUCB &amp; DISCOUNTED UCB

<b>THROUGHPUT</b>	<b>SLEEPING MAB WITH DISCOUNTED UCB</b>	<b>PROPOSED SLEEPING MAB WITH SWUCB</b>
	7.5mbps	11mbps

in the table shown clearly how much maximum through put is possible by using sleeping MAB with discounted UCB, sleeping MAB with upper confidence bound. Compared to discounted UCB throughput increases by 1.5times.

We can plot the graph time vs bit rate of the selected machine type device is shown below. We are comparing the with different methods are shown below



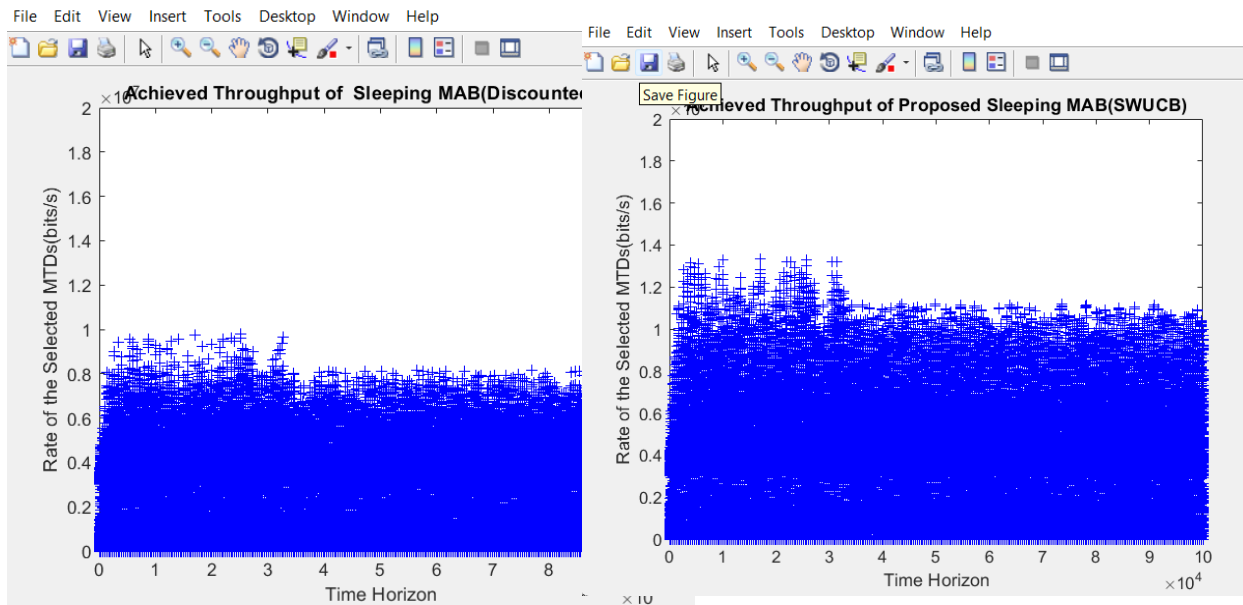


Figure 6: throughput comparison of SWUCB, Discounted UCB

## V. CONCLUSION

In this paper, we have studied the potential of incorporating the fast uplink grant as an enabler for massive MTCs in the IoT. First, we have reviewed the challenges faced by conventional access schemes in MTC and discussed the use of the fast uplink grant using SWUCB. Then, we have presented the shortcomings of the fast uplink grant, and outlined solutions to address them. In particular, we have elaborated on the methods for source traffic prediction, for both periodic and event-driven traffic. Then, we have proposed machine learning techniques for the optimal selection of MTDs to be used in the fast uplink grant. In a nutshell, this work can be thought of as a stepping stone towards a better understanding of how the fast uplink grant can be effectively leveraged for massive MTCs.

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## REFERENCES

1. S. Ali, A. Ferdowsi, W. Saad, and N. Rajatheva, "Sleeping multi-armed bandits for uplink grant allocation in machine type communications," in Proc. IEEE Global Communications Conference (GLOBECOM), Workshop on Ultra-High Speed, Low Latency and Massive Connectivity Communication for 5G/B5G, Abu Dhabi, UAE, Dec 2018, pp. 1–6.
2. W. Saad, M. Bennis, and M. Chen, "A vision of 6G wireless systems: Applications, trends, technologies, and open research problems," arXiv preprint arXiv:1902.10265, 2019.
3. M. R. Palattella, M. Dohler, A. Grieco, G. Rizzo, J. Torsner, T. Engel, and L. Ladid, "Internet of things in the 5G era: Enablers, architecture, and business models," IEEE Journal on Selected Areas in Communications, vol. 34, no. 3, pp. 510–527, March 2016.

4. A. Ferdowsi and W. Saad, "Deep learning for signal authentication and security in massive Internet of Things systems," *IEEE Transactions on Communications*, vol. to appear, pp. 1–1, 2018.
5. M. T. Islam, A. e. M. Taha, and S. Akl, "A survey of access management techniques in machine type communications," *IEEE Communications Magazine*, vol. 52, no. 4, pp. 74–81, April 2014.
6. A. Ferdowsi, U. Challita, and W. Saad, "Deep learning for reliable mobile edge analytics in intelligent transportation systems," *CoRR*, vol. abs/1712.04135, 2017. [Online]. Available: <http://arxiv.org/abs/1712.04135>
7. M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Unmanned aerial vehicle with underlaid device-to-device communications: Performance and tradeoffs," *IEEE Transactions on Wireless Communications*, vol. 15, no. 6, pp. 3949–3963, June 2016.
8. Z. Dawy, W. Saad, A. Ghosh, J. G. Andrews, and E. Yaacoub, "Toward massive machine type cellular communications," *IEEE Wireless Communications*, vol. 24, no. 1, pp. 120–128, February 2017.
9. C. Bockelmann, N. Pratas, H. Nikopour, K. Au, T. Svensson, C. Stefanovic, P. Popovski, and A. Dekorsy, "Massive machine-type communications in 5G: physical and MAC-layer solutions," *IEEE Communications Magazine*, vol. 54, no. 9, pp. 59–65, September 2016.
10. W. Chen, H. Zhang, H. Ji, and X. Li, "Dynamic QoS-aware resource allocation for narrow band internet of things," in *2018 IEEE/CIC International Conference on Communications in China (ICCC Workshops)*, Aug 2018, pp. 107–111.
11. N. Abuzainab, W. Saad, C. S. Hong, and H. V. Poor, "Cognitive hierarchy theory for distributed resource allocation in the Internet of Things," *IEEE Transactions on Wireless Communications*, vol. 16, no. 12, pp. 7702, Dec 2017.
12. R. S. Sutton, A. G. Barto et al., *Reinforcement learning: An introduction*. MIT press, 1998.
13. R. Kleinberg, A. Niculescu-Mizil, and Y. Sharma, "Regret bounds for sleeping experts and bandits," *Machine learning*, vol. 80, no. 2-3, pp. 245–272, 2010.
14. 3GPP, "Radio frequency (RF) requirements for LTE pico node B," *3rd Generation Partnership Project (3GPP), Technical Specification (TS) 36.931*.