Effective Traffic Intensity of Prioritized IoT Networks with Packet Deadlines in Non-Preemptive M/M/1/2

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Effective Traffic Intensity of Prioritized IoT Networks with Packet Deadlines in Non-Preemptive M/M/1/2

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Abstract The intelligent traffic monitoring would be considered as one of the most important techniques to handle a great deal of data in Internet of Things (IoT) Networks. We consider an IoT network with three class of sensors which transmit their data to a Monitoring Center (MC). The MC with a great demand for fresh data, is equipped with one server and one buffer of capacity equal to one packet as a queueing model, representing an M/M/1/2 system. The characteristics of the group of devices, are specified with high, medium and low priorities, respectively. We consider a Rayleigh fading channel over the links between devices and the MC. We assume a non-preemptive system in the MC so that the packets with lower priority can be replaced by higher priority packets, as well. The arrival packets have different deadlines due to the diversity of information in the network. The average number of successfully served packets are obtained as the effective traffic intensity of the whole network to measure the performance of the system. The simulation results show that increasing the number of classes with priorities, does increase the traffic intensity up to service rate of the monitoring center.

Keywords Effective traffic intensity, non-Preemptive buffer, packet priority, packet deadline, IoT, M/M/1/2.

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1 Introduction

Daily increasing of deploying Internet of Things (IoT) devices and machine type communications (mMTC) in 5G networks and beyond, has become an alluring interest for the researches to investigate the corresponding challenges such as age of information [3], throughput [16], packet delivery ratio [17], outage probability [11], energy efficiency [2] and etc. The wide variety of IoT/MTC applications like industrial automation and control, intelligent transportation, smart-grid, smart environment, security and public safety and e-health, create the throng of miscellaneous telecommunication devices which are called massive IoT (mIoT) and massive MTC (mMTC) [18, 21]. Although the existing protocols would support conventional human-type communications (HTC), they are not capable of handling the huge traffic load on the nodes, and consequently, the generation of a large number of packets results in the system misbehaviour like network congestion. Some of these networks require a ubiquitous and ultra-reliable low latency communication (URLLC) [9], thus, the processing schedule on the received data, would improve the network performance by decreasing the loss of packets which have expiring date or by decreasing the number of arriving packets which experience blocking due to lack of enough room in the buffer. The strategy of grouping devices based on their priority would be an effective method to increase the performance of the mIoT networks [10].

One of the pioneer works on the traffic intensity, has analyzed the peak traffic of communication systems by statistical estimations [13]. The IoT traffic patterns and corresponding challenges for different issues have been widely discussed and a comprehensive classification has been represented for various applications in [23]. A new model to collect, process, and store real-time traffic data for critical decision-making scenario has been proposed and its accuracy has been tested on vehicle detection [20]. On the other hand, the variety of data in IoT systems has been classified and characterized upon the traffic of smart cities and campuses in [22]. The priority-based initial access for mIoT/mMTC devices has been facilitated by enabling device grouping based on device vicinity or/and their URLLC requirements. It has been shown that the flexible slot allocation decreases the delay and increases the reliability in the network [26]. One of the most important impacts of successfully served traffic in the system, is to decrease the age of information as the fundamental parameters of IoT networks [8]. The impact of traffic intensity has been investigated on the spectrum sensing of the network where multiple changes in traffic could result in degradation of the throughput and fairness in the network [4, 24, 25]. Likewise, Y.Chen et al have shown that the frequent state transitions in the system have destructive effect on detectors' performance which depends on the traffic intensity of the network[5]. Another approach in [7], has studied the role of priority in traffic intensity in terms of packet delay in two scenarios; the first scenario depicts the mutual impact of different priorities on each other while the second scenario discuses the delay in the system for low priority traffic packets with and without high priority traffic packets. Also, it has been shown that prioritizing traffic, could decrease the waiting time of the high priority packets in comparison with the low priority packets for non-preemptive systems [12]. The classification of services with different qualities and priorities has been developed considering the minimum required rate (MRR) for each service and the effect of higher class on the lower one has been investigated which could be used for efficient resource dimensioning and capacity planning of the queuing systems [1]. The Effective Traffic Intensity (ETI) is one of the major parameters to determine the age of information in IoT networks [15]. Likewise, N. Pappas et al have characterized the throughput and delay in IoT networks where the data transmitting devices are divided into two groups and each group transmits its data to an aggregator as a relay between the IoT devices and the destination. The authors have investigated the stability of queuing system in the aggregators and have shown that how their existence would provide significant gain for IoT networks [14].

