International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 02, February-2021

# Dynamic Aggregation of Foggy IoT Traffic in LTE Network

Christantus O. Nnamani[1*], Chidera L. Anioke[2] and Cosmas I. Ani[3]
[1,2,3]Department of Electronic Engineering,
University of Nigeria Nsukka, Nigeria

***Abstract* – The third-generation partnership project's (3GPPP) long-term evolution (LTE) network is the harbinger to the next generation network (NGN). The major issue to LTE vendors and researchers is the effective and efficient provisioning of the required QoS to the IoT traffic traversing simultaneously with the traditional human triggered traffic through the network. This is primarily due to the unique characteristics of IoT traffic as defined in several works of literature. However, to maintain the required QoS of the network, a proper understanding of the dynamism introduced by the IoT traffic is necessary. Thus, an investigation into the influence of the foggy IoT traffic on the QoS parameters of existing LTE network was conducted by simulating the traditional human triggered LTE traffic (video and VoIP) using ns-3 (ns 3.26) simulator, and then systematical introducing a modelled IoT traffic to the setup of this work. It was shown that the increase of IoT traffic adversely affects the average delay and the achieved data-rate experienced by human triggered uplink traffic. We also report that contrary to popular expectation, the network reacts similarly to periodic and non-periodic IoT traffic arrival pattern based on the analysis carried out with regression analysis. Furthermore, since the size of IoT packet degrades the performance of the network, we proposed a dynamic mobile aggregator for delay-tolerant IoT applications and showed the network performance in terms of data-rate.**

***Keywords: IoT, LTE, traffic, NGN, QoS, Data aggregation, Simulation.***

## I. INTRODUCTION

The Internet of things (IoT) is the road map towards a global technological singularity. Current statistics show that the number of connected devices to the internet has exceeded the current world population. By 2020, about 50 billion connected devices will traverse the sphere of the globe via the Internet [1]. Everybody seeks global connectivity to other people around the globe. This connectivity explores options ranging from hardware (e.g. gadgets) to software (e.g. social networking) connectivity. Thus, this great technological revolution has stretched the boundaries of communication, business, economy and military milieus. Currently, with little/no constraints in time and space, harnessing human capacity from any part of the world is quite easy under this technological singularity. More reliable power source, computing power, cheaper smart objects and devices becoming proliferated have contributed to the rise of IoT systems [1, 2]. Although from a business perspective, the booming IoT technology is a fundamental key to unlocking some global economic problems; predominantly a universal marketing strategy; it will simultaneously lead to greater network integration issues for network managers/administrators due to its required infrastructure [3].

To buttress this, we note that at the core of this technological singularity is the communication network. This network is unique with swift system integration and inter-operability to accommodate the numerous variations in the properties, characteristics and requirements of IoT [4]. In this relation, some researchers are proposing the development and deployment of the next-generation network (NGN) having ascertained that the current network standards will perform below expectation under the stringent requirement of IoT traffic [5, 6, 7]. Nevertheless, the NGN is still in its developmental/early stage. This predisposes the third-generation partnership project's (3GPPP) fourth-generation (4G) long-term evolution (LTE) network (the current leading mobile network standard) to assume the role of the harbinger to the NGN [5, 8].

One of the major issues LTE vendors and researchers encounter is the effective and efficient provisioning of the required QoS to the IoT traffic traversing simultaneously with the traditional human triggered traffic through the network. This is primarily due to the unique characteristics of IoT traffic as defined in several works of literature [3, 9, 10]. Nevertheless, to maintain the required QoS of the network, a proper understanding of the dynamism introduced by the IoT traffic is necessary. Thus, this work investigated the influence of the "foggy" IoT traffic on the QoS parameters of the existing LTE network as an expansion to the conference review paper of [10]. The conference review paper of [10] elucidated the unique characteristics of IoT traffic concerning LTE network. We also focused on uplink implementation because several works of literature have predisposed that one of the fundamental properties of IoT traffic is that they are mostly uplink bound as enumerated in [10].

This work was carried out by simulating the traditional human triggered LTE traffic using ns-3 (ns 3.26 [11]) simulator, and then systematical introducing the IoT traffic to the setup. We carried out our analysis using LTE uplink traffic comprising of 50% video trace traffic, 50% VoIP traffic and the generated IoT traffic model as recommended in the literature. It showed that the increase of IoT traffic would greatly affect the average delay experienced by human triggered uplink traffic. Furthermore, we report that the network reacts similarly to any IoT traffic arrival pattern although this reaction is negative in terms of network performance. Finally, we recommend that the aggregating IoT traffic make their payload significant and improve the LTE network performance. However, with the introduction of a relay node in LTE, [19] proposed aggregation of LTE/IoT traffic on a gateway in a static manner. This method could not describe the practical scenario of mobile IoT traffic and congestion on the gateway. To ameliorate this scenario and

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 02, February-2021

considering the inherent characteristics of IoT, we also propose a novel dynamic mobile aggregation. The dynamic mobile aggregation showed better performance in terms of achieved data-rate and loss, than directly integrating IoT and static relay node aggregator as proposed in [19].

