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Modelling IoT devices communication employing representative operation modes to reveal traffic generation characteristics

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ABSTRACT
Several traffic models for the Internet of Things (IoT) have been proposed in the literature. However, they can be considered as heuristic models since they only reflect the stochastic characteristic of the generated traffic. In this paper, we propose a model to represent the communication of IoT devices. The model was used to obtain the traffic generated by the devices. Therefore, the proposed model is able to capture a wider understanding of device behaviour than existing, state-of-the-art traffic models. The proposed model illustrates the behaviour of Machine-to-Machine uplink communication in a network with multiple-access limited information capacity shared channels. In this paper, we analysed the number of transmitted packets using the traffic model extracted from our proposed communication model and compared it with the state-of-the-art traffic models using simulations. The simulation results show that the proposed model has significantly higher accuracy in estimating the number of transmitted packets compared with the current models in the literature.

KEYWORDS
Internet of Things Communication; Communication System Traffic; Traffic Model; Stochastic Process.

1. Introduction

The amount of data carried through wireless networks has increased by more than 100 fold in the past decade [1]. Several market research studies have predicted that the amount of data will continue to grow exponentially [2]. Furthermore, the number of connected devices is also expected to grow exponentially. The increase in the number of connected devices is occurring due to the variety of new applications coming on to the market, such as smart homes and wearable devices. Handling this extraordinary increase in the amount of communication data and number of connected devices is the driving force for researchers around the world investigating the next generation of wireless communication, i.e., the fifth generation (5G).

For the previous two generations of wireless communications, the typical challenges were energy efficiency [3], data throughput [4,20], coverage [5] and end-to-end latency. For 5G, these issues are still considerably challenging; however, serving the expected

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number of connected devices might be overwhelming. The Internet of Things (IoT) is one of the leading forces in increasing the number of connected devices. The IoT can be defined as the network connecting billions of Machine-to-Machine communication (M2M) devices. M2M, also known as Machine-Type-Communications (MTC), is defined as the communication between machines or from machine to the network with little or no human intervention [6]. IoT is expected to play a crucial role in several sectors, including smart grids [7], environmental monitoring, surveillance, healthcare [8], and intelligent transport systems [9]. Several market studies have predicted that there will be more than 50 billion M2M devices in operation by 2020 [10]. Providing a ubiquitous service for this extraordinary number of connected devices and the consequent volume of data generated by those devices is the biggest challenges for network operators [14,18].

To design a network that can serve a large number of IoT devices, it is critical to have a comprehensive understanding of IoT communication and the traffic generated by its devices. It is known that the characteristics and the traffic patterns of M2M differ significantly from the conventional Human-to-Human (H2H) communication (mobile phone calls and computer video calls)[11,13,33]. For instance, commonly M2M applications generate short bursts of periodic data, and the cellular network is not well adapted for such short messages [14–17].

In this paper, a model for IoT communication is proposed. The model is used to represent the traffic generated by IoT devices extending the work done in [37]. To better understand the communication model, let us consider a conference as an analogy. If it is intended to model the noise that will be produced generated by the audience, we can model it as a random process (an Analytical approach shown in section 2.1), or alternatively, use a sensor to record the noise level at several conferences and then generalise the measured noise level (an empirical approach that will be presented in section 2.2). However, it would be much more comprehensive to perceive the conference program and use it to estimate the noise level. The conference program here is analogous to the communication model.

Consequently, the traffic extracted from the IoT communication model considers several related factors (as shown in Fig.1). The first factor is the channel information capacity. The channel information capacity plays a significant role in the time required to transmit data. Most traffic models available in the literature do not consider the information capacity as they are mainly based on the Erlang model [19] (such as [6]). The Erlang model was proposed for telephone networks (i.e., circuit switched networks) and are arguably not valid for M2M traffic.

The second factor not accounted for in the existing M2M traffic models is the blocking incidence in which the user requires access to the shared channels, but the channels are fully occupied [21–23]. Additionally, the multiple-access technique is missing in the existing M2M traffic models [21–23]. For a shared channel, there are two main multiple-access techniques (i) Centralised Scheduled Access in which a centralised device determines what part of the channel is allocated to each user, and (ii) Distributed Access in which each user locally decides the channel to access.