Contribution: It can be perceived that in spite of valuable investigations on the network traffic, a comprehensive study, considering the priority and packet deadlines, seems insufficient. In this paper, we study the effective traffic intensity in the network as the number of successfully served packets in the server. The packets arrive from different sources with different priorities and deadlines for each class. Also, we consider the channel gains under Rayleigh fading over all transmission links to investigate its effects on the total network traffic. our contribution is as following:

- We consider an IoT network consisting of several devices distributed in the area and a Monitoring Center (MC) to gather their data. Since the devices have different priorities for transmitting the packets, we use the class concept to separate different priorities in several groups of devices. Hence, each class includes the devices with the same priority and a given transmission rate. We call the explained model as IoT multi-class network. To update the status of data in the MC, we consider a deadline for each packet to ensure the freshness of data.
- We obtain the Markov model to evaluate the performance of the non-preemptive queuing system in the MC, then, we calculate the transition rate between all states, the probability of being in each state, the effective packet rate and the effective traffic intensity of the system.
- To verify the analytical results, we perform a simulation for different packet deadlines and packet rates from each class.

The rest of the paper is as follows: The system model and mathematical expressions for non-preemptive scheme over deterministic deadlines are studied in section II. The simulation results are depicted in section III and the section IV, briefly concludes the paper.

2 System Model

We consider an IoT multi-class network shown in Fig. 1, in which three classes (consisting of several devices) denoted by m_i for $i = 1, 2, 3$ transmit their data to a MC in which m_1, m_2 and m_3 have high, medium and low priorities, respectively. Each class, m_i, sends its data with rate ν_i over the corresponding channel C_i so that all transmitted signals undergo Rayleigh Fading phenomenon. The channel coefficient over link C_i is denoted by $h_i(t)$ for $i = 1, 2, 3$. Thus, the signal received by MC corresponding to the channel C_i could be

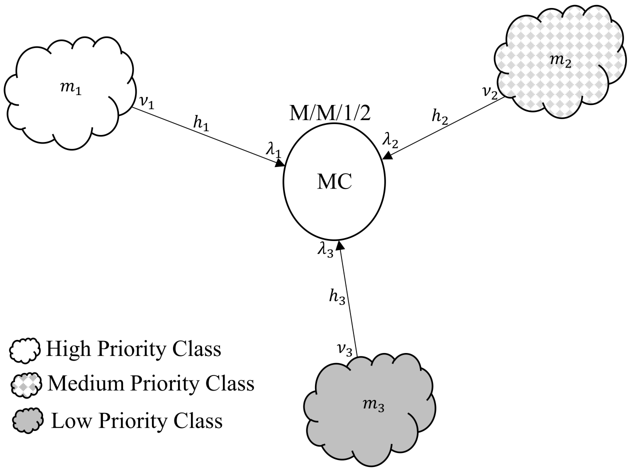

Fig. 1: System model: An IoT network consisting of three different classes with different packet priorities and deadlines

