Harmonising Coexistence of Machine Type Communications with Wi-Fi Data Traffic under Frame-based LBT

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***Abstract*—The existence of relatively long LTE data blocks within the Licensed-Assisted Access (LAA) framework results in bursty Machine type communications (MTC) packet arrivals, which cause system performance degradation and present new challenges in Markov modelling. We develop an embedded Markov chain to characterise the dynamic behaviour of the contention arising from bursty MTC and Wi-Fi data traffic in the LAA framework. Our theoretical model reveals a high contention phenomenon caused by the bursty MTC traffic, and quantifies the resulting performance degradation for both MTC and Wi-Fi data traffic. The Markov model is further developed to evaluate three potential solutions aiming to alleviate the contention. Our analysis shows that simply expanding the contention window, although successful in reducing congestion, may cause unacceptable MTC data loss. A TDMA scheme instead achieves better MTC packet delivery and overall throughput, but requires centralised coordination. We propose a distributed scheme that randomly spreads the MTC access processes through the available time period. Our model results, validated by simulations, demonstrate that the random spreading solution achieves a near TDMA performance while preserving the distributed nature of the Wi-Fi protocol. It alleviates the MTC traffic contention and improves the overall throughput by up to 10%.**

***Index Terms*—Licensed-assisted access, Internet of Things, Machine Type Communications, LTE-Wi-Fi coexistence, listen-before-talk.**

I. Introduction

It is predicted that 50 billion devices will be connected to mobile networks worldwide by 2020 [1]. These are not just devices communicating among humans; embedded devices, sending bits of information to other devices, will account for a large percentage of the devices. Researchers and the telecom industry all over the world are envisioning new networks referred to as fifth generation, or 5G, that will transform our lives and unleash enormous economic potential [2], [3]. We now have the opportunity to redefine our networks with 5G technologies not only to enable faster data access and to support greater capacity, but also to accommodate a wealth of new and diverse connected devices that comprise the Internet of Things (IoT).

The scarcity of licensed spectrum for cellular communications below 6 GHz has motivated the consideration of unlicensed bands for the operation of LTE, namely Licensed-Assisted Access (LAA) to unlicensed spectrum [4]. Shared use of radio spectrum is particularly useful for IoT device and machine communications [5]. However, the usage of LTE in unlicensed spectrum creates numerous challenges since LTE physical channels have largely been designed on the basis of uninterrupted operation on licensed carriers [6]. As a result, one of the 3GPP Study Items is fair coexistence with existing Wi-Fi networks with minimum impact. One of the new functionalities required of LAA, from a coexistence perspective, includes a mechanism for clear channel assessment based on Listen-Before-Talk (LBT) [7].

There have been several papers discussing the coexistence of LTE and Wi-Fi in unlicensed spectrum. Simulation evaluations were conducted in [8] and [9] to reveal that Wi-Fi performance would deteriorate significantly while LAA system performance would be only slightly affected. These performance evaluations indicate that appropriate coexistence mechanisms are necessary to prevent the degradation of Wi-Fi systems from the impacts of LTE traffic. LBT is specified in [10] as a method that enables the coexistence of LTE in unlicensed spectrum with other technologies. LBT is analysed in terms of the coexistence of LAA systems with Wi-Fi in [11]. LBT is also analysed in terms of the coexistence of LTE and Wi-Fi in [6]. Simulation results in both papers show that LBT is effective for enabling the coexistence even in dense deployment. A theoretical framework based on Markov chain models was established in [12] to calculate the downlink throughput of LAA and Wi-Fi systems. Their work confirmed the effectiveness of LBT in LTE and Wi-Fi coexistence scenarios.

Recently, many popular IoT devices, e.g. Raspberry Pi 3, Arduino UNO, and Waspmote, are equipped with Wi-Fi radios. These IoT devices are sharing the unlicensed spectrum with Wi-Fi users. Under the LAA framework, the introduction of LTE in the unlicensed spectrum will have impacts on both normal Wi-Fi users and MTC/IoT devices. Existing literatures focus on the impact of LTE on Wi-Fi users under the LAA framework. However, the impacts on IoT devices haven't been considered so far. As such, the scenarios we consider are MTC/IoT devices using Wi-Fi technology, coexisting with normal Wi-Fi users and LTE under the LAA framework.

MTC/IoT have a very different traffic pattern from human communications. Each IoT device has infrequent data transmissions, but the IoT system involves a potentially very large number of IoT devices (in the order of 10,000s per square kilometre). The presence of the relatively long LTE data blocks within the LAA framework gives rise to a bursty MTC packet arrival process, where many newly awoken IoT devices have to defer their access until the LTE data block

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finishes, and then simultaneously start accessing the channel, using the CSMA/CA protocol. Such simultaneous starts induce high contention among IoT devices, which not only causes delay and packet loss for the MTC traffic, but also degrades the Wi-Fi data traffic, resulting in wasted radio resources.

Analysing the contention behaviour of the IoT devices is challenging. Although many Markov models, e.g. [13]–[16], have been used to analyse Wi-Fi protocols, the existing Markov models provide only stationary system properties. They are unable to characterise the dynamic behaviour of the MTC contentions. In our previous work [17], we developed an embedded Markov chain to characterise the time-varying transmission and collision probabilities in large scale IoT device deployments, where the IoT devices woke periodically at the beginning of an allocated 100 ms *beacon Period* and competed with other IoT devices allocated to the same *beacon Period*, using the CSMA/CA protocol. In the current exploration, IoT devices additionally compete with Wi-Fi stations and an eNB using FB-LBT in the LAA framework. The network traffic comprises infrequent MTC traffic from the IoT devices, saturated data traffic from the Wi-Fi stations, and large periodic data blocks from the eNB. A new set of embedded Markov chains are developed to characterise the dynamic behaviour of MTC contentions in the LAA framework.

This paper aims to investigate the impacts of MTC traffic and provide congestion mitigation solutions to improve the coexistence of MTC traffic with Wi-Fi data traffic in the LAA framework. We first develop a new embedded Markov model to characterise the dynamic interactive behaviours of the IoT devices and Wi-Fi stations. Our theoretical model confirms the high contention phenomenon caused by the bursty MTC traffic, and provides insights into the dynamic contention behaviour.

The Markov model is then extended to characterise three potential solutions that aim to alleviate the traffic congestion. The first solution is to simply increase the contention window size for the IoT devices to alleviate contention. Although this solution requires only minor modifications to the IoT device protocol (and the Markov model), it may result in unacceptable MTC packet loss. The second solution is a TDMA-like protocol aiming to evenly space the starting times of the IoT devices through the available time period. Although this solution can provide better performance in terms of MTC packet delivery and overall throughput, it requires centralised coordination, which is incompatible with Wi-Fi distributed protocols. The third solution is to randomly spread the starting times of the IoT devices through the available time period.

Our model results, validated by simulations, demonstrate that the random spreading solution achieves a near TDMA performance in terms of MTC packet delivery and overall throughput, while preserving the distributed nature of the Wi-Fi protocol. Our results show a 25% reduction in collision probability and a 25% lift in instantaneous total (Wi-Fi plus IoT) throughput when applying random spreading to the IoT devices in a typical setting. Our proposed random-spreading solution achieves up to 10% gain in overall throughput.

The rest of the paper is organised as follows. Features of the system are presented in Section II and the exploration motivated. Markov models are developed in Section III to reveal the contention phenomenon and characterise potential solutions. Theoretical models are validated and performance evaluations are conducted in Section IV to support our proposal. Concluding remarks are given in Section V.

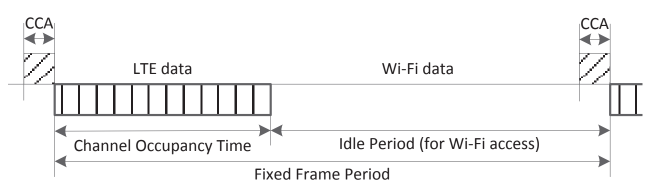
II. Background and Motivations

We consider a hybrid network comprising LTE LAA operating in frame-based LBT sharing an unlicensed spectrum band with IEEE 802.11, where both Wi-Fi stations and IoT devices are present. We consider a typical use case of meter reading and environmental monitoring, where each IoT device has infrequent data transmissions, but the IoT system involves a potentially very large number of IoT devices.