Modelling the communication can be insightful to better understand the behaviour devices in networks. For instance, it can help the researchers to model the traffic generated by the devices. Another example application can be the modelling of the energy consumption of the devices. One application that the authors believe that the contribution made in this paper can be very insightful; is the modeling for real-time systems. In particular, the work done on the Age of Information, in which several researchers assumed that the traffic is generated according to Poisson distribution

[24,25].

This paper is organised as follows, section 2 briefly present the state of the art traffic models. Section 3, presents the proposed Machine Communication Model; section 4 shows the simulation results in which we present the number of transmitted packets in a predefined time period. This paper is concluded in section 5.

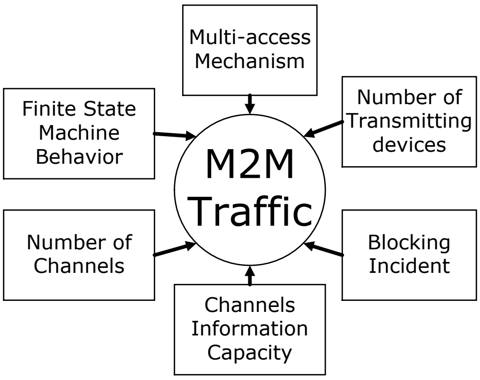

Figure 1. Factors affecting M2M communication traffic.

2. Traffic Models proposed in literature

In the literature, two main approaches have been taken to model the traffic generated by the M2M devices (M2MDs). The first approach was to propose a stochastic model to evaluate the traffic (analytical approach) and the second approach was to measure the traffic generated by the M2MDs (an empirical approach) as shown in Fig. 2.

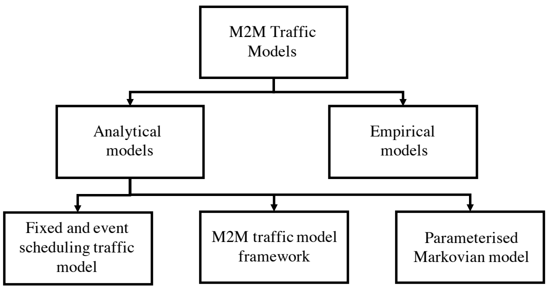

Figure 2. Traffic models proposed in literature.

2.1. Analytical Approach

2.1.1. Fixed Scheduling and Event-driven M2MDS Traffic Model

The authors in [21,23,29] proposed splitting the M2MDs' traffic modelling into two distinct models according to the transmission periodicity. The first model considers the traffic generated by the periodic updates referred to as Fixed Scheduling (FS) nodes, e.g., sending a sensor measurement. The traffic generated by an FS node was assumed to follow a deterministic process. The second modelling problem was focusing on the non-periodic data traffic referred to as Events-Driven (ED) nodes, e.g., the report of an emergency alarm. The traffic packets generated by the ED notes are modelled as a Poisson Process with rate λ_D (number of packets sent in an explicitly defined time). Table 1 summarises the modelling classification:

Table 1. Machine-to-Machine communication devices classification proposed in [23].

M2MD node group	Traffic transmission periodicity	Transmission statistical distribution
Fixed Scheduling	Periodic	Deterministic
Events-Driven	Non-periodic	Poisson

Although the authors of [23] remarked on the inaccuracy of conventional traffic models, they made some inaccurate simplifying assumptions in their modelling. The first assumption made was to assume that the M2MDs can be either FS nodes or ED nodes. This assumption makes the model only applicable to specific devices. These devices can do only a particular job (such as periodically report the temperature, but where it cannot report an event such as when the temperature is higher than a set threshold), while most of the M2MDs at the moment in the market can be both types. Assuming that the Fixed Scheduling nodes are synchronised is another one of the inaccurate assumptions. Hence, the authors in [30] investigated the synchronisation of machine-generated traffic such as router states update messages (a message reporting the current link states). It was demonstrated (analytically and empirically) that behaviour transition from asynchronous to synchronous is practically abrupt even if it was affected by an external influence (such as turning the devices *On* simultaneously). The synchronisation in the case of M2MDs would be an even more significant challenge. Hence most of the M2MDs will be connected to the network through a wireless connection; the propagation delays and multipath will play a vital role in preventing synchronisation.

2.1.2. M2M Traffic Model Framework [21]

The authors in [21], made a remarkable contribution in demonstrating the differences between human to human communication (H2H) and M2M traffic. They proposed an M2M traffic model similar to the Engset Traffic model (also known as *On-Off* model [27]). The only difference between the two models was that in the model proposed they assumed a Semi-Markov chain while in the Engset model, it is a Markov chain. The principal difference between a Markov chain and a Semi-Markov chain is the time between successful states transitions. In particular, in the Semi-Markov process, the states transitions times are random variables [31].