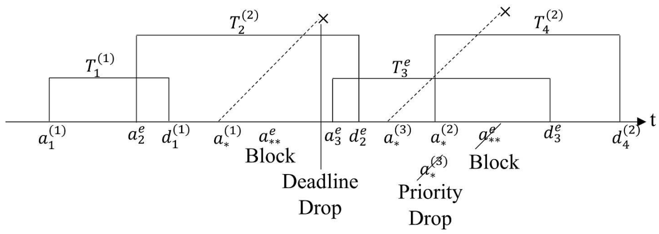

Fig. 2: Typical Time Line of MC

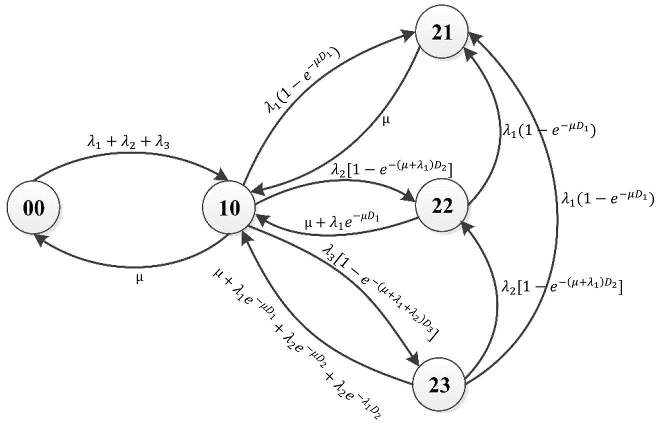

Fig. 3: Markov Model of Non-Preemptive MC with Prioritized Buffer

written as follows

$$Y_i(t) = \sqrt{P_i} h_i(t) X_i(t) + n_i(t), \tag{1}$$

where P_i is the transmission power of the devices in the class, $X_i(t)$ is the signal sent by each device with zero mean and $E[|X_i(t)|^2] = 1$ for simplicity and $n_i(t)$ is the circularly symmetric complex Gaussian (CSCG) noise on the link between the class and the MC, also, it is assumed that they are independent and identically distributed (i.i.d) random process with zero mean and variance $E[|n_i(t)|^2] = \sigma^2$. Therefore, SNR for each link could be obtained as

$$\gamma_i = \frac{P_i h_i^2}{\sigma^2}. \tag{2}$$

Since h_i^2 has an exponential PDF, $\overline{\gamma}_i e^{-\overline{\gamma}_i t}$, We define the probability of successful transmission based on the outage probability of each link denoted by $P_{out,i}$ as below

$$\varUpsilon_i = 1 - P_{out,i} = \int_{\gamma_0}^{\infty} f_{\gamma_i}(\gamma) d\gamma = e^{-\gamma_0 \overline{\gamma}_i} = e^{-\frac{\sigma^2 \gamma_0 \overline{\gamma}_i}{P_i}}, \tag{3}$$

where γ_0 is the minimum threshold at the receiver side in MC. Finally, all received packets from any priority, enter the MC or simply arrive with a Poisson process with rate λ_i. Then, we could write

$$\lambda_i = \nu_i \varUpsilon_i = \nu_i e^{-\frac{\sigma^2 \gamma_0 \overline{\gamma}_i}{P_i}}. \tag{4}$$

Let the packets be served with rate μ in the monitoring center, consisting of one server and one buffer indicating an M/M/1/2 queuing system. We assume a non-preemptive system with priority so that the packets with medium priority are replaced by high priority packets and the low priority packets are replaced by medium and high priority packets in the buffer due to importance of data sent by those devices, but the packets of the same priority are not replaced with each other. In other words, the buffer prefers to update the system's data with higher priority packets. It is considered that the arrival packets experience different deadlines equal to D_i for $i = 1, 2, 3$. If the arrival packet's deadline expires or it is dropped due to arriving a high priority packet, the packet in the system will not receive the service. That is, entering the server before deadline, guarantees that the expiration time of the packet will be cancelled and the service will be completed. Fig. 2 shows a typical timing diagram of the system where $a_k^{(p)}$ and $d_k^{(p)}$ are the arrival and the departure times of k^{th} packet with priority $p = 1, 2, 3$ and $p = e$ indicates that the packet could belong to either of priorities. Also, $a_*^{(p)}$ shows the discarded packets due to deadline drop, priority drop or blocking because of a full buffer. T_k^p denotes the total time that the packet k with priority p spends in the MC.

2.1 Effective Traffic Intensity for Deterministic Deadlines

The ratio of successfully served packets considering the deterministic deadline for arriving packets, would be considered as the performance evaluation for the network traffic. Thus, ETI for whole network could be calculated as following

$$ETI = \frac{\lambda_{eff}}{\mu}, \tag{5}$$

where λ_{eff} is the effective packet rate to the MC which will be calculated later.