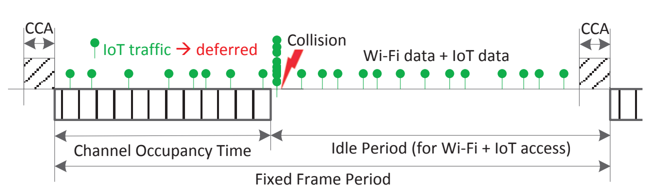
A. Listen-Before-Talk

Listen-Before-Talk (LBT) [10] is an important functionality for the coexistence of LTE and Wi-Fi. It is defined as a mechanism by which an equipment applies a clear channel assessment (CCA) check prior to transmitting on the channel. Two types of LBT procedures are defined: frame-based LBT and load-based LBT.

In frame-based LBT, CCA is performed periodically at predefined time instances according to a predetermined frame structure as shown in Fig. 1a. The Channel Occupancy Time is designated for transmissions of up to 10 LTE subframes, and shall not exceed 10 ms. The Idle Period is left for access by other technologies, e.g. other LTE systems, Wi-Fi hot spots, and IoT systems. The minimum Idle Period shall be at least 5% of the Channel Occupancy Time. If the equipment finds the Operating Channel(s) to be clear, it may transmit immediately. If the equipment finds an Operating Channel occupied, it shall not transmit on that channel during the next Fixed Frame Period. LBT has the advantage that similar operations are already supported by Frame structure type 2 defined in LTE TDD [7].



(a) LBT Timing



(b) High contention by IoT traffic

Fig. 1. LBT Frame Structure and Timing

The load-based LBT is not restricted to a certain frame structure or to transmitting at fixed defined times. Instead, load-based LBT may perform CCA whenever it has data to transmit. If the equipment finds the Operating Channel(s) to be clear, it may transmit immediately. The Channel Occupancy Time shall be less than 13 ms. If the equipment finds an Operating Channel occupied, it will perform an Extended CCA check which includes a random backoff before transmitting (details can be found in [10]).

In this paper, we focus on Frame-based LBT with a periodic frame structure as shown in Fig. 1a. In practice, the frame period in frame-based LBT may not be fixed due to channel occupancy by Wi-Fi data frames. Such variation has been captured in our Markov model.

B. High contention among IoT devices in LAA operations

Most existing literatures [8]–[12] study the fair share of the unlicensed spectrum between LTE traffic in the Channel Occupancy Time and Wi-Fi traffic in the Idle Period. In addition to the current mobile services, future 5G networks are expected to integrate IoT services. The machine-type communications (MTC) of the IoT devices exhibit a very different traffic pattern from Wi-Fi or LTE traffic. The IoT devices stay in doze mode most of the time to save power. A device might only wake up every few hours or days to send a single packet, and go back to sleep. The traffic from these devices include sensor/meter readings in the uplink and actuation/control messages in the downlink. Although the traffic from a single IoT device is very light, the number of devices can be very large. Due to the high and unpredictable number of IoT devices expected to simultaneously access the network, congestion and overloading of radio access and core networks are the prime issues to be solved in order to guarantee low-latency and low-energy for IoT devices and to minimize the impact of MTC traffic on these network segments [18].

The high contention situation can be exacerbated by the presence of LTE data frames and the specific MTC traffic pattern. In particular, as shown in Fig. 1b, MTC packets arriving during the Channel Occupancy Time are not able to access the channel immediately. They are deferred until the Channel Occupancy Time finishes. In this case, all the deferred MTC packets will start their backoff process simultaneously at the beginning of the Idle Period. Such simultaneous starts can cause high collision, as also shown in Fig. 1b.

III. Markov Models for IoT in LAA

In this section we develop a series of new models to reveal the high contention phenomenon caused by the MTC traffic and to characterise potential solutions that aim to alleviate the traffic congestion.

An initial model is presented, in Section III-B, for the scenario in which both Wi-Fi and MTC traffic use the standard CSMA/CA protocol. The modelling is based on jointly evolving embedded Markov chain distributions that represent the IoT devices and Wi-Fi STAs through the Idle Period, and then converting the embedded Markov chains to time-based distributions and properties. This uncontrolled scenario has temporarily high congestion. Three solutions to this high congestion are then presented and modelled in which the CSMA/CA protocol is altered for the IoT devices, with the aim of reducing contention.

- The first solution, presented in Section III-C, is to simply increase the contention window size for the IoT devices to alleviate contention.
- The second solution, presented in Section III-D, is a TDMA-like protocol aiming to evenly space the transmission-process starting times of the IoT devices through the Idle Period. Although this solution provides the best results based on spreading the MTC traffic, it requires centralised coordination which is incompatible with Wi-Fi and MTC distributed protocols. Nevertheless it is seen as providing the upper limit of the possible gains obtained from spreading the transmission-process starting times of the IoT devices.
- The third solution, presented in Section III-E, is to randomly distribute the starting times of MTC packets arriving during the Channel Occupancy Period through the Idle Period. This solution achieves statistical spreading of the MTC while preserving the distributed nature of IoT protocol.

A. Model Set-up and Methodology

We consider a LAA framework comprising LTE, Wi-Fi and IoT networks, with timing as depicted in Fig. 1b. In particular, we investigate the collision and throughput performance of a number of saturated Wi-Fi stations and IoT devices contending for channel access during the Idle Period. The Wi-Fi STAs and IoT devices are assumed to use the 802.11 DCF protocol. We assume that there are many IoT devices and that a fixed number wake from a doze mode each FFP with a single packet to deliver, with the arrival times distributed randomly through the FFP. If a packet is not successfully transmitted after a short period, the packet is dropped and the IoT device goes to a doze mode to conserve energy[1]. The LTE blocks are assumed to be of fixed duration and to commence as soon as the channel is free after a periodic target time, making the Idle Period approximately of fixed duration. Transmission failures are assumed only to occur due to collisions from concurrent transmissions. All the devices are assumed to be within the carrier sensing range of each other.

Our analysis is based on embedded Markov chains that model the 802.11 DCF protocol. Embedded Markov chains have been used to model the 802.11 DCF protocol for a single Wi-Fi station (STA) by many authors, with state transitions occuring at, or embedded in, the MAC-slot transitions. The steady-state distributions provide per-MAC-slot properties and the Markov-chain states are then weighted by their expected durations to convert the per-MAC-slot properties to time-based properties.

Various embedded Markov-chain models have been used, but the general approach to obtaining network properties is the same. The nonlinear per-STA embedded Markov-chain models (most often all identical), are solved simultaneously with a nonlinear network-interaction model. The collision and

[1] Information loss due to packet loss can be compensated for by IoT application layer retransmission or data fusion.

transmission probabilities feed between the two components. In particular, there is:

- a per-STA model for each STA, which is a function of the collision probability for the particular STA and from which the STA's probability of transmitting can be extracted; and
- a network-interaction model that combines all the per-STA transmission probabilities of the other STAs in the network to give a collision probability for a partucular STA.

In [13], [15], and multiple other papers, a single embedded Markov chain, with a stationary Poisson packet-arrival process, is used for the per-STA model of each STA and the steady-state distribution of the Markov chain is used to estimate stationary system properties. In [17], a single packet arrives at each active STA at the beginning of each *Beacon Period*, but then no more arrive during the *Beacon Period*, making the model non-stationary. The two interacting model components are iteratively propagated to obtain simultaneous solutions, giving time-varying transmission and collision probabilities, estimated at each network count.