The M2M traffic model proposed in [21] is shown in Fig. 3. It assumes that the transmission of data occurs in one the following instances: (1) Periodic Update data referred to as PU; (2) Event-Driven data referred to as ED; or, (3) Payload Exchange which refers to the data traffic following the PU and ED traffic. A Timer or an Event drive the transition from the OFF state to ON state. On the other hand, the transition between the ON state and OFF state occurs when data transmission finishes.

They also proposed a model for the Sensor-Based Alarm and Event Detection device shown in Fig. 4. In this model, they used the sub-states of the ON state in Fig. 3 as main states. However, they did not use the PE exchange sub-state as they assumed that PU and ED are implicitly included in the PE state.

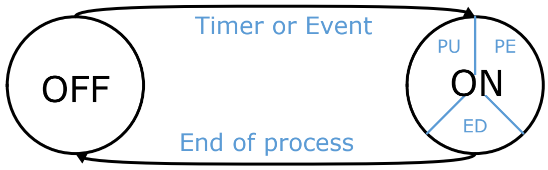

Figure 3. M2M traffic model proposed in [21]. PU refers to Periodic Update, ED refers to Event Driven and PE refers to Payload Exchange.

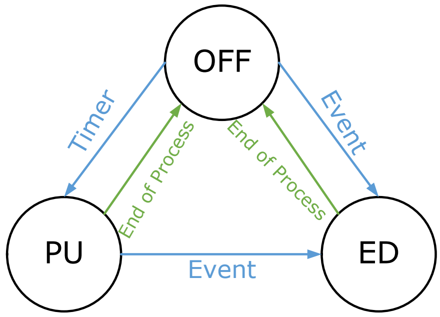

Figure 4. Sensor based alarm and event detection model used in [21]. PU refers to Periodic Update, ED refers to Event Driven.

The inter-departure times between the states and the size of the packets are assumed to be identical and independent random variables. However, in practical cases, this does not reflect the situation of M2MD traffic unless it is an exceptional case in which the device transmits a very short burst of data traffic. Additionally, the researchers did not take into consideration the channel characteristics and the number of devices.

2.1.3. Coupled Markov Modulated Poisson Process Model [22]

The authors in [22] proposed a traffic model for M2MDs relying on the Markov Modulated Poisson Process (shown in Fig. 5). However, they used a Coupled Markov Modulated Poisson Process (CMMPP) to illustrate the M2MDs' synchronisation effect. The CMMPP refers to multiple Markov chains that influence each other's transition probabilities $P_n[t]$. The transition probability is defined as the probability of changing from one state into the next state in a defined unit of time. The CMMPP were initially proposed in the context of pattern recognition. They assumed that the arrival is a Poisson process. The arrival rate in the proposed model depends on the current state of the MMPP, e.g., λ_1 represents the rate of arrival of the first state.

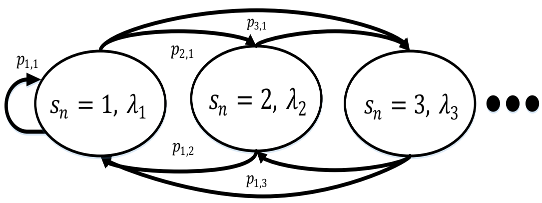

Figure 5. Markov Modulated Poisson Process model used in [22]. s_n represent the number of M2MD transmitting data and λ represent the state arrival rate.

The model proposed was compared with those models proposed by 3GPP. That was developed to model the aggregated traffic of several M2MDs. The focus of the comparison was to evaluate the complexity of computing and simulating the traffic. The simulation results showed that the CMMPP model would require a slightly higher simulation duration, but it can provide a better representation of the M2MD traffic than the 3GPP model.

Although the model proposed added a new aspect to the simulation, (i.e., the effect of the M2MDs synchronisation) as compared it with the conventional traffic models, it still inherited various assumptions employed in the conventional models. In particular, they rely on the Markov Modulated model. As a result, they assumed that the arrival rates are still being considered as a Poisson Process. The Poisson Process arrivals assumption is very commonly used in the literature because of its simplicity. However, it is not the best representation of M2MD traffic. The principal reason for that is that typically M2MDs generate traffic periodically. Therefore, each periodically generated packet relies on the timing of the previous packet, which contradicts with the memory-less property of Poisson Processes [27].