Defining P_{mn} as probability of being in state S_{mn} for non-preemptive system, the Markov model can be shown by Fig. 3 where m is the number of packets in the system and n is the priority of the packet in the queue, respectively. This approach has been illustrated based on the Markov model used in [15]. The zero subscript specifies that there is no packet in the system or in the queue. Since data could arrived from all the class, the transition rate from $S_(00)$ to $S_(11)$ will be equal to $\lambda_1 + \lambda_2 + \lambda_3$. The transition from $S_(10)$ to $S_(00)$ occurs if the service time of the packet under service is completed before arriving any other packet, hence, the transition rate from $S_(00)$ to $S_(11)$ will be equal to μ. The transition from $S_(10)$ to $S_(21)$ occurs if a packet of kind λ_1 arrives the system and stay at the queue before its deadline. The probability of being dropped due to deadline for this packet is equal to $e^{-\mu D_1}$, thus, the transition rate from $S_(10)$ to $S_(21)$ will be equal to $\lambda_1(1 - e^{-\mu D_1})$. Also, the transition from $S_(21)$ to $S_(10)$ occurs if the service time of the packet under service is completed with rate μ. The transition from $S_(10)$ to $S_(22)$ occurs if a packet of kind λ_2 arrives the system without being dropped due to deadline or being substituted because of arriving a packet of kind λ_1. Then, we could write

$$\begin{aligned}
&Pr\{\text{Arriving packet of kind } \lambda_2 \text{ is dropped}\\
&\quad \text{due to deadline or is substituted}\\
&\quad \text{due to arriving the packet of } \lambda_1\}\\
&\quad = Pr\{S > D_2 \cap X_1 > D_2\} = e^{-(\mu+\lambda_1)D_2},
\end{aligned} \tag{6}$$

where S and X_1 denote the service time and arrival time of the packet of kind λ_1, respectively. Thus, the transition rate from $S_(10)$ to $S_(22)$ will be equal to $\lambda_2(1 - e^{-(\mu+\lambda_1)D_2})$. The transition from $S_(22)$ to $S_(21)$ occurs if a packet of kind λ_1 arrives in this state without being dropped. Similar to the transition rate from $S_(10)$ to $S_(21)$, the transition rate from $S_(22)$ to $S_(21)$ is equal to $\lambda_1(1 - e^{-\mu D_1})$. The transition from $S_(22)$ to $S_(10)$ occurs if the service time of the packet under service is completed before arriving the packet of kind λ_1 or the arriving packet of this kind encounters the deadline drop, hence, the transition rate from $S_(22)$ to $S_(10)$ will be equal to $\mu + \lambda_1 e^{-\mu D_1}$. Going from $S_(10)$ to $S_(23)$ happens if a packet of kind λ_3 arrives the system without being dropped due to deadline or being substituted because of arriving a packet of kind λ_1 or λ_2. Then, we could write

$$\begin{aligned}
&Pr\{\text{Arriving packet of kind } \lambda_3 \text{ is dropped}\\
&\quad \text{due to deadline or is substituted}\\
&\quad \text{due to arriving the packet of } \lambda_1 \text{ or } \lambda_2\}\\
&\quad = Pr\{S > D_3 \cap X_1 > D_3 \cap X_2 > D_3\}\\
&\quad = e^{-(\mu+\lambda_1+\lambda_2)D_3},
\end{aligned} \tag{7}$$

where X_2 denotes the arrival time of the packet of kind λ_2. Thus, the transition rate from $S_(10)$ to $S_(23)$ will be equal to $\lambda_3(1 - e^{-(\mu+\lambda_1+\lambda_2)D_3})$. The transition from $S_(23)$ to $S_(21)$ occurs if a packet of kind λ_2 arrives in this state without being dropped or substituted. Similar to the transition from $S_(10)$ to $S_(22)$, the transition rate from $S_(23)$ to $S_(21)$ will be equal to $\lambda_1(1 - e^{-\mu D_1})$ and also, similar to the transition from $S_(10)$ to $S_(22)$, the transition rate from $S_(23)$ to $S_(22)$ is equal to $\lambda_2(1 - e^{-(\mu+\lambda_1)D_2})$. Finally, departing $S_(23)$ to $S_(10)$ is the result of service completion of the packet under service before being dropped or substituted by any higher kind, hence, the transition rate from $S_(23)$ to $S_(10)$ is equal to $\mu + \lambda_1 e^{-\mu D_1} + \lambda_2 e^{-\mu D_2} + \lambda_2 e^{-\lambda_1 D_2}$. Consequently, the probabilities of each state, P_{mn}, could be calculated by applying the balance equation [6], as equation (8) at the top of next page.