## II. IoT TRAFFIC MODELING

Considering the functions of the majority of IoT applications, IoT has three fundamental traffic arrival patterns – Periodic Update (PU), Event-Driven (ED) and the Payload Exchange (PE) [5, 12]. PU describes a non-real-time deterministic, time-based traffic with constant data size that is subject to delay, with little or no loss tolerated. ED in contrast, describes real-time stochastic traffic with variable time and data size that is subject to lose with little or no delay tolerated. The third class of traffic, the PE, defined as IoT traffic with either the PU or ED characteristic but with larger appended data size or payload. In summary, PU and ED are control traffic while PE is burst traffic [12]. The type of IoT application and the service requirements determines the assigned priority granted to any of the IoT traffic arrival patterns. Such applications include eHealth, self-driving cars, sensor monitoring systems, etc. In this work, we emphasize on a generic PU and ED since they describe typical IoT traffic with small payload. The two different classes of IoT traffic were modelled using On/Off approach as shown in Fig. 1. While the on-time of the On/Off application is used to set the holding time of the traffic, the data rate is used to set the inter-arrival times [9, 14].

In the ED, the inter-arrival time and packet size have probability density function (PDF) that are identical and independent distributed (iid) while the holding time has an arbitrary independent distributed PDF [9, 12, 14]. We modelled the on and off times of the On/Off traffic with the Poisson distribution. The packet size and inter-arrival time were modelled with Pareto distribution. Table 1 presents the values for the parameters used in the modelling of the PU and ED traffic patterns and the arrival pattern illustrated in Fig. 1.

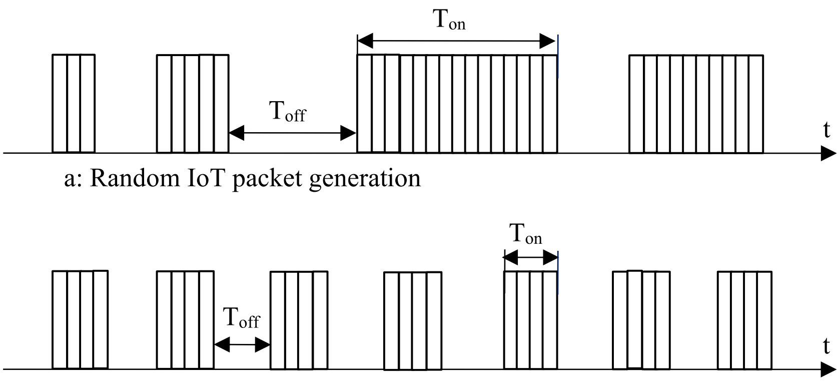


Fig. 1: IoT packet generation

Table 1: IoT traffic model parameters

| Parameter | Value |
|---|---|
| **Description** | **Periodic Update** |
| On time | 0.5 [sec] (constant) |
| Off time | 0.3 [sec] (constant) |
| Packet size | 16 [bits] (constant) |
| Data rate | 5 [kbps] (constant) |
| QoS classification identity (QCI) | 9 |
| **Description** | **Event-driven** |
| On-time mean | Exp. With mean = 0.05 and bound = 0.05 |
| Off time | Exp. With mean = 0.5 and bound = 0.3 |
| Packet Size | Pareto with mean = 20, shape = 5, bound = 32 |
| Data rate | Pareto with mean = 3, shape = 5, bound = 5 |
| QCI | 9 |

The human-triggered traffic modelled as buffered video trace and VoIP traffic with a proportion of 50% each of the uplink traffic. Integrating the video trace obtained from [13] and the VoIP files as an application domiciled in the mobile user terminal or uploaded to a server at a remote location. Furthermore, using a G.711 codec we generate the VoIP traffic. This codec describes the modelling of VoIP as a non-compression On/Off Application with parameters as shown in Table 2.

Table 2: Video and VoIP traffic model and QoS requirement

| Parameter | Value |
|---|---|
| **Description** | **G.711 VoIP codec (ON/OFF Model)** |
| On time | 0.352 [sec] |
| Off time | 0.650 [sec] |
| Data rate | 64 [Kbps] |
| Packet Size | 200 [bits] |
| QoS classification identity (QCI) | 1 |
| **Description** | **Video H.264 (Trace-based) [13]** |
| Data rate | 128 [Kbps] |
| QCI | 3 |

In this work, a simple proportion fairness medium access control (MAC) scheduling algorithm was adopted to select

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 02, February-2021

IoT and human triggered users depending on their satisfactory key performance indicators.

## III. FOGGY IoT TRAFFIC

Using the Network Simulator 3 (version 3.26) as proposed in [11] to simulate the LTE network with parameters enumerated in Table 3. The IoT traffic was deterministically added to the simulation model in groups of ten (10) while the human-triggered user nodes were made constant throughout the simulation. Each set of human-triggered user node scenarios (with incremental IoT traffic) were simulated independently and the results obtained were averaged over three (3) simulations. These results are shown in Figs. 2 – 7. The users were randomly displaced within the coverage region of the cell sector. However, this displacement was constant for each of the scenarios under consideration to achieve similar simulation condition and new users were placed in other random positions.

Table 3: Simulation Parameters

| **Simulation Parameter** | **Value** |
|---|---|
| Bandwidth (Downlink and Uplink) | 20 [MHz] |
| MAC Scheduler | Proportional fairness |
| Simulation time | 20 [sec] |
| Antenna transmission power | 46 [dBm] |
| Cell radius | 500 [m] |
| Path Loss Model | Cost231 |
| Carrier Frequency | 2120 [MHz] |

### *A. Discussions on Foggy IoT Traffic*

At the end of the simulations, the data obtained were analysed and plotted as shown in Figs. 2 – 7. The number of uplink users was statically fixed and represented with "ULX" (where X is the number of uplink users), while the number of IoT users was varied on the horizontal axis of the graph. Fig. 2 deduced that as the number of event-driven IoT user increases with a fixed number of uplink users, the network data-rate reduces exponentially. This implies that with the growth of IoT traffic added to the LTE network, a reduction in the performance of the network ensues. Similarly, the result obtained from the periodic update of IoT traffic as depicted in Fig. 3 shows the same performance traits.