2.1.4. Parameterised Markoven Model [14]

The authors of [14] proposed a traffic model based on a Markov Process. Their main contribution was to evaluate the Blocking Probability [1] in a network that services both M2MD and H2H communication. The traffic model they used was similar to the model represented in Fig. 5 in [22]. The parameters used in the evaluation of the traffic model blocking probability was adapted from field trails in literature. Fig. 6 represents the approach they used to obtain the results by combining parameters from simulations and lab measurements.

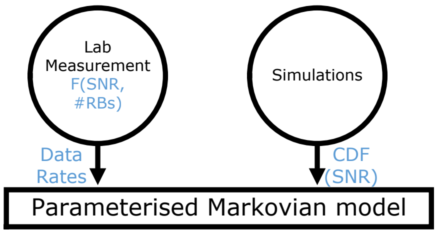

Figure 6. The parameters used in the traffic model in [14]. The model proposed used the data rate (i.e., the data throughput achievable in terms of the number of bits that can be communicated using a communication channel) from a lab measurement. The lab measurement relies on the Signal to Noise Ratio (SNR) and the number of Resources Blocks (RB) to measure the Data Rate. The simulations were used to obtain SNR statistical properties. In particular, the Cumulative Distribution Function (CDF).

Although the authors in [14], tried to bridge the gap between the Analytical and Empirical models. Their analytical model still needs further enhancement. The analytical model used can be described as theoretical and does not reflect all the M2MD characteristics. The next subsection represents a brief introduction to the empirical models introduced in the literature.

2.2. Empirical Model

Empirical models rely on experiments and tests to evaluate a certain model. Typically, the models proposed using this methodology start by running the experiment, and

[1]Blocking Probability is the probability that a device would not be able to transmit data because of a lack of available channels.

afterwards, they try to fit the collected data into a certain statistical distribution. The seminal paper by Willinger et al. [32] used this approach to prove the deficiency of modelling computer network communication traffic as a Poisson Process. At the time of publication of that paper, the Poisson Process was the most commonly used approach, and it was highly accepted [28,32,34]. They also proposed the *Self-Similar Traffic* Model for *Local Area Networks* (LANs). The self-similar process refers to a type of Stochastic Process that seems to have the same behaviour when viewed at different scales [32].

Recently, the authors of [12,33] used an empirical approach and measured the M2M traffic in a cellular network. They concluded that M2MDs traffic would have a significant impact on the connectivity of smartphones. In particular, the M2MD would compete with the smartphones on the available channels, and therefore, the blocking probability would increase. Although the empirical models illustrate the behaviour of several communication networks, they also have their shortcomings. Especially that they are a reactive approach to solve already existing problems. The empirical approach can only evaluate the considered scenario and is not be able to give a generalised model. This approach can only model aggregated traffic throughout the network. Therefore, modelling the source traffic (per device) is not possible.

3. PROPOSED M2M COMMUNICATION MODEL (MCM)

3.1. Overview

Most of the research done in the literature has focused on modelling the traffic generated by IoT devices; in this paper, we are modelling the communication that generates the traffic. In our investigation, we started with understanding the M2MDs, which are typically a low computational complexity finite state machine that mainly consist of sensor(s), a microprocessor/controller and a communication unit. The M2MD's main function is to monitor the environment and send a report to a centralised node so that the data can be analysed along with data collected from other similar nodes. Fig. 7 illustrates a generic M2MD data communication flow chart. The M2MD initially, at start-up, monitors the environment (e.g., senses the motion in a room). After a predefined period, the M2MD sends a periodic update (i.e., Round Robin state update) to the base station or a centralised node. In the occurrence of a triggered interrupt (an event occurs, e.g., a movement detected), the M2MD also transmits exceptional, i.e., non-periodic data to report it.

The proposed M2MD Communication Model (MCM) is shown in Fig. 8. MCM is a discrete stochastic process that consists of four states: Sleep (s), Round Robin (r), Interrupt (i) and Buffer (b). At any time, the M2MD is considered to be in one of these four states and would change to another state with a certain probability referred to as the Transition Probability (TP). The TPs shown in Fig. 8 represent the Starting State and Finishing State. For example, for a TP $P_{(s,b)}$ the Starting State would be s and the Finishing State would be b.