Solving the balance equation, the probability of being in state S_{mn} for the Semi-Markov model [19], could be given as

$$\begin{aligned}
&P_{00} = \frac{1}{1 + A_1 + A_2 + A_3 + A_4},\\
&P_{10} = A_1 P_{00}, \quad P_{21} = A_2 P_{00},\\
&P_{22} = A_3 P_{00}, \quad P_{23} = A_4 P_{00},
\end{aligned} \tag{9}$$

in which

$$A_1 = \frac{\lambda_1 + \lambda_2 + \lambda_3}{\mu}, \tag{10}$$

$$\begin{aligned}
A_2 =&\frac{\lambda_1(\lambda_1 + \lambda_2 + \lambda_3)}{\mu^2}(1 - e^{-\mu D_1})\times\\
&\Bigg[\Big(1 + \frac{\lambda_3(1 - e^{-(\mu+\lambda_1+\lambda_2)D_3})}{\mu + \lambda_1 + \lambda_2}\Big)\\
&\Big(1 + \frac{\lambda_2[1 - e^{-(\mu+\lambda_1)D_2}]}{\mu + \lambda_1}\Big)\Bigg],
\end{aligned} \tag{11}$$

$$\begin{cases} P_{00}(\lambda_1+\lambda_2+\lambda_3) = \mu P_{10} \\ P_{10}\left[\mu+\lambda_1(1-e^{-\mu D_1})+\lambda_2(1-e^{-(\mu+\lambda_1)D_2})+\lambda_3(1-e^{-(\mu+\lambda_1+\lambda_2)D_3})\right] \\ \quad = \mu P_{21}+(\mu+\lambda_1 e^{-\mu D_1})P_{22}+(\mu+\lambda_1 e^{-\mu D_1}+\lambda_2 e^{-(\mu+\lambda_1)D_2})P_{23} \\ \mu P_{21} = \lambda_1(1-e^{-\mu D_1})(P_{10}+P_{22}+P_{23}) \\ (\mu+\lambda_1)P_{22} = \lambda_2\left[1-e^{-(\mu+\lambda_1)D_2}\right](P_{10}+P_{23}) \\ (\mu+\lambda_1+\lambda_2)P_{23} = \lambda_3\left[1-e^{-(\mu+\lambda_1+\lambda_2)D_3}\right]P_{10} \\ P_{00}+P_{10}+P_{21}+P_{22}+P_{23} = 1. \end{cases} \tag{8}$$

$$\begin{aligned} A_3 =& \frac{\lambda_2(\lambda_1+\lambda_2+\lambda_3)}{(\mu+\lambda_1)\mu}[1-e^{-(\mu+\lambda_1)D_2}]\times \\ & \left[1+\frac{\lambda_3(1-e^{-(\mu+\lambda_1+\lambda_2)D_3})}{\mu+\lambda_1+\lambda_2}\right], \end{aligned} \tag{12}$$

$$A_4 = \frac{\lambda_3(\lambda_1+\lambda_2+\lambda_3)}{(\mu+\lambda_1+\lambda_2)\mu}(1-e^{-(\mu+\lambda_1+\lambda_2)D_3}). \tag{13}$$