In our current modelling endeavours, one per-STA model represents each of the IoT devices and another per-STA model represents each of the saturated Wi-Fi STAs. The premise is that all the IoT devices exhibit a particular behaviour and can, by symmetry, be approximately represented by the one per-STA model; similarly for the Wi-Fi STAs. All the STAs and devices change their backoff state simultaneously at the end of each MAC slot. As such, the joint embedded Markov chain, comprising both per-STA models, can capture the interactions between them and the dynamics of the process. The transition points also mark the points when successfully transmitted packets leave the process; for the IoT devices, the input buffer then becomes empty, whereas for the saturated Wi-Fi stations, a new transmission process begins for the next packet in the input buffer.

In the initial, uncontrolled scenario considered in this paper, the saturated Wi-Fi STAs have a stationary arrival process (with the input buffer being assumed always full), whereas the periodic LTE block creates a non-stationary, yet periodic, arrival process for the IoT devices, with a burst of packets arriving at the beginning of each Idle Period. As such, the network effectively has a periodic arrival process, so rather than obtaining a steady-state solution to the network, we strive to estimate a steady-cycle solution and understand the dynamics within the cycle.

B. Markov Model for Uncontrolled MTC Access

The network comprises an eNB, a number of IoT devices and a number of Wi-Fi stations (STAs). The eNB employs a framed-based access mechanism. At the start of each Fixed Frame Period (FFP), the eNB transmits a data block of duration T_{LTE}. The channel is then left to non-LTE traffic for the Idle Period, which has average duration T_{IP}. The eNB nominally commences each FFP periodically, with period T_{FFP}. To reduce collisions, if the channel is busy, the eNB is assumed to wait until the end of the current non-LTE transmission, then to jump in before any further transmissions, giving $T_{IP} = T_{FFP} - T_{LTE}$.

The Wi-Fi STAs and IoT devices contend for the channel during the Idle Period. There are N saturated Wi-Fi STAs. Each FFP, M IoT devices become active with a single new packet that arrives with uniform probability throughout the FFP. The STAs and devices follow the 802.11 CSMA/CA protocol. The IoT devices have only zero or one packet in their input buffer, whereas the Wi-Fi STAs always have a full input buffer. Hence, the current state of each device or STA can be described by a (backoff stage, backoff counter) combination, or the idle state. The IoT devices are assumed to drop their packet T_{FFP} after first attempting to transmit, which may involve two partial Idle Periods.

The devices and STAs are modelled by evolving the marginal state probabilities corresponding to the different possible DCF (backoff stage, backoff counter) combinations through the Fixed Frame Period (FFP). The devices and STAs change states simulataneously at the end of each MAC slot, after either a slot time, σ, of channel silence or, in the case of a transmission by any device or STA, after T_{Tx}, which includes a final DIFS of silence. Each state change increments a 'virtual' MAC-slot count, which is set to one at the beginning of each Idle Period. By symmetry, the marginal state probability distributions of all the devices of a particular type (either IoT device or Wi-Fi STA), during a given MAC-slot, are the same. Hence, only two evolving interacting marginal probability distributions need to be modelled.

Let W_i denote the size of the backoff window for backoff stage-i, such that each time backoff stage-i is initiated, an initial backoff counter is selected uniformly from $\{0, .., W_i - 1\}$, where $W_i = W_0 \times 2^{\min(m,i)}$, $i = 0, .., s$. Superscripts D and M are respectively used to represent the Wi-Fi STA data traffic and the IoT device MTC traffic. Let $S_k^T(i,j)$ denote the marginal state probabilities of a device of type T being in backoff stage-i, with backoff count j, at MAC-slot k, where $T \in \{D, M\}$, $i \in \{0, .., s\}$, $j \in \{0, .., W_i - 1\}$, and $k \in \{1, 2, ..\}$.

The marginal state probabilities are jointly propagated from their initial distributions at MAC-slot one through to the end of the Idle Period, based on the assumption that the state distributions of all the STAs and devices at MAC-slot k are independent of each other, so that their joint distribution is a product of their marginal distributions, $S_k^D(i,j)$ or $S_k^M(i,j)$. In particular, their transmission probabilities are treated as independent when estimating collision probabilities for each device or STA. The comparison of the model output to simulation results in Section IV-A demonstrates that this is a weak assumption.

The saturated Wi-Fi STAs start processing a new packet immediately after the DCF proccess is completed for its previous packet, so the packet arrival process for the saturated devices equals the departure process. The IoT devices instead return to the Idle state after the DCF process is completed, or once its packet times out. So, the IoT device state distribution propagation includes a packet arrival probability, a current packet DCF-process propagation, and a time-out departure probability.

Let τ_k^T, $T \in \{D, M\}$, be the probability that a particular type-T device transmits in MAC-slot k, and let p_k^T, $T \in \{D, M\}$, be the conditional probability that, given a type-T device transmits in MAC-slot k, it has a collision with at least one other transmitting device, resulting in packet failure. Given the assumption of independent state distributions between devices, these per-device transmission and conditional collision probabilities are:

$$\tau_k^T = \sum_{i=0}^{s} S_k^T(i,0), \quad T \in \{D, M\}, \tag{1}$$
$$p_k^D = 1-(1-\tau_k^D)^{N-1}(1-\tau_k^M)^M, \tag{2}$$
$$p_k^M = 1-(1-\tau_k^D)^{N}(1-\tau_k^M)^{M-1}. \tag{3}$$

Combining (1)-(3) give the probabilities that, at MAC-slot k, a particular type-T device, $T \in \{D, M\}$, completes a successful transmission, denoted $P_{Suc,k}^T$, or has a collision, denoted $P_{Col,k}^T$, as:

$$P_{Suc,k}^T = \tau_k^T(1-p_k^T), \ T \in \{D, M\}, \tag{4}$$
$$P_{Col,k}^T = \tau_k^T p_k^T, \ T \in \{D, M\}. \tag{5}$$

Let $P_{\mathrm{noTx},k}$ be the probability that no device or STA transmits during MAC slot k and $P_{\mathrm{anyTx},k}$ be the probability that at least one device or STA transmits during MAC slot k. Then

$$P_{\mathrm{noTx},k} = (1-\tau_k^D)^N(1-\tau_k^M)^M, \tag{6}$$
$$P_{\mathrm{anyTx},k} = 1-P_{\mathrm{noTx},k}, \tag{7}$$

and the expected duration of MAC slot k, denoted $E_{s,k}$, is

$$E_{s,k} = \sigma P_{\mathrm{noTx},k} + T_{\mathrm{Tx}} P_{\mathrm{anyTx},k}. \tag{8}$$

The MTC packets arrive uniformly through each T_{FFP}, so have a T_{LTE}/T_{FFP} chance of commencing at the start of the Idle Period and an $E_{s,k}/T_{FFP}$ chance of commencing after MAC slot k. When a new packet arrives, backoff stage-0 is initiated, so the arrival probability is distributed evenly across the backoff stage-0 states. Type-M device arrivals during the Channel Occupancy Time are accounted for in the initial state, $S_1^M(i,j)$, which is left to Section III-B2; arrivals throughout the Idle Period are accounted for at each MAC slot transition.

In general, backoff stage-0 is initiated as the first step in processing a new packet and backoff stage-i, $i > 0$ is initiated after a collision. Denote the probability that a type-T device, $T \in \{D, M\}$, initiates backoff stage-i at the end of MAC-slot k, $k > 0$, and hence selects an integer random-backoff counter uniformly from $\{0, .., W_i - 1\}$, by $P_{fan,k}^T[i]$. Then

$$P_{fan,k}^D[i] = \begin{cases} P_{Suc,k}^D + p_k^D S_k^D(s,0), & i=0, k>0, \\ p_k^D S_k^D(i-1,0), & i>0, k>0, \end{cases} \tag{9}$$
$$P_{fan,k}^M[i] = \begin{cases} E_{s,k}/T_{FFP}, & i=0, k>0, \\ p_k^M S_k^M(i-1,0), & i>0, k>0, \end{cases} \tag{10}$$

Let $P_{dep,k}^M(i,j)$ be the probability that a type-M device drops its packet from backoff stage-i with backoff count j due to a timeout, after attempting to transmit the packet for T_{FFP}. The model for $P_{dep,k}^M(i,j)$ is presented in Section III-B4. Given, initial state distriubtions $S_1^D(i,j)$ and $S_1^M(i,j)$, the state distributions $S_k^D(i,j)$ and $S_k^M(i,j)$ are propagated according to:

$$S_{k+1}^D(i,j) = \begin{cases} P_{fan,k}^D[i]/W_i + S_k^D(i,j+1), \\ \qquad j=0,..,W_i-2, \\ P_{fan,k}^D[i]/W_i, \qquad j=W_i-1, \end{cases} \tag{11}$$

$$S_{k+1}^M(i,j) = \begin{cases} P_{fan,k}^M[i]/W_i + S_k^M(i,j+1) - P_{dep,k}^M(i,j), \\ \qquad j=0,..,W_i-2, \\ P_{fan,k}^M[i]/W_i - P_{dep,k}^M(i,j), \quad j=W_i-1, \end{cases} \tag{12}$$

for $i = 0, .., s$ and $k > 1$.