The Sleep state represents the starting state of the finite state machine in which the M2MD is not transmitting any data. The Round Robin state represents the epoch in which the M2MD is transmitting routine periodic updates data, e.g., a periodic report of room temperature. During the Buffer state, the M2MD has data to be sent, but it is still waiting to access the shared channels to transmit it. Additionally, in the case of fully occupied channels, the M2MD buffers the data packets until it can access a

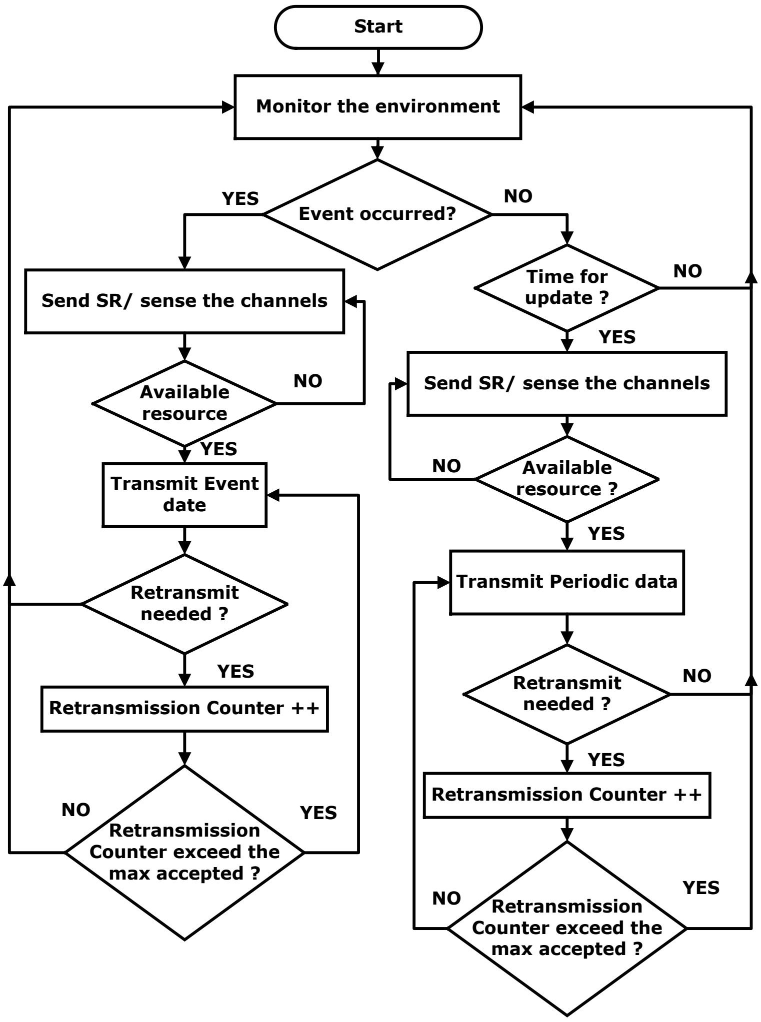

Figure 7. Generic M2MD data communications flow chart. The flow chart shows the two types of data generated by an M2MD i.e., periodic updates and a-periodic event reporting data.

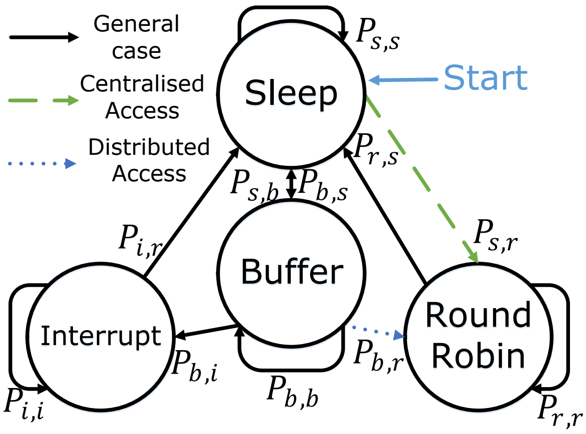

Figure 8. Proposed M2MDs communication Model i.e. MCM. Showing the four states that represents the IoT devices communication. Also, the probability of changing from one state to another.

channel. The Interrupt state represents a non-periodic update event occurring in the M2MD in which it sends data representing the event, e.g., a burglar alarm is activated.