2.2 Effective Packet Rate

To find the average packet rate of the whole network, λ_{eff}, first, we have to find the probability that in each state the coming packet with packet rate of λ_i experiences the service. It means that, the packet lays in state S_{mn} with probability P_{mn} and receives service with probability equal to $1-Pr\{\text{Drop or Block}\}$ corresponding to that state. The high priority packets are blocked with probability equal to P_{21} whereas the medium priority packets experience blocking with probability equal to $P_{21}+P_{22}$; Also, a full buffer always blocks the arriving packets of kind with low priority with probability $P_{21}+P_{22}+P_{23}$. Besides the deadline drop for each packet, the packets with medium and low priorities are dropped because of arriving a packet with higher priority. Considering P_{DS_2} and P_{DS_3} as the probabilities of being dropped due to deadline or being replaced by the packet of kind λ_1 for the packet of kind λ_2 and being replaced by the packet of kind λ_1 or λ_2 for the packet of kind λ_3, respectively, λ_{eff} could be calculated as

$$\begin{aligned} \lambda_{eff} =& \sum_{i=1}^{3}\lambda_i[1-Pr\{\text{Block/Deadline Drop/Substitution}\}_i] \\ =& \lambda_1\{1-[(P_{10}+P_{22}+P_{23})e^{-\mu D_1}+P_{21}]\} \\ & +\lambda_2\{1-[(P_{10}+P_{23})Pr(DS_2)+P_{21}+P_{22}]\} \\ & +\lambda_3\{1-[P_{10}Pr(DS_3)+P_{21}+P_{22}+P_{23}]\}. \end{aligned} \tag{14}$$

P_{DS_2} and P_{DS_3} would be considered as the complementary probability of the packet of kind λ_2 and λ_3 will receive the service, respectively. This probability for the packet of kind λ_2 at state S_{22} is equal to $\frac{\mu}{\mu+\lambda_1}$ multiplied by the probability of not being dropped which is equal to $1-e^{-(\mu+\lambda_1)D_2}$. Likewise, the mentioned probability for the packet of kind λ_3 at state S_{23} is equal to $\frac{\mu}{\mu+\lambda_1+\lambda_2}$ multiplied by the probability of not being dropped which is equal to $1-e^{-(\mu+\lambda_1+\lambda_2)D_3}$. Thus,

$$P_{DS_2} = 1-\frac{\mu}{\mu+\lambda_1}(1-e^{-(\mu+\lambda_1)D_2}). \tag{15}$$

$$P_{DS_3} = 1-\frac{\mu}{\mu+\lambda_1+\lambda_2}(1-e^{-(\mu+\lambda_1+\lambda_2)D_3}). \tag{16}$$

Finally, the effective traffic intensity of the network is formulated by combining the equations (14), (15) and (16) in the equation (5).

3 Numerical Results

In this section, we provide some numerical results comparing the theoretical calculations with simulation results. We use Python programming language for our simulations. First, we produce 10000 samples for each ν_1, ν_2 and ν_3 with exponential distribution, as arrival packets from each class. We combine the samples in a single time line which actually represent the time stamp for each packet. Then, the 10000 first samples are chosen for simulation which approximately show a duration of 1 hour of system running time, depending on the packet rate. Also, a time duration produced by an exponential distribution with service rate μ is assigned for each sample. Then, we apply the non-preemptive queuing system and deadline properties for each sample during this interval. Some of the parameters are considered as following: $\sigma^2 = -50dBm$, $\gamma_0 = -20dBm$, $P_i = 10dBm$, and $\overline{\gamma}_i = 10$ for $i = 1, 2, 3$. Since the demonstration of ETI for all classes in 4-dimensional coordination is impossible, we provide 3-dimensional diagrams. The red-colored diagrams in the left-hand and the green-colored diagrams in the right-hand represent the simulation and theoretical approach for the same

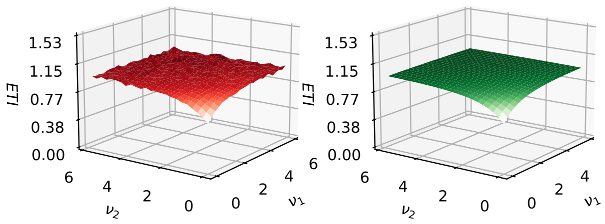

Fig. 4: ETI vs. ν_1 and ν_2 ($\nu_3 = 1$, $D_1 = 1$, $D_2 = 1$, $D_3 = 1$, $\mu = 1$)