However, under the same number of IoT users with an increasing number of uplink users, the data-rate increases because more packet flows were initiated during the simulation as observed from the flow monitor statistics. Thus, with an increase in the number of IoT users, the data-rate of the network was expected to increase since more packet flows were to be created. Nevertheless, observation showed the reverse as depicted in Fig. 2 and Fig. 3. This is because the size of IoT data is small and under the available network resources when it is scheduled. Since data-rate is a function of the size of the packet, aggregation of the small-sized IoT packet as proposed in [6] and [19], to form can increase the network performance in terms of data-rate. The implication is that IoT traffic will adversely influence the maximum achieved data-rate of the LTE network. This observation was further analysed by quantitatively studying the impact of the IoT traffic on the average data-rate and average round-trip delay of the LTE network as shown in Figs. 4 – 7. Fig. 4 and Fig. 5 observed that the growth of IoT users generating IoT traffic is linear and inversely related to the average data-rate of the network for both event-driven and periodic update IoT traffic.

Furthermore, in Fig. 6 and Fig. 7, the relation between the growth of IoT users and the average round-trip delay experienced by packets traversing through the network is exponentially distributed. This relation is necessary because it was used to accurately establish that as the number of IoT traffic increases, the network will begin to experience a greater delay of the human-triggered traffic leading to network degradation soon although the size of the IoT packets is small. Hence, using linear and logarithmic regression analysis on the data analysed in Fig. 4 and Fig. 5, and Fig. 6 and Fig. 7 respectively. There is no significant difference between the impact of PU and the ED IoT traffic on the average data-rate of the network considering the regression equations. The correlation regression coefficient ($R^2$) value of 99.77% and 99.84% respectively elaborates the accuracy of the prediction or regression equations. However, observe a significant difference in the average round-trip delay as shown in the regression equations of figures 6 and 7, although the distribution is similar. The $R^2$ value of 92.78% and 71.59% respectively shows the variability of the predictor. Although the values of the $R^2$ are high indicating the good performance of the predictor, the difference in the corresponding value of PU and ED is pragmatic. Hence, the type of IoT traffic generated, in terms of traffic arrival pattern, will greatly influence the delay of the network rather than the achieved data-rate of the network.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 02, February-2021