In MCM, the data traffic is transmitted during two distinct states, i.e., Interrupt and Round Robin. It differentiates between the two states for the following reasons:

- typically, the data that has to be sent in the Round Robin updates are short data bursts; while in the Interrupt state data packet size is comparatively large. For instance, motion detectors would periodically send comparatively short data bursts (e.g., data sent containing the device identifier and, say, the battery state information). On the other hand, in the case of an exceptional event (e.g., a moving object had been detected), the M2MD would send a longer data burst that contains information of the event (e.g., a picture or the coordinates of the moving object);
- in the Round Robin state the communication is synchronised while communication in the Interrupt state is asynchronised;
- consequently, the communication that occurs in the two states (Round Robin and Interrupt) would differ in their channel access approach, which relies on the network access technique.

3.2. MCM Transitions

The MCM is modelled as a discrete stochastic process in which at each time unit a state transition occurs. The transition can be to any possible state (including the starting state itself). The TPs determine which state is the one most likely to be moved to in the next time slot. The summation of the TPs going out of any state must equal to unity, as follows:

$$\begin{aligned} &P_{s,s} + P_{s,r} + P_{s,b} = 1 \\ &P_{b,b} + P_{b,i} + P_{b,s} + P_{b,r} = 1 \\ &P_{r,r} + P_{r,s} = 1 \\ &P_{i,i} + P_{i,s} = 1. \end{aligned} \tag{1}$$

The self-transition probabilities, i.e., staying in the same state, rely on several factors. In particular, $P_{(s,s)}$, which represents the probability of remaining in the Sleep state, depends on the frequency of both the periodic updates and the event occurring. The availability of channel resources directly affects the value of $P_{(b,b)}$. In particular, the value of $P_{(b,b)}$ is equal to the channel's instantaneous Blocking Probability. The length of the M2MD data packet and the channel quality, e.g., Signal to Noise Ratio (SNR), determines the value of both $P_{(r,r)}$ and $P_{(i,i)}$. Currently, let us only consider the SNR to be affecting the information data rate. Hence, the maximum achievable information rate by the kth M2MD in the jth channel ($R_{(k,j)}$) can be obtained by the Shannon capacity formula:

$$R_{k,j} = BW log_2(1 + SNR_{k,j}) \tag{2}$$

and the probability to remain in the round robin and the interrupt states can be calculated by,

$$\begin{aligned} P_{(r,r)/(i,i)} &= \frac{1}{\gamma(t)_{(r,r)/(i,i)}} \\ \gamma(t)_{(r,r)/(i,i)} &= \left\lceil \frac{DR_{(r)/(i)}}{R_{k,j}(t)} \right\rceil \end{aligned} \tag{3}$$

where BW is the channel bandwidth, γ represents the number of time units the data needs to be transmitted, $\lceil . \rceil$ refers to the ceiling function, t refers to the instantaneous time, and DR is the state data requirements.

In a network with shared channels, there are two main multi-access techniques, as classified in [26]. The first technique is Centralised Scheduling, in which the M2MD must send a Scheduling Request (SR) to a centralised device such as, a Base Station (BS) to access the channel. The Base Station controls the M2MDs' channel's multiple-access scheduling [6]. The second technique is Distributed Scheduling where each M2MD makes a local decision whether it should access any particular channel based on channel sensing techniques, such as in [35].

In a Centralised Scheduling network, a central device such as a BS schedules the M2MD shared channel access. Consequently, the M2MD is required to send a Scheduling Request (SR) before starting to transmit data. After the BS receives the SR, it schedules a specified Resource (such as a time and bandwidth pair) for the M2MD. Thus, when an interrupt occurs (i.e., asynchronous data transmission is required) the M2MD needs to store the data in its buffer (i.e., the Buffer state). The time duration the data packets spend in the buffer represents the time of sending the SR to the BS, and for a resource to be scheduled. On the other hand, in a Round Robin update, data packets are transmitted in a predefined epoch (i.e., at an explicitly defined time). Accordingly, the M2MD sends the SR to the BS in advance, and M2MD periodic updates do not require data buffering.

However, in a Distributed Scheduling network all the data transmission (i.e., the data transmission owing both the Interrupt and Round Robin states) has to be buffered until the M2MD senses the channel and determines an unoccupied channel then transmits the data. Table 2 illustrates both data communication types (i.e., Round Robin state data and Interrupt state data for both multi-access approaches (i.e., Centralised and Distributed Scheduling).