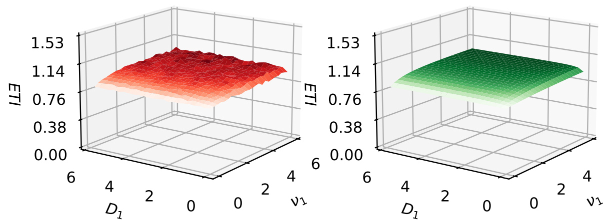

Fig. 6: ETI vs. D_1 and ν_1 ($\nu_2 = 1$, $\nu_3 = 1$, $D_2 = 1$, $D_3 = 1$, $\mu = 1$)

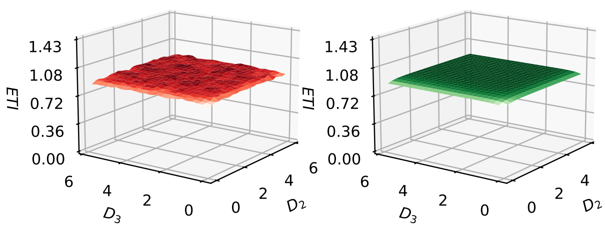

Fig. 5: ETI vs. D_2 and D_3 ($\nu_1 = 1$, $\nu_2 = 1$, $\nu_3 = 1$, $D_1 = 1$, $\mu = 1$)

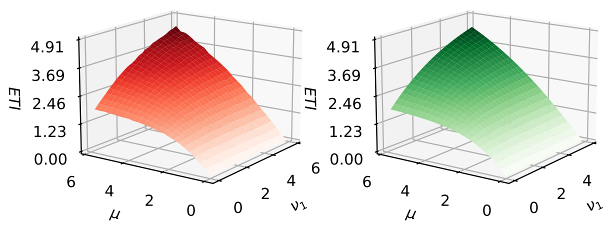

Fig. 7: ETI vs. μ and ν_1 ($\nu_2 = 1$, $\nu_3 = 1$, $D_1 = 1$, $D_2 = 1$, $D_3 = 1$, $\mu = 1$)

numerical assumptions, respectively. Regarding the various parameters in the proposed model and also to avoid the duplicate diagrams, we provide numerical results for some of the parameters and the other parameters are not represented due to similarity of their behavior.

Fig. 4 shows the ETI vs. different packet rates. The ETI rises and tends to a constant value by increasing the packet rates of each class. It can be perceived that classification of IoT devices in the network does not significantly affect the traffic intensity, that is, the different classes would be considered for IoT devices to configure collateral parameters such as AoI, delay and etc without any deep impact in the ETI performance. Fig. 5 exhibits the ETI vs. deadline of different classes. For constant values of packet rates, the effect of packet deadline is negligible. Increasing the packet deadline could increase the network congestion and decrease the performance of the system. The result of Fig. 5 shows that the lower packet deadline could be chosen for each class without any changes in ETI behavior, hence, the lower packet deadline the lower buffer size would be needed in the system. Also, Fig. 6 depicts the ETI vs. the packet rate and corresponding deadline which shows the same behavior explained in previous figures.

Fig. 7 demonstrates the ETI vs. service and packet rate of each class. For constant amount of packet rate, as μ increases, the ETI inclines to a given value. On the contrary, for the constant amount of service rate,

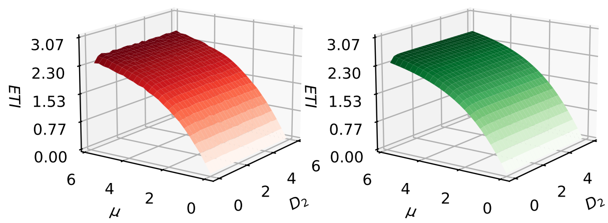

Fig. 8: ETI vs. μ and D_2 ($\nu_1 = 1$, $\nu_2 = 1$, $\nu_3 = 1$, $D_1 = 1$, $D_3 = 1$)

as ν increases the ETI increases intensely. However, this increment is not the same for all service rates and deeply effects the ETI for higher service rates. Fig. 8 shows the ETI vs. service rate and packet deadlines for each class which indicates a monotonic increasing function. Unlike, Fig. 7, the effect of packet deadline is suppressed by the effect of service rate. The ETI vs. service rate has been demonstrated in Fig. 9 for different values of packet rate and deadline. The more packet rate, the more ETI is obtained. As μ increases, the ETI approaches to a steady state value for all amounts of ν and packet deadlines. However, for lower amount of ν, the steady state value is achieved for lower amount of service rate, while for higher amount of ν, the steady state value is achieved for larger amount of service rate.