1) Properties at time t: The STAs and devices all change backoff states simultaneously, however the timings of the transitions are stochastic. To be in MAC slot k at time t, either MAC slot k starts in the interval $(t-\sigma, t]$ and is a no-transmission MAC slot; or MAC slot k starts in the interval $(t - T_{\mathrm{Tx}}, t]$ and is a transmission MAC slot. Let t_k^{end} denote the time at the end of MAC slot k, which is stochastic. Then, the probability of being in MAC slot k, given it is time t, denoted $P(k|t)$ is

$$P(k|t) = P_{\mathrm{anyTx},k} P(t_{k-1}^{end} \in (t-T_{\mathrm{Tx}}, t]) + P_{\mathrm{noTx},k} P(t_{k-1}^{end} \in (t-T_\sigma, t]). \tag{13}$$

The number of transmission MAC slots during MAC slot 1 to MAC slot k, is modelled as the sum of the outcomes from k independent Bernoulli trials[2], with probabilities $P_{\mathrm{anyTx},\kappa}$, for $\kappa = 1, .., k$. Let $P(c|k)$ be the probability of c transmission MAC slots occurring during MAC slot 1 to MAC slot k. Then

$$P(c|k) = \begin{cases} \prod_{\kappa=1}^{k} P_{\mathrm{noTx},\kappa}, & c=0, k \geq 1, \\ P_{\mathrm{anyTx},1}, & c=1, k=1, \\ 0, & c>1, k=1, \\ P(c-1|k-1)P_{\mathrm{anyTx},k} + P(c|k-1)P_{\mathrm{noTx},k}, \\ & c>0, k>1. \end{cases} \tag{14}$$

Next, let $t^{end}(c,k)$ be the time at the end of MAC slot k, when c of the k MAC slots are transmission MAC slots, so that

$$t^{end}(c,k) = k\sigma + c(T_{\mathrm{Tx}} - \sigma). \tag{15}$$

Then

$$P(t_k^{end} \in (t-T_{\mathrm{Tx}}, t]) = \sum_{c=0}^{k} P(c|k) \mathbf{I}_{(t-T_{\mathrm{Tx}}, t]}(t^{end}(c,k)), \tag{16}$$

$$P(t_k^{end} \in (t-\sigma, t]) = \sum_{c=0}^{k} P(c|k) \mathbf{I}_{(t-\sigma, t]}(t^{end}(c,k)), \tag{17}$$

where $\mathbf{I}_A(t)$ is the indicator function for set A; and equals 1 when $t \in A$, and 0 otherwise.

Values of device properties at time t are then evaluated as the weighted average of the property during MAC slot k, weighted by the probability that MAC slot k is occurring at time t. Let $S^T(i,j)(t)$, $T \in \{D, M\}$, denote the probability of being in backoff stage-i, with backoff count j, at time t for

[2]Note that the assumption of independent Bernoulli trials is not strictly correct, because, for example, it allows the small probability of there being no transmission after W_0 network counts, which is obviously incorrect. However, it is a close approximation.

a type-T device; let $p^T(t)$, $T \in \{D, M\}$, be the probability of a collision for a type-T device transmitting at time t; and let $\mathrm{Thr}^T(t)$, $T \in \{D, M\}$, be the average throughput, in packets per second, for a type-T device at time t. Then

$$S^T(i,j)(t) = \sum_k P(k|t) S_k^T(i,j), \ T \in \{D, M\}, \quad (18)$$

$$p^T(t) = \sum_k P(k|t) p_k^T, \ T \in \{D, M\}, \quad (19)$$

$$\mathrm{Thr}^T(t) = \sum_k P(k|t) P_{Suc,k}^T / E_{s,k}, \ T \in \{D, M\}. \quad (20)$$

2) State distribution at MAC-slot one: The MAC-slot-one distributions are estimated by iteratively propagating the system from the current MAC-slot-one distributions to the end of the Idle Period, then using the end-of-Idle-Period distributions to evaluate the next MAC-slot-one distributions. The process is stochastically cyclic, with periodicty is T_{FFP}, however, the Wi-Fi STAs and IoT devices 'freeze' their DCF processes during the Channel Occupancy Time, so the model periodicity is T_{IP}.

The saturated Wi-Fi STAs have full input queues and 'freeze' their backoff counters during the Channel Occupancy Time, so their state distribution at MAC-slot one is the same as at the end of the Idle Period. The IoT devices instead have at most one packet, and there is a T_{LTE}/T_{FFP} probability that the packet arrives during the Channel Occupancy Period. Hence, their state distribution at MAC-slot one is the sum of their state distribution at the end of the Idle Period and the distribution from new arrivals.

Let $S_f^T(i,j)$, $T \in \{D, M\}$, be the state distribution for a type-T device at the end of the Idle Period. To evaluate $S_f^T(i,j)$, first note that we are assuming the eNB allows any current transmission to be completed before transmitting its LTE block, and that the eNB's target transmission time is periodic, with periodicity T_{FFP}. As such, the eNB could transmit up to T_{Tx} after its target time, making the next target Idle Period duration up to T_{Tx} shorter. Assuming this delay is uniformly distributed over $[0, T_{\mathrm{Tx}})$,

$$S_f^T(i,j) = \frac{1}{T_{\mathrm{Tx}}} \int_{T_{IP}-T_{\mathrm{Tx}}}^{T_{IP}} S^T(i,j)(t) dt \quad (21)$$

$$\approx \frac{1}{n} \sum_{h=0}^{n-1} S^T(i,j)(T_{IP} - hT_{\mathrm{Tx}}/n)). \quad (22)$$

for some n. Then, the initial state distributions at MAC slot one are

$$S_1^D(i,j) = S_f^D(i,j), i \geq 0, \ \ j = 0,..,W_i - 1, \quad (23)$$

$$S_1^M(i,j) = \begin{cases} S_f^M(i,j) + \frac{T_{LTE}}{T_{FFP} W_i}, & i = 0, j = 0,..,W_i - 1, \\ S_f^M(i,j), & i > 0, j = 0,..,W_i - 1. \end{cases} \quad (24)$$

For the first iteration, the saturated MAC-slot-one distribution is initialised to the analytical solution of Bianchi's saturated-STA Markov chain model [13], and the MTC devices are initiated to $S_1^M(0,j) = T_{LTE}/(T_{FFP} W_0)$, for $j = 0,..,W_0 - 1$; otherwise 0. However, the model converges from all initial distributions tried.