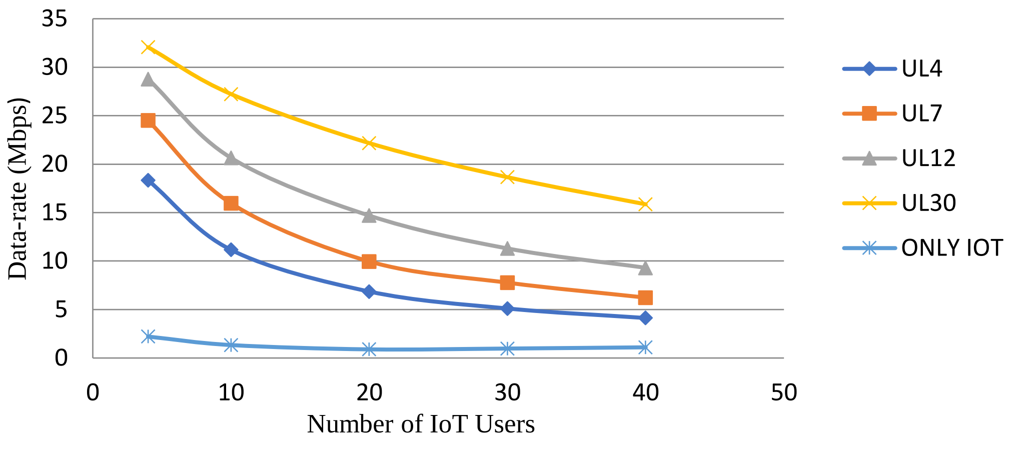


Fig. 2: Influence of Event-driven IoT traffic on uplink user data-rate

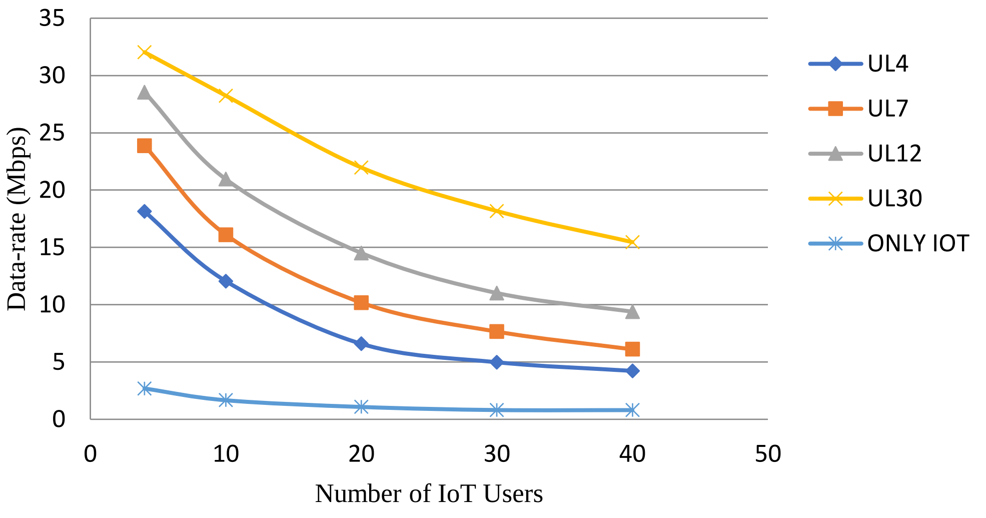


Fig. 3: Influence of Periodic update IoT traffic on uplink data-rate

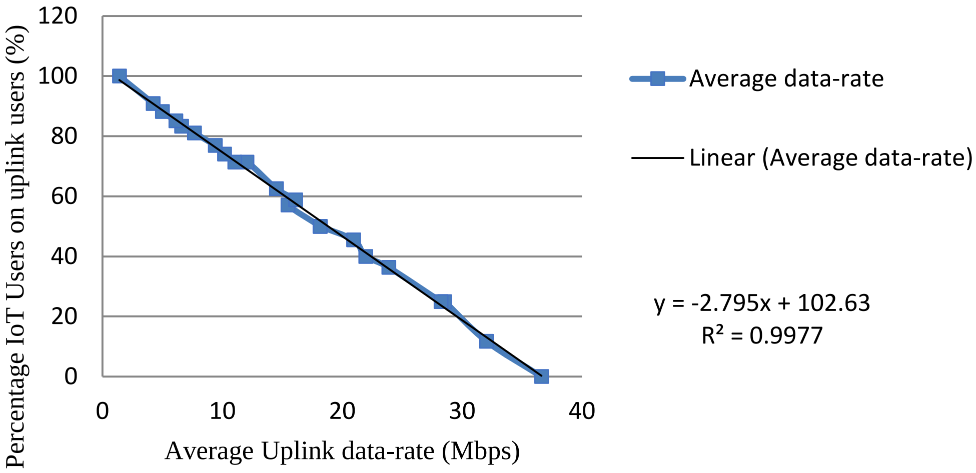


Fig. 4: Impact of Event-driven IoT traffic on Uplink user

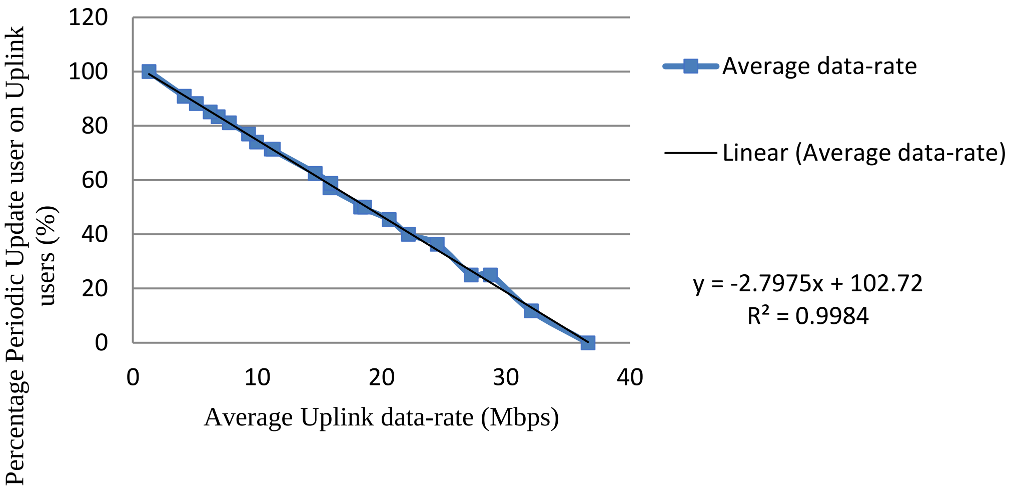


Fig. 5: Impact of Periodic Update IoT users on Uplink data-rate

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 02, February-2021

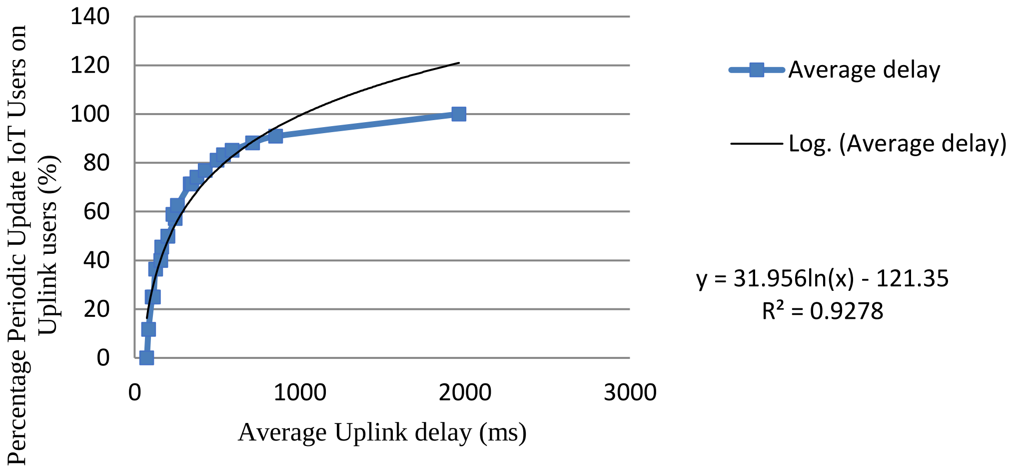


Fig. 6: Impact of Periodic Update IoT traffic on Uplink users

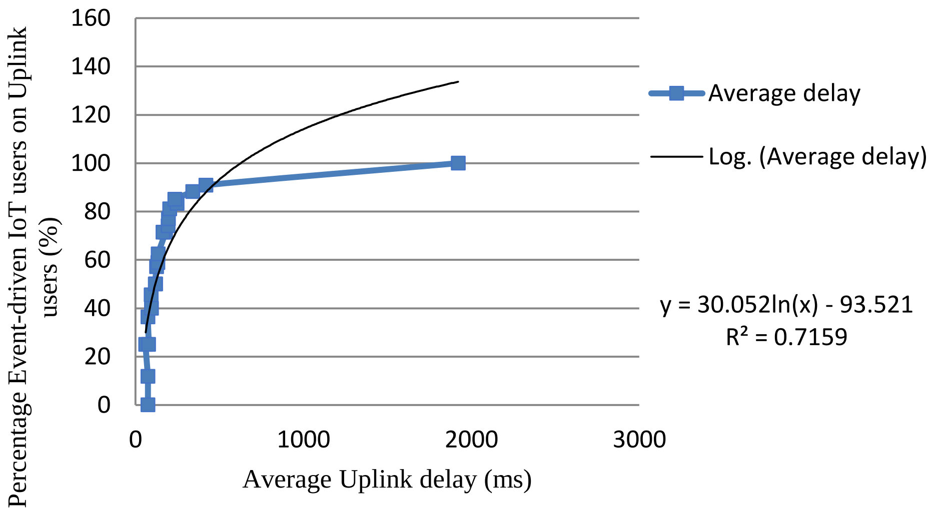


Fig. 7: Impact of Event-driven IoT traffic on Average network delay

## IV. DYNAMIC AGGREGATION

Based on the observations of Fig. 2 and Fig. 3, we propose the use of a dynamic aggregation technique for delay-tolerant IoT application to improve on the performance of the LTE/LTE-A network. A scenario represented in Fig. 8 shows the physical architecture of the LTE network with IoT integration. The algorithm proposed herein takes into consideration the traffic requests of both the IoT traffic and the uplink user traffic. Assuming all the user nodes (IoT + H2H) is connected to the LTE base station (eNB) and are requesting for transmission; the eNB divides its coverage region into 6 sub-regions (A – F) of the IoT nodes. The IoT nodes represented in Fig. 8 are identical and have at least one packet to transmit. Observe that sub-region A in Fig. 3 is sparsely populated with IoT nodes compared to other sub-regions. Thus, under static aggregation technique presented in [15, 16], traffic aggregated on the HEAD of sub-region A may not be optimized since fewer devices are classified to the region. In the proposed algorithm, IoT nodes from nearby sub-regions, such as B and F, can be classified under sub-region A. This will reduce the load on the sub-regions while balancing out the load requirement of sub-region A.