Table 2. Data procedures for both types of Network Acess i.e., Centralised and Distributed Scheduling.

Data generating state	Data transmission procedure
Interrupt	Initially, the M2MD is in the Sleep state. When the data is ready to be transmitted the M2MD stores it in the Buffer. The M2MD remains in the buffer state until it either detects an unoccupied channel (for Distributed Scheduling) or it has been allocated a channel (for Centralised Scheduling).
Round Robin	In Centralised Scheduling the M2MD changes from the Sleep State (i.e., initial state) to the Round Robin State. In Distributed Scheduling, the M2MD changes from the initial state to the buffer state and stays there until it senses an unoccupied channel.

The Round Robin updates occur in a predefined epoch, so in a Centralised Scheduling network, $P_{(s,r)}$ follows a Deterministic distribution with a rate of λ. It is worth mentioning that the assumption that $P_{(s,r)}$ is deterministic is only acceptable if the SR was sent in sufficient time for the centralised device to allocate a channel resource to the M2MD. On the other hand, the interrupts occur randomly and hence $P_{(s,b)}$ can be modelled as a Discrete Poisson distribution with a mean μ. $P_{(b,s)}$ represents the probability of the M2MD discarding the packets it has previously prepared to transmit. This incident occurs when the packets have been blocked for a period of time; therefore, the information represented in the packet is not relevant anymore.

The TPs in the MCM model can thus be represented as a Transition Matrix (δ):

$$\delta = \begin{bmatrix} P_{s,s} & P_{s,r} & P_{s,b} & P_{s,i} \\ P_{r,s} & P_{r,r} & 0 & 0 \\ P_{b,s} & P_{b,r} & P_{b,b} & P_{b,i} \\ P_{i,s} & 0 & 0 & P_{i,i} \end{bmatrix} \tag{4}$$

where the probabilities in each row have the same Starting State and the probabilities in each column share the same Finishing State.

The steady-state probabilities of the Sleep, Round Robin, Buffer and Interrupt states are referred to as P_s, P_r, P_b and P_i respectively. Accordingly, the steady-state probabilities can be expressed as a Stationary Vector (Q):

$$Q = [P_s \; P_r \; P_b \; P_i] \tag{5}$$

where,

$$P_s + P_r + P_b + P_i = 1. \tag{6}$$

The steady-state probabilities for the M2MD for the MCM can be obtained using the Balance equation:

$$\delta \times Q = Q \text{ or } Q(\delta - 1) = 0 \tag{7}$$

where (I) is the identity matrix. Accordingly, from (2) and (4), expression (5) can be represented as:

$$P_s(P_{s,s} - 1) + P_r(P_{r,s}) + P_i(P_{i,s}) = 0 \tag{8}$$

$$P_s(P_{s,r}) + P_r(P_{r,r} - 1) = 0 \tag{9}$$

$$P_s(P_{s,b}) + P_b(P_{b,b} - 1) = 0 \tag{10}$$

$$P_s(P_{s,i}) + P_b(P_{r,i}) + P_i(P_{i,i} - 1) = 0. \tag{11}$$

Finally, by solving (5),(8),(9),(10) and (11), the values of Q and, hence, steady-state probabilities can be obtained.

The M2MD only transmits data in two states, i.e., Round Robin and Interrupt. Therefore, the number of transmitted packets (NP) can be derived from the MCM by using the probability of a device transmitting data (P_T) and the number of devices in the area of interest (n):

$$NP = P_T \times n \text{ where } P_T = P_r + P_i. \tag{12}$$

4. Evaluating the Number of Transmitted Packets

For simulating the M2MDs a discrete event simulator [36] was used to evaluate the network behaviour. In [26], it was shown that the Distributed Scheduling approach could outperform the Centralised Scheduling approach where there is delayed Channel State Information (CSI). In a high user density network (such as a network handling many M2MDs), the probability of delaying the CSI is high, therefore, in this report, let us study the packet transmission in a Distributed Scheduling network. The channel access probability is assumed to be equiprobable access across the M2MDs, i.e., all M2MDs are considered to have the same priority. For the simulations, five M2MDs (i.e., $n = 5$) sharing three channels was considered. The parameters and the associated values used to obtain the numerical and simulation results are given in Table 3. The parameters were chosen to be representative of a simple network, however, the model can also represent the traffic in other networks. The number of packets transmitted by the M2MDs with respect to the time units is shown in Fig. 9. As shown in the figure, the MCM can model the simulated M2MD traffic more accurately. In particular, in the case where $\gamma_((r, r))$ and $\gamma_((i, i))$ are equal to unity and three respectively (i.e., SNR 1), the MCM is able to predict the number of transmitted packets with significantly higher accuracy than the Poisson model (MMPP). For instance, in SNR1 the number of packets achieved by simulation is 3×10^4 for the 5×10^4 time unit, and using MCM is 3.041×10^4, that is less than 1.4% error. However, using the MMPP model, which does not adapt with respect to the SNR, the predicted number is 2.5×10^4, which is about 16.7% error.