3) Total Throughput: Let P_k^{IP} be the probability that MAC slot k occurs during the Idle Period. Again noting that the target Idle Period duration can be up to T_{Tx} shorter than T_{IP}, P_k^{IP} is evaluated as

$$P_k^{IP} = \frac{1}{T_{\mathrm{Tx}}} \int_{T_{IP}-T_{\mathrm{Tx}}}^{T_{IP}} P(t_k^{end} \in (0, t]) dt \quad (25)$$

$$\approx \frac{1}{n} \sum_{h=0}^{n-1} P(t_k^{end} \in (0, T_{IP} - hT_{\mathrm{Tx}}/n]) \quad (26)$$

$$= \frac{1}{n} \sum_{h=0}^{n-1} \sum_{c=0}^{k} P(c|k) \mathbf{I}_{(0, T_{IP} - hT_{\mathrm{Tx}}/n]}(t^{end}(c,k)). \quad (27)$$

Then the average total throughput during the Idle Period per type-T device, $T \in \{D, M\}$ and denoted Thr_{IP}^T, is evaluated as

$$\mathrm{Thr}_{IP}^T = \sum_k P_k^{IP} P_{Suc,k}^T, \ T \in \{D, M\}. \quad (28)$$

4) Timeout-departure distribution: MTC packets can arrive at the IoT devices throughout the FFP and the IoT devices are assumed to drop their packets T_{FFP} after commencing their backoff process. Hence, at each MAC slot there is a chance of a new MTC packet arriving, of a current MTC packet progressing through the backoff process and of a MTC packet departing due to a timeout. The evolving state distribution represents the combination of these processes, and has no memory of how long the packet has been in the process. The timeout, or departure, process aims to account for the packets that have been in the process for T_{FFP}.

We start by calculating the distribution of the number of MAC slots it takes to reach each state of the backoff process. We then estimate the distribution of the number of MAC slots it takes to reach T_{IP} of Idle-Period time. Combining the two, we obtain a proportion of each current state that has reached T_{IP} and hence departs due to a timeout.

Let $x(i,j)[k]$ be the probability that it takes k MAC slots to reach state $S^M(i,j)$ from the start of backoff stage-i; and let $y(i,j)[k]$ be the probability that it takes k MAC slots to reach state $S^M(i,j)$ from the start of backoff stage-0. Then

$$x(i,j)[k] = \begin{cases} \frac{1}{W_i - j}, & j = 0,..,W_i - 1; k = 1,..,W_i - j, \\ 0, & \text{else}, \end{cases} \quad (29)$$

and

$$y(0,j)[k] = x(0,j)[k], \quad (30)$$

$$y(i,j)[k+m] = \begin{cases} \sum_{n=0}^{m-1} x(i,j)[k+n] y(i-1,0)[m-n], \\ \qquad \text{for} \begin{cases} i = 1,..,s, \\ j = 0,..,W_i - 1, \\ k = 1,..,W_i - j, \\ m = i,.., \sum_{\alpha=0}^{i-1} W_\alpha, \end{cases} \\ 0, \quad \text{else}. \end{cases} \quad (31)$$

Let $z(i,j)[k]$ be the probability of having reached state $S^M(i,j)$ in k MAC slots since the start of backoff stage-0, given the backoff process is in $S^M(i,j)$ and that paths longer than k MAC slots have been removed from the backoff process. Then

$$z(i,j)[k] = \frac{y(i,j)[k]}{\sum_{h=1}^{k} y(i,j)[h]}. \quad (32)$$

$P(k|T_{IP})$ approximates the distribution of the number of MAC slots it takes to reach the end of the Idle Period and $z(i,j)[k]$ approximates the proportion of probability mass $S^M(i,j)$ that took k MAC slots to reach $S^M(i,j)$. So, the probability of departure due to a timeout from state $S^M(i,j)$, $P^M_{dep,k}(i,j)$, is approximated as

$$P^M_{dep,k}(i,j) = \sum_k P(k|T_{IP}) z(i,j)[k]. \quad (33)$$

C. Solution 1: increase W_0 for IoT access

One way to reduce the increased congestion caused by the simultaneous CSMA/CA process starts of the M IoT devices is to increase the IoT devices' W_0, which proportionally increases their contention windows for all backoff stages. This requires minor modifications to the process. In particular, let the new minimum backoff window width be W_0^M. Then all that is needed is to replace W_i, in (12), (24), (29) and (31), with W_i^M, where $W_i^M = W_0^M \times 2^{\min(m,i)}$, $i = 0,..,s$.

D. Solution 2: Equally space IoT commencements

Assume now that the MTC packets are equally spaced using a TDMA-like process such that the M IoT devices initiate their backoff-transmission processes at equal intervals through the Idle Period. That is, one IoT device intiates its transmission process at each of the times jT_{IP}/M, $j = 0,..,M-1$. Assume again that MTC packets that are unsuccessfully transmitted T_{FFP} after their transmission process is intiated are then dropped. All the devices freeze their backoff processes during the Channel Occupancy time, so the system model now has a periodicty of T_{IP}/M.

The system is modelled by evolving state distributions for a saturated device and an IoT device from when the IoT device intiates its transmission process, through T_{IP} seconds, to when the IoT device would drop its packet if undelivered. Each state-distribution trajectory is then used to represent devices of its type, starting at any of the times jT_{IP}/M, $j = 0,..,M-1$.

In particular, S_k^D and S_k^M now represent the evolution of state distributions starting equally spaced through the Idle Period, with one IoT device starting at each of jT_{IP}/M, $j = 0,..,M-1$, and with the N saturated devices starting at jT_{IP}/M, $j = 0,..,M-1$, with equal probability. The state distributions are evolved as per (1)-(31), except that the collision probabilities, (2) and (3), and the probability of no device transmitting, (6), are replaced by equations that account for the other $M-1$ state-trajectory starting points; and equations based on the arrival process for the IoT devices, (10) and (24), now reflect that one packet arrives at MAC slot one, then no others arrive.

The collision probability is based on the transmission probablity of the other devices in the system, with their states, at MAC slot k, estimated as the expected state distributions at equally spaced times through T_{IP} relative to the expected start time for MAC slot k, where $S^T(i,j)(t)$ is evaluated as in Section III-B1.

Denote the probability of a type-T device, $T \in \{D, M\}$, transmitting at time t as $\tau^T(t)$, which is evaluated from $S^T(i,j)(t)$ as $\sum_j S^T(0,j)(t)$. Given a representative device is at time t through its evolved trajectory, denote the probability of: no IoT device transmitting $P^{\text{allM}}_{\text{noTx}}(t)$; no other IoT device transmitting $P^{\text{otherM}}_{\text{noTx}}(t)$; no saturated Wi-Fi station transmitting $P^{\text{allD}}_{\text{noTx}}(t)$; and no other saturated Wi-Fi station transmitting $P^{\text{otherD}}_{\text{noTx}}(t)$. Also, denote the M times equally spaced, $\mod T_{IP}$, through $[0, T_{IP})$, starting at t, $T_t^M[j]$, $j = 0,..,M-1$, such that $T_t^M[j] = (t + jT_{IP}/M) \mod T_{IP}$. Then,

$$P^{\text{allM}}_{\text{noTx}}(t) = \prod_{j=0}^{M-1} (1 - \tau^M(T_t^M[j])), \quad (34)$$

$$P^{\text{otherM}}_{\text{noTx}}(t) = \prod_{j=1}^{M-1} (1 - \tau^M(T_t^M[j])), \quad (35)$$

$$P^{\text{allD}}_{\text{noTx}}(t) = \left(\prod_{j=0}^{M-1} (1 - \tau^D(T_t^M[j])) \right)^{N/M}, \quad (36)$$

$$P^{\text{otherD}}_{\text{noTx}}(t) = \left(\prod_{j=0}^{M-1} (1 - \tau^D(T_t^M[j])) \right)^{(N-1)/M}. \quad (37)$$

Denote the expected starting time of MAC slot k, E_k^{start}, such that

$$E_k^{start} = \begin{cases} 0, & k = 1, \\ \sum_{\kappa=1}^{k-1} E_{s,\kappa}, & k > 1. \end{cases} \quad (38)$$

Then, (2) and (3) are replaced with

$$p_k^D = 1 - P^{\text{otherD}}_{\text{noTx}}(E_k^{start}) P^{\text{otherM}}_{\text{noTx}}(E_k^{start})(1 - \tau_k^M), (39)$$
$$p_k^M = 1 - P^{\text{otherD}}_{\text{noTx}}(E_k^{start}) P^{\text{otherM}}_{\text{noTx}}(E_k^{start})(1 - \tau_k^D), (40)$$

and (6) is replaced with

$$P_{\text{noTx},k} = P^{\text{otherD}}_{\text{noTx}}(E_k^{start}) P^{\text{otherM}}_{\text{noTx}}(E_k^{start})(1 - \tau_k^D)(1 - \tau_k^M). \quad (41)$$