Consider a set of IoT users requesting access to an LTE eNB station for uplink transmission amidst other traditional H2H LTE users. Note that the users are connected to the eNB but remain in IDLE mode (a user can only transmit/receive in an LTE network when it has switched state to CONNECTED mode [18]). The access connection mechanism was achieved via random access schemes like access class baring algorithms. In the IDLE mode, each i-th IoT users computes its distance from the eNB, $x_i$, and sends it together with other scheduling information (e.g. buffer status report (BSR), received signal strength (RSRP), etc.) to the

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 02, February-2021

eNB station. The eNB divides its coverage region into j-subregions and assigns a mean value.

If the probability of a user been classified under, a sub-region is a Normal/Gaussian distribution as shown in Eq. 1. We, thus, compute the conditional probability of the i-th user, belonging to the j-th sub-region. The choice of a Gaussian distribution is because the "bell" shape of the distribution can be effectively used to describe the area covered by the sub-regions. Secondly, it has the desirable property to fit an arbitrary distribution by appropriate parameter settings.

$$P\left({x_i}/{S_j}\right) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x_i-\mu)^2}{2\sigma^2}}, \qquad (1)$$

where $\sigma^2$ and $\mu$ represents the variance and mean value respectively. Using a standard normal distribution with standard deviation $\sigma = 1$, Eq. 1 reduces to Eq. 2. The constant standard deviation was used to ensure that we

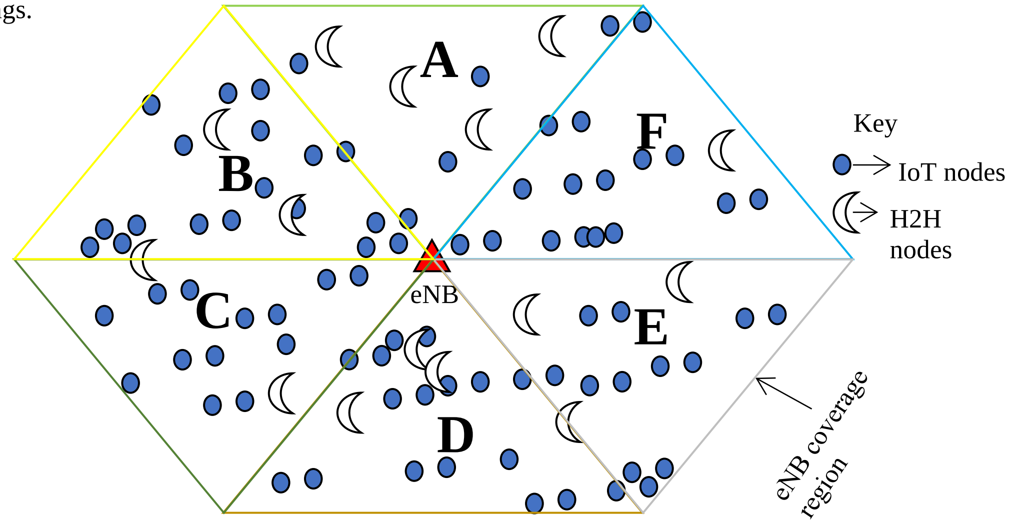


Fig. 8: Physical Scenario Architecture

have an equal spread opportunity for each of sub-regions.