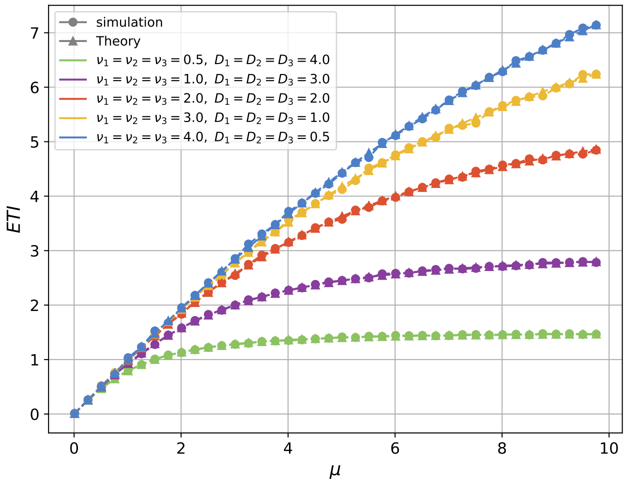

Fig. 9: ETI vs. μ

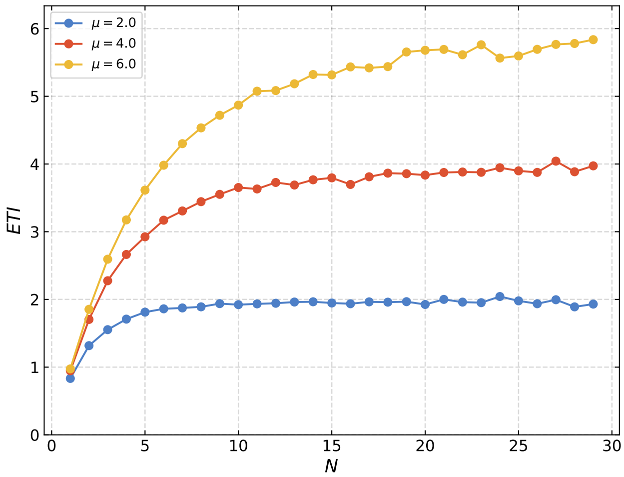

Fig. 10: ETI vs. Number of Classes (N)

Since increasing the number of classes in the network, increases the complexity of the equations, the traffic intensity vs. the number of classes in the network has been simulated for various amounts of service rate, shown in Fig. 10. The figure shows that increasing the number of the classes in the network, considering that the priority of ν_i is greater than the priority of ν_{i+1} for $i = 1, 2, ..., 30$, does not increase the effective traffic intensity more than the service rate of the server which would increase the age of information in real time applications.

4 CONCLUSION

The effective traffic intensity has a great role in the performance of IoT networks which have a high penchant for fresh data to decrease the age of information. We considered a monitoring center as an M/M/1/2 queuing system to serve the arriving packets from different classes of IoT devices. We studied the behaviour of the traffic intensity under constraints of packet rates of different classes with different priorities and packet deadlines. We used the Markov model to obtain the close form expression for the effective traffic intensity of the system, then, we simulated the network under the mentioned constraints to verify the theoretical results. The simulation results implies that the effect of packet rates for higher service rates is more significant than its effect for lower service rate, also the impact of increasing the service rate of the server surmounts the effect of packet deadlines. The more classes in the network, the more service rate is needed to increase the ETI.

5 Declarations

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. Also, the authors declare that they have not use or involve access to any collection of private or sensitive data, and have not used any financial funding.

All of the authors have participated in preparing the whole manuscript such as text, figures and calculations.

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