To reflect the change to the IoT device arrival process, (10) becomes

$$P^M_{fan,k}[i] = \begin{cases} 0, & i = 0, k > 0, \\ p_k^M S_k^M(i-1, 0), & i > 0, k > 0, \end{cases} \quad (42)$$

and (24) becomes

$$S_1^M(i,j) = \begin{cases} 1/W_0, & i = 0, j = 0,..,W_i - 1, \\ 0, & i > 0, j = 0,..,W_i - 1. \end{cases} \quad (43)$$

Given the estimated representative state-distribution trajectories, $S^T(i,j)(t)$, and hence $\tau^T(t)$, $\text{Thr}^T(t)$ and $p^T(t)$, are now evaluated as

$$\text{Thr}^T(t) = \frac{1}{M} \sum_{j=0}^{M-1} \frac{\tau^T(t) P^{\text{allM}}_{\text{noTx}}(t) P^{\text{allD}}_{\text{noTx}}(t)}{E_s(t)(1 - \tau^T(t))}, \quad (44)$$

and

$$p^T(t) = \frac{1}{M} \sum_{j=0}^{M-1} \frac{P^{\text{allM}}_{\text{noTx}}(t) P^{\text{allD}}_{\text{noTx}}(t)}{1 - \tau^T(t)}, \quad (45)$$

TABLE I
SIMULATION SETTINGS

Channel Occupancy Time			10 ms
Idle Period			20 ms
Slot time σ	9 μs	basic rate	2 Mbps
SIFS	16 μs	ACK	20 byte
DIFS	34 μs	data rate	72.2 Mbps
Preamble	96 μs	headers	64 byte
W_0	16	payload	500 byte
W_m	512		

where $E_s(t)$ is the expected duration of a MAC slot, if it were to commence at time t, given by

$$E_s(t) = \sigma P_{\text{noTx}}(t) + T_{\text{Tx}}(1 - P_{\text{noTx}}(t)), \tag{46}$$

and in turn, $P_{\text{noTx}}(t)$ is the probability of no device transmitting during a MAC slot that commenced at time t, such that

$$P_{\text{noTx}}(t) = P_{\text{noTx}}^{\text{allM}}(t) P_{\text{noTx}}^{\text{allD}}(t). \tag{47}$$

E. Solution 3: Randomly spread IoT commencements

Assume now that the IoT devices that receive their single new packet during the Channel Occupancy Period have been programmed to wait a random time from the end of the LTE block transmission, selected uniformly over $[0, T_{IP})$, before commencing their backoff-transmission process and that if their packet is still unsuccessfully transmitted after a further T_{FFP} it is dropped. Instead of there being a burst of MTC packets at the beginning of the Idle Period, all the MTC packets from the M IoT devices now effectively arrive throughout the Idle Period, with uniform distribution. To reflect this change to the IoT device arrival process, (10) becomes

$$P_{fan,k}^{M}[i] = \begin{cases} E_{s,k}/T_{IP}, & i = 0, k > 0, \\ p_k^M S_k^M(i-1, 0), & i > 0, k > 0, \end{cases} \tag{48}$$

and (24) becomes

$$S_1^M(i,j) = S_f^M(i,j), \quad i \geq 0, j = 0, .., W_i - 1. \tag{49}$$

IV. PERFORMANCE EVALUATIONS

The Markov models developed in the previous section were validated against simulations performed in R [19], using the system parameters summarized in Table I, setting N = 10 Wi-Fi stations and M = 20 IoT devices, and running the simulations for 100,000 Fixed Frame Periods. These system parameters correspond to the IEEE 802.11n(20MHz) standard. All packets were assumed to have 500 byte payloads, giving $T_{\text{Tx}} = 288\mu s$. The contention windows used for the CSMA/CA processes was $W_0 = 16$, $m = 5$ and $s = 7$. The performance degradation caused by uncontrolled MTC access is quantified, the effectiveness of the potential solutions are evaluated, and a proposal is put forward. For Solution 3: Randomly spread IoT commencements, it is assumed that the IoT devices can sense the Idle Period within a few FFPs and that they do so when joining the network.

A. Model validation for uncontrolled IoT Access

The model developed in Section III-B aims to characterise the high contention caused by uncontrolled IoT access. The model results are shown in Fig. 2. Fig. 2a shows the collision probability for the Uncontrolled sytem of Section III-B for the settings just given. The solid red line and dotted black line are the modelled collision probability for the saturated Wi-Fi STAs and IoT devices respectively. The red circles and black crosses are the corresponding simulated collision probabilities. The horizontal dashed grey line is the collision probability for the network with with no IoT devices active (i.e. just the N Wi-Fi STAs), obtained from Bianchi's saturated-network model [13]. Our model closely matches the simulation results and demonstrates the increased collision probability at the begining of the Idle Period, which is 40% higher than at the end of the Idle Period.

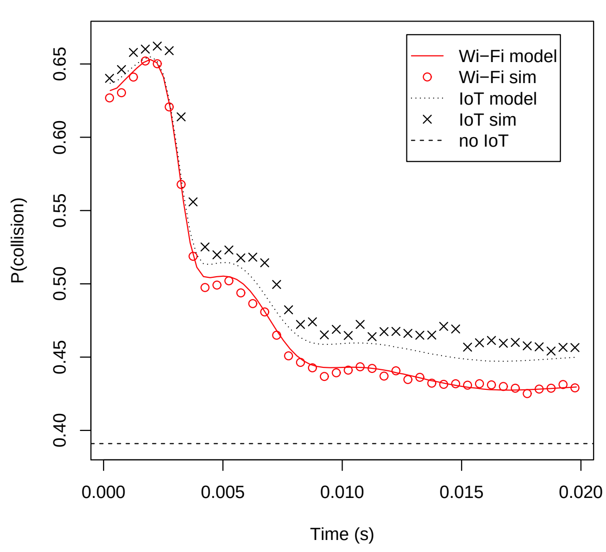
Fig. 2b shows the throughput (in packets/s/STA) for the same settings as for Fig. 2a. The dot-dashed blue line is the modelled total throughput (from both Wi-Fi STAs and IoT devices) divided by N (in packets/s/STA) and the blue +'s are the values obtained from the simulation. The close match between the model and simulation results is again apparent. Our model demonstrates that there is a significant drop in Wi-Fi throughput and in overall throughput at the start of the Idle Period, as a result of the high contention caused by simultaneous MTC access. By the end of the Idle Period, the Wi-Fi throughput is more than twice its lowest value and the total throughput plateaus at 30% above its lowest value.

The first potential solution for the high-contention problem, presented in Section III-C, was to increase the contention window size for IoT access. The Markov model for this solution required only minor modification to the uncontrolled IoT access model. We confirm that the results match the simulation results, with the collision probability and average throughput given by the Markov model and the simulation agreeing within approximately 3%, using the validation settings. Due to space limitations, graphs will not be presented here.

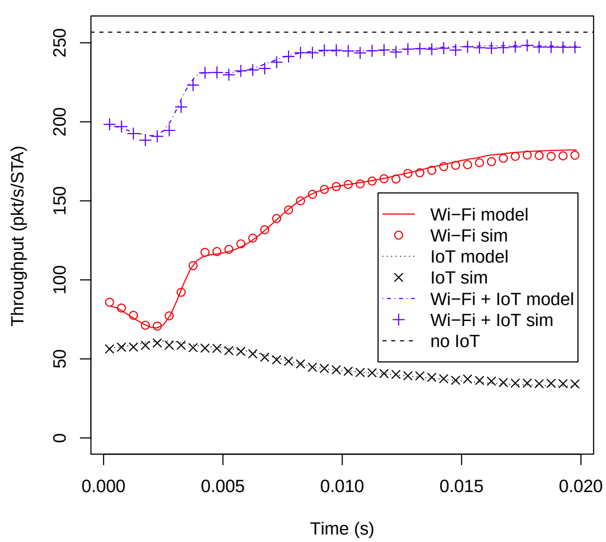
B. Model Validation for Spreading IoT Access (Solutions 2 & 3)

In Sections III-D and III-E, we presented two solutions that spread the IoT accesses equally (Section III-D), or randomly (Section III-E) throughout the Idle Period in order to reduce the high contention.