$$P\left({x_i}/{S_j}\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x_i-\mu)^2}{2}}. \qquad (2)$$

The mean values were obtained as the ratio of IoT traffic to the total traffic (IoT traffic + Uplink traffic) as shown in Eq. 3. Thus, the amount of IoT traffic already existing in a sub-region was used in classifying which sub-region a user will be allotted.

$$\mu = \frac{IoT\ traffic}{Total\ sub\ region\ traffic}. \qquad (3)$$

The computed probability is used to place the user in a sub-region using a variant of Baye's a-posterior rule called likelihood ratio test (LRT). Baye's a-posteriori rule is shown in Eq. 4 while the LRT is shown in Eq. 5. However, the apriori probability, $P(S_j)$ that a user is classified in a subregion is assumed to be equal, thereby ensuring that no subregion is prioritised.

$$P\left({x_i}/{S_1}\right) P(S_1) > P\left({x_i}/{S_2}\right) P(S_2) \rightarrow sub-region\ 1 \qquad (4a)$$

$$P\left({x_i}/{S_1}\right) P(S_1) < P\left({x_i}/{S_2}\right) P(S_2) \rightarrow sub-region\ 2 \qquad (4b)$$

$$\frac{P\left({x_i}/{S_1}\right)}{P\left({x_i}/{S_2}\right)} > \frac{P(S_2)}{P(S_1)} \rightarrow sub-region\ 1 \qquad (5a)$$

$$\frac{P\left({x_i}/{S_1}\right)}{P\left({x_i}/{S_2}\right)} < \frac{P(S_2)}{P(S_1)} \rightarrow sub-region\ 2 \qquad (5b)$$

Once the user has been allotted to a sub-region, the eNB selects the user with the highest received signal strength and best channel quality. It tags such user as the HEAD of the sub-region. Hence, all IoT traffic from the other IoT users will be aggregated on the sub-regional HEAD using periodic per-hop approach (packets are aggregated until the number of buffered packets reach maximum defined threshold) under high traffic load or periodic simple (packets are aggregated until the expiry of a set timer) under low traffic load. (This assertion is carried out based on the results shown in [19]). The pseudocodes of the algorithm to determine the load in a sub-region for the ns3 model simulation is a subset of algorithm 1 while the algorithm to perform classification is illustrated in algorithm 2.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 10 Issue 02, February-2021

**Algorithm 1:** Sub-region load determination

```
struct eNB_load_Info {
RNTI (User Identifier);
Cell ID (CID);
Transport Block Size (TBS);
} eNB_load_Info;
map <CID, re_Node> rInterface;
set load_threshold;
procedure storeUserInfo
        for all Users do:
                map <RNTI, TBS> userInfo;
        return userInfo;
procedure storeENBInfo
        for all eNB do:
                map <CID, TBS> enbInfo;
        return enbInfo;
Schedule load functions:
storeUserInfo ();
storeENBInfo ();
end;
```

**Algorithm 2:** IoT Classification Algorithm

```
Max buffer size = B;
Max aggregation time = t;
procedure ENB_Region
        for all ENB:
          j = Create j sub-regions of equal size
      return j;
end procedure;
procedure getIoTInfo
        for all IoT Get:
          dist = Distance of IoT node from ENB;
          RSRP;
        return Get;
end procedure;
procedure ComputeIoTProbability
        for each IoT in getIoTInfo:
             value = Compute equation (6.4.2)
        return value;
end procedure;
procedure Compare_Classify
      for each IoT in ENB:
           Evaluate max (value, j);
        Classify IoT to j;
      return j;
end procedure;
procedure Aggregate_data
for each IoT in j:
           head = Evaluate min (dist);
        Send packets to head()
        Until:
            Buffer <= B;  //for high load
            Time <= t;  //for low load
        head->Send to remotehost
      return 0;
end procedure;
```

The aggregated packets are formatted to an LTE frame and transmitted to the eNB. In this model, the eNB uses the proportional fairness scheduler to schedule both the aggregated IoT and uplink users. The grouping of IoT user nodes is to be carried out every, t, seconds to accommodate the dynamics of mobile IoT nodes. At the eNB, the aggregated IoT traffic is separated based on its tags to uniquely identify a user as the source. The individual packets are further routed to their respective destinations.

*A. Discussions on Dynamic Mobile Aggregation*

Algorithms 1 and 2 were simulated to obtain the results showing the performance evaluation of the proposed mobile aggregation. For clarity, this evaluation has been analysed with two other competing techniques to handle the introduction of IoT to LTE/LTE-A network using a fixed number of IoT nodes (40). These techniques include the direct integration of the IoT nodes into the network identified as "Direct" in Fig. 9 and Fig. 10. In this technique, the network treats the IoT as any other LTE user node. Furthermore, when it has been justified that direct integration of IoT nodes to the network will suddenly cause a glitch in the operation of the network; several aggregation techniques have been proposed in the literature using a 3GPP defined relay node approach [17, 20]. In Fig. 9 and Fig. 10, the technique is referred to as "Fixed Agg". Finally, the proposed dynamic mobile aggregation technique as described in section 4.0 is captured as "Mobile Agg" in the figures.