Table 3. Numerical Parameters and Values.

Parameter	Value
Simulation duration	10×10^4 Time Units
Number of M2MD n / Channels	5/3
SNR 1 $\gamma_{(r,r)/(i,i)}$	1 for (r, r) / 10 for (i, i)
SNR 2 $\gamma_{(r,r)/(i,i)}$	3 for (r, r) / 30 for (i, i)
Round Robin update distribution in MCM	Deterministic with mean of 10
Interrupts Distribution in MCM	Poisson with mean 50
Data Requirements DR_r/DR_i	150 / 1500 Kbit
P_T for the Poisson model	Exponential distribution with mean 10
$P_{(b,s)}$	0

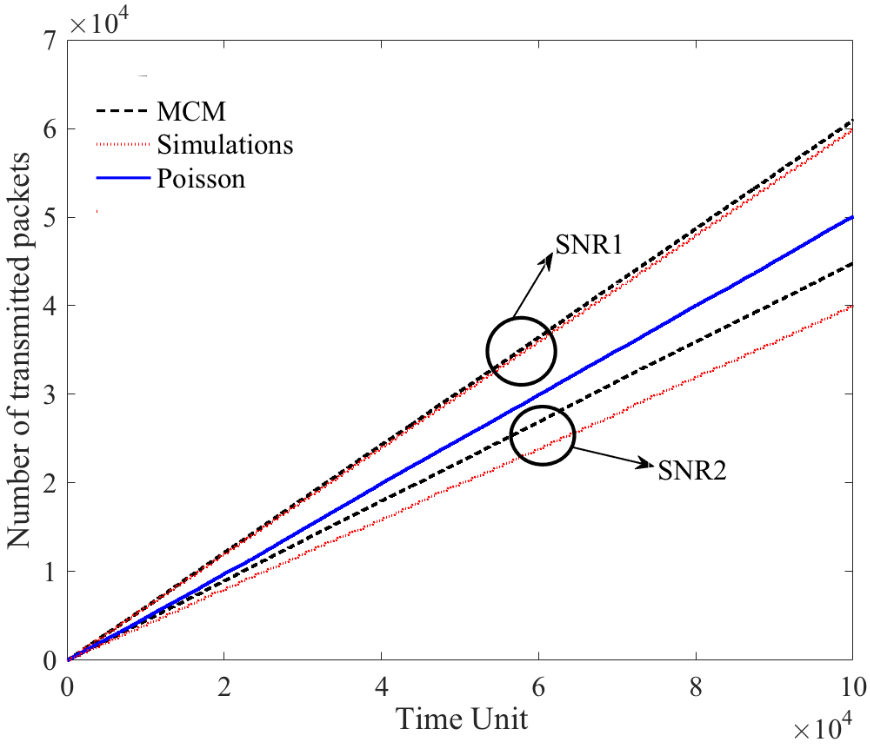

Figure 9. Number of successfully transmitted packets with respect to the time unit.

5. Conclusions

In the literature, several traffic models for M2M communications traffic have been proposed. Those models are able to represent M2M traffic for a specific set of scenarios, but, they do not cope well with a different set of scenarios. In this paper, a model for IoT communications was proposed by looking more closely at M2MD behaviour. The communication model was used to extract the traffic generated by the M2MDs. In the proposed method, the data traffic does not only rely on the statistical characteristics of the M2MD traffic. The extracted traffic has several other factors affecting it, such as the channel information capacity and multi-access technique used. The traffic model commonly used in the literature was simulated using a discrete event simulator and compared it with the analytical results obtained by extracting the generated traffic out of the proposed communication model. The results showed a significant improvement in predicting the number of packets with respect to time by using the proposed model.

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