Fig. 3a and Fig. 3b show the collision probability and throughput obtained when the MTC transmission starting times are equally spaced through the Idle Period (Solution 2) for the same settings as for Fig. 2a. The repeated sawtooth throughput pattern per TDMA slot in the simulation is closely reproduced by the model. When the MTC transmission starting times are instead uniformly randomly started through the Idle Period (Solution 3), again under the same settings, the average collision probabilities and throughputs given by the model and simulation are constant through the Idle Period. Average model collision probabilities and throughputs have been included in Fig. 3a and Fig. 3b as green horizontal dashed lines, which cut

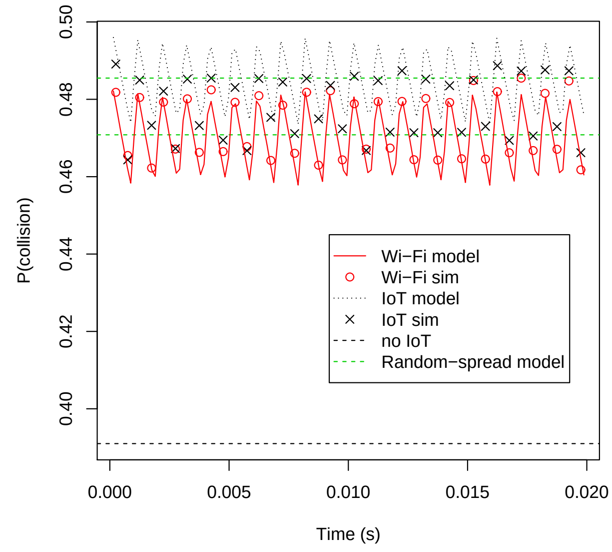


(a) Collision probability

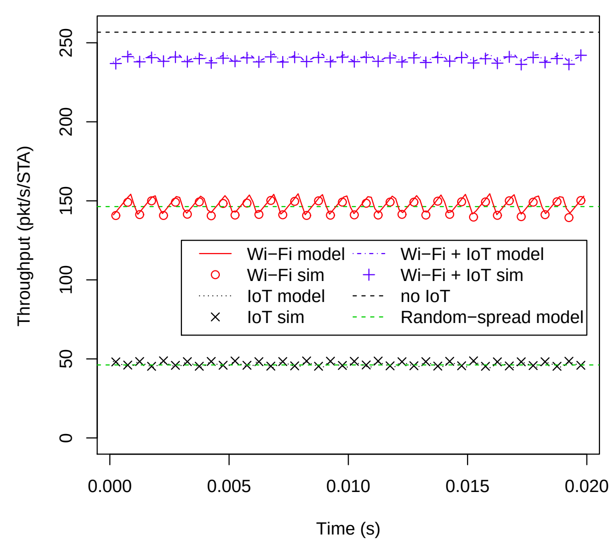


(b) Throughput

Fig. 2. Model validation for Uncontrolled IoT access. N = 10, M = 20



(a) Collision probability



(b) Throughput

Fig. 3. Model validation for Equally spaced IoT packet starts solution. N = 10, M = 20.

through the periodic patterns of the equally-spaced IoT-start model.

Compared to the uncontrolled scenario, the system properties provided by Solutions 2 and 3 are more constant through the LAA Idle Period. In particular, the high contention at the beginning of the LAA Idle Period in Fig. 2a for the uncontrolled IoT access is avoided. The collision probability is reduced from 0.66 for the uncontrolled access (Fig. 2a) to around 0.49 for Solution 2 and Solution 3 (Fig. 3a). This represents a 26% reduction in the collision probability. Such reduced contention lifts the throughput from 200 pkt/s/STA in Fig. 2b to a close-to-stationary total throughput of 240 pkt/s/STA (Fig. 3b) for Solution 2 and Solution 3, giving an increase of 20%. The percentage gain varies with the numbers of IoT devices and Wi-Fi STAs active, as presented in the next section.

C. Solution comparison

We compare the solutions presented in Section III using the Markov chain models developed therein and validated above. The model average throughputs closely matched the simulation average throughputs, so the models were used to compare the throughputs of the different solutions across a range of the number of IoT devices, M, for $N = 20$ Wi-Fi stations. Fig. 4 compares the average Total (Wi-Fi plus MTC) throughput normalised by the average Wi-Fi throughput in the absence of any IoT devices. To gain insights into the performance comparisons, the total throughput of Fig. 4 is decomposed into Wi-Fi and MTC compoenents in Fig. 5. Fig. 5a presents the average Wi-Fi throughput, normalised by the average throughput in the absence of any IoT devices and Fig. 5b presents the MTC throughput, as a proportion of the offered MTC load.

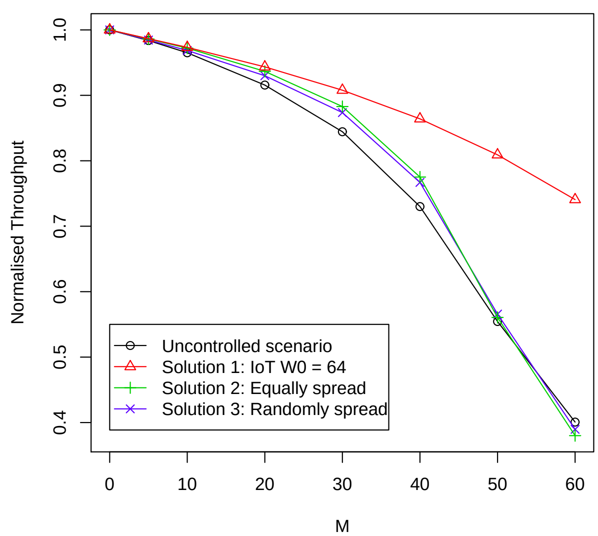
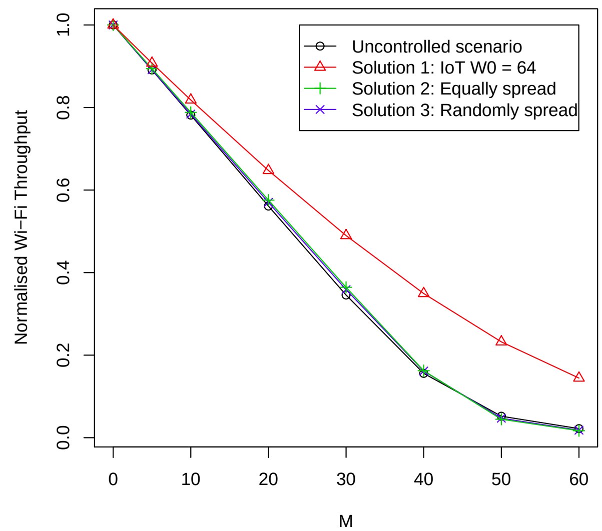


Fig. 4. Normalised average total throughput (Wi-Fi plus IoT) over different M and protocol variations, for $N = 10$.