Table 4: Mobile aggregation simulation parameter

| Simulation Parameters | Value |
|---|---|
| Bandwidth | 20 [MHz] |
| Number of Sectors per eNB | 3 |
| Number of eNB | 3 |
| Scheduler | Proportional fairness, priority-based EXP/PF |
| Number of IoT Users | 40 |
| Number of LTE Uplink users | 4 – 40 |
| eNB transmitter power | 46 [dBm] |
| Simulation time | 100 [sec] |
| Video traffic source [13] | MPEG4 high-quality video trace (Jurassic Park 1) as shown in Table 2 |
| IoT traffic source | Refer to Table 1 |

In this model, each user node, depending on its description (H2H or IoT) is expected to either download a video streaming file from a server or transmit short aperiodic IoT traffic. The ns3 simulation parameters are elucidated in Table 4. As the number of LTE users with a fixed number (40) of IoT nodes, observations from Fig. 9 and Fig. 10 show that the average achieved data-rate and the average delay experienced by users increases respectively. This is expected given that more traffic tends to be generated and propagated across the network, hence, a summation of all the user's data-rate and delay is expected to increase (See relevant figs. in sections 3). Nevertheless, we observe that the Mobile aggregation technique proposed herein performed better that the Fixed aggregation and the Direct integration techniques with a proportion of 17% and 26.4% respectively. However, this great improvement in data-rate was undermined with the Mobile aggregation technique under-performing when compared to the other two techniques in terms of average delay experienced by users. The Fixed aggregation and the Direct integration techniques showed 9.1% and 11.7% respectively less prone to delay when compared with the proposed mobile aggregation technique. Based on these observations, it is recommended that the mobile aggregation technique be employed for IoT traffic that is delay insensitive.

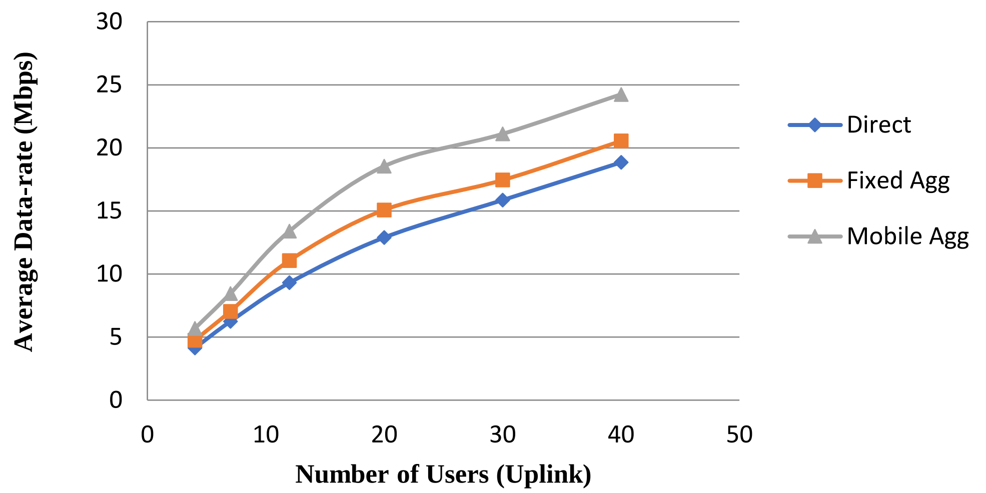


Fig. 9: Comparative assessment of the proposed Mobile Aggregation technique

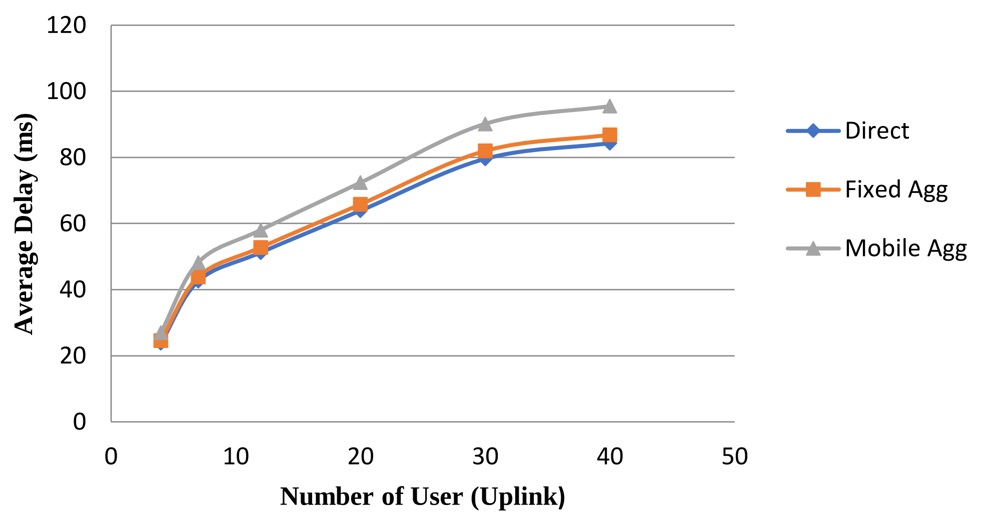


Fig. 10: Average delay assessment of proposed Mobile Aggregation technique

## V. CONCLUSION

In conclusion, the impact of increasing IoT traffic on the uplink LTE network traffic was studied. The average round-trip delay and the achieved data-rate were used as the QoS parameters in this work. This work reports that the network reacts similarly to every IoT traffic arrival pattern; although this reaction is negative in terms of network performance. It recommends that the IoT traffic with significant traffic payload (characterized by the PE) be analyzed for proper generalization of the behaviour of IoT traffic arrival patterns. To ensure that scarce LTE/LTE-A network resources are not under-utilized due to the small-sized IoT traffic, a mobile aggregation technique was further proposed. The technique aggregates only IoT traffic on a node and transmits it to the eNB using the available scheduled resources. Finally, subject to industrial data analysis, it is proposed that the impact of IoT traffic in terms of round-trip delay and data-rate on networks be estimated using the regression or predictor equations as shown in the work.

## REFERENCES

[1] D. Evans, "The Internet of Things: How the Next Evolution of the Internet is Changing Everything", *Cisco Internet Business Solutions Group (IBSG) (White Paper)*, April 2011.

[2] C.O. Nnamani, M. R. A. Khandaker and M. Sellathurai "UAV-aided jamming for secure ground communication with unknown eavesdropper location", *IEEE Access*, vol. 8, issue 1, 72881--72892, 2020.

[3] L. Atzori, A. Iera, and G. Morabito, “The Internet of Things: A survey”, *Computer Networks*, 2787 – 2805, 2010.

[4] 4G Americas Technical Paper, “Inside 3GPP Release 13: Understanding the Standards for HSPA+ and LTE-Advanced Enhancements”, *4G Americas*, September 2015.

[5] X. Wang, M. Sheng, Y. Lou, Y. Shih and M. Chiang, “Internet of things session management over LTE – Balancing signal load, power and delay”, *IEEE Internet of Things J.*, vol. 3, issue 3, 339 – 353, 2016.

[6] L. Costantino; N. Buonaccorsi, C. Cicconetti, and R. Mambrini, “Performance analysis of an LTE gateway for the IoT*,” IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks (WoWMoM)*, 25-28 June 2012, 1-6.

[7] D. Lin, G. Charbit and I. K. Fu, “Uplink Contention Based Multiple Access for 5G cellular IoT”, *IEEE VTC 2015-Fall Advance Program*, September 2015.

[8] A. M. Maia, D. Vieira, M. F. de Castro and Y. G. Doudane, “A mechanism for uplink packet scheduler in LTE network in the context of machine-to-machine communication”, *GC14 SAC Internet of things*, 2014, 2776 – 2782.

[9] M. Z. Shafiq, L. Ji, A. X. Liu, J. Pang and J. Wang, “A first look at cellular machine-to-machine traffic – Large scale measurement and characterization”, *in ACM SIGMETRICS Performance evaluation review*, vol. 40, no. 1, ACM, 2012, 65 – 76.

[10] C. O. Nnamani, C. L. Anioke, O. Ezeja, and C. I. Ani, “Review on the Implementation of IoT on LTE/LTE-A Networks”, *in Proc. 1st University of Nigeria Nsukka, Faculty of Engineering International Conference*, Nigeria, April, 2018.

[11] T. R. Henderson, M. Lacage, G. F. Riley, C. Dowell, and J. Kopena, “Network simulations with the ns 3 simulator,” *in SIGCOMM’08*, Seattle, Washington, USA, 2008.

[12] N. Nikaein, M. Laner, K. Zhou, et. al., “Simple traffic modelling framework for machine type communication”, in Wireless Communication Systems (ISWCS 2013), *in Proc. of the Tenth Intl. Symposium on VDE*, 2013, 1 – 5.

[13] “Directory listing for Star-Wars.”, Internet: http://www2.tkn.tu-berlin.de/research/trace/pics/FrameTrace/h263/index1b73.html [21/01/2018].

[14] F. Metzger, T. Hossfeld, A. Bauer, S. Kounev and P. E. Heegaard, “Modeling of Aggregated IoT Traffic and Its Application to an IoT Cloud,” *in Proc. IEEE*, vol. 107, no. 4, 679-694, 2019.

[15] L. Kiwoli, A. Sam, and E. Manasseh, “Performance Analysis of Carrier Aggregation for Various Mobile Network Implementations Scenario Based on Spectrum Allocated”, *Intl. J. Wireless. Mobile. Networks*, vol. 9, no. 5, 41–53, 2017.

[16] A. L. R. Madureira, F. R. C. Araújo, L. N. Sampaio, “On supporting IoT data aggregation through programmable data planes”, *Computer Networks*, **v**ol. 177, 2020.

[17] H. Beshley, M. Klymash, M. Beshley and I. Kahalo, "Improving the Efficiency of LTE Spectral Resources Use by Introducing the New of M2M/IoT Multi-Service Gateway," *IEEE 15th Intl. Conf. on the Experience of Designing and Application of CAD Systems (CADSM)*, Polyana, Ukraine, July, 2019, 114-117.

[18] Y. Mehmood, Gorg C. and Giel A. T. “A radio resource sharing scheme for IoT/M2M communication in LTE-A Downlink”, *IEEE ICC 2016 Workshop on Convergent IoT*, 2016.

[19] P. Arnold, V. Rakocevic, C. Ramos and J. Habermann, “Algorithms for Adaptive Radio Resource Management in Relay-Assisted LTE-A networks”, *IEEE 77th Veh. Technol. Conf. (VTC Spring),* Dresden, June, 2013, 1-5.

[20] S. N. K. Marwat, Y. Mehmood, C. Görg and A. Timm-Giel, “Data aggregation of mobile M2M traffic in relay enhanced LTE-A networks”, *EURASIP J. on Wireless Commun. and Networking*, no. 110, 2016.