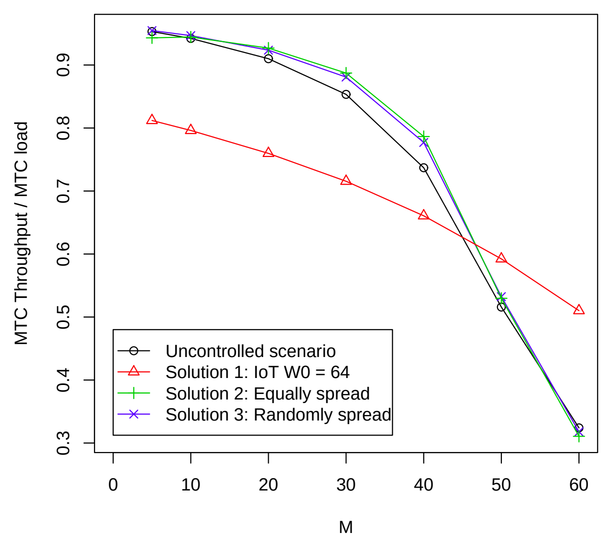
Fig. 4 shows that all the methods considered for controlling the contention improve the average total throughput over the uncontrolled scenario. Increasing W_0 of the IoT devices to 64 increases the total throughput more than the other presented solutions; however, as demonstrated by Fig. 5b, it does so at a substantial expense to the MTC throughput. In contrast, equally spacing the MTC starts through the Idle Period increases both the average Wi-Fi throughput and the average MTC throughput, as demonstrated by Fig. 5a and Fig. 5b respectively. The average throughputs obtained by randomly spreading the MTC starts through the Idle Period are very similar to, though predominantly slightly less than, those obtained by equally spacing the MTC starts through the Idle Period.

D. Discussion and Proposals

This last presented solution: randomly spreading the IoT starts through the LAA Idle Period, is a distributed protocol. It improves the system performance and is practical. In its operation, when a packet arrives at an IoT device during the Channel Occupancy Time, rather than using the standard CSMA/CA Wi-Fi protocol, the initiation of the backoff-transmission process is delayed beyond the beginning of the



(a) Average Wi-Fi Throughput normalised by the average throughput achieved with no active IoT devices.

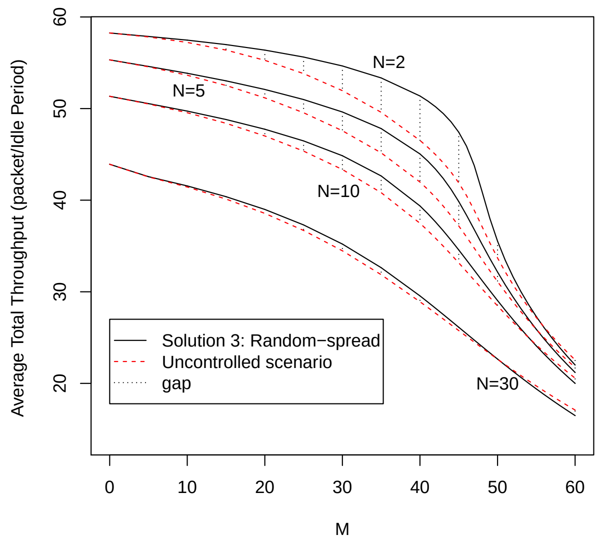


(b) Proportion of IoT offered load sent (IoT Throughput / IoT load).

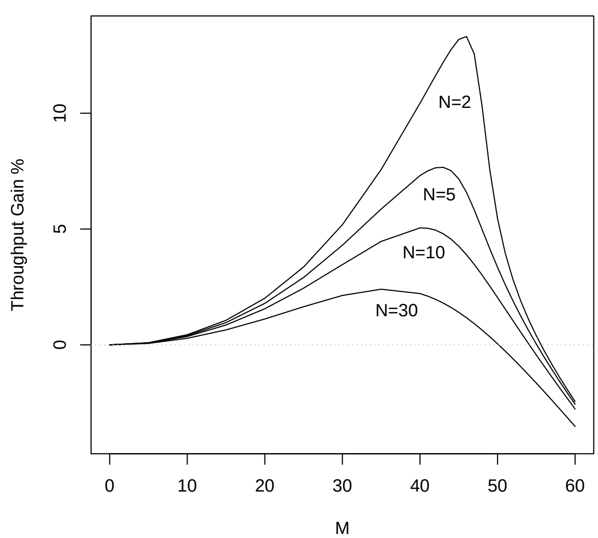
Fig. 5. Measures of average throughput decomposed into Wi-Fi and IoT components, for different M and protocol variations, for $N = 10$.

Idle Period an additional random time, selected uniformly over the Idle Period.

The throughput obtained by randomly spreading the IoT starts (Solution 3), is compared to the Uncontrolled scenario in Fig. 6, for a range of N and M. Fig. 6a presents the average total throughput per Idle Period for the Uncontrolled scenario (red dashed line) and the Randomly-spread-MTC-starts solution (black solid line), with vertical (black dotted) lines connecting the two scenarios for the same N and M values. The vertical lines represent the additional average



(a) Average total throughput for Solution 3 and Uncontrolled scenario



(b) Throughput gain (%) of Solution 3 compared to Uncontrolled scenario

Fig. 6. Throughput and gain for Solution 3: Randomly-spread IoT starts

throughput obtained by implementing randomly-spread MTC starts over the Uncontrolled scenario. This gain is presented as a percentage gain in Fig. 6b.

The model can be used to explore different network settings and loads. For the network settings we have used and with $N = 5$, for example, the drop-off in average total throughput is much less severe when the IoT devices use randomly spread starts (Solution 3). Even with $M = 30$ IoT devices, there is little drop-off in the average total throughput.

The highest percentage gains for our network settings are made for M in the range 44 to 53, depending on N, with the highest average total througput percentage gain being 13% for $N = 2$ and $M = 46$.

The randomly spread MTC start solution produces throughput gains for loads up to $N = 30$ Wi-Fi stations and $M = 50$ IoT devices. Although the network will perform miserably when trying to support $M = 50$ IoT devices, even in the absense of contention, using randomly-spread IoT starts will help.

Our modelling has assumed fixed numbers of saturated Wi-Fi stations and IoT devices are active during each Fixed Frame Period. In practice, their numbers will vary, however, for a given number of each, our modelling shows that delaying the MTC starts for a random time, selected from a uniform distribution over the Idle Period, will increase the average throughput for both the IoT and Wi-Fi streams, relative to just applying the standard CSMA/CA Wi-Fi protocol, and that the average throughput achieved will be very close to the logically-lowest-peak-congestion case of equally spacing the MTC starts through the Idle Period.

We briefly report on the findings obtained from a limited number of simulations for unsaturated Wi-Fi traffic. We use the normalised offered load, λ, to specify the Wi-Fi load, where $\lambda = 1$ corresponds to the maximum Wi-Fi load that could be transmitted if every MAC slot were a successful Wi-Fi transmission. For the settings used in Fig. 2 and Fig. 3, the Wi-Fi traffic becomes saturated for $\lambda \gtrsim 0.3$. For unsaturated Wi-Fi loads, instead of the Wi-Fi STAs always having a packet queued in their input buffers, there is a chance of no packet being queued at the end of the LTE Idle period, and the probability of a packet being queued increases through the LTE Channel Occupancy Time, in a similar fashion as for the IoT devices. This effect adds to the congestion at the start of the LTE Idle period and reduces the congestion towards its end.

On the other hand, for pure Wi-Fi systems, the maximum throughput occurs for slightly undersaturated loads, producing a slightly higher throughput [15]. This effect occurs in the IoT plus Wi-Fi scenario as well, with the total (IoT plus Wi-Fi) throughput increasing, for the settings used in Fig. 2 and Fig. 3, from 47.2 pkt/FFP for saturated Wi-Fi loads ($\lambda \gtrsim 0.3$) to 48.1 pkt/FFP for $\lambda = 0.28$.

For $\lambda = 0.2$ and $\lambda = 0.1$, the total (IoT plus Wi-Fi) throughput decreased to 40.7 pkt/FFP and 30.6 pkt/FFP respectively, allowing the network to accommodate more IoT devices. Adding 7 and 16 IoT devices per FFP respectively achieved a maximum total (IoT plus Wi-Fi) throughput of 46.4 pkt/FFP and 44.7 pkt/FFP respectively. By randomly spreading the IoT commencements through the Idle period, the total (IoT plus Wi-Fi) throughputs for the same settings were increased to 47.6 pkt/FFP and 46.3 pkt/FFP respectively.

V. Conclusion

The presence of the relatively long LTE data blocks within the proposed LAA framework causes an effectively bursty packet arrival process during the contention-based Idle Period in LAA. Simulations show that such bursty arrivals give rise to temporarily high congestion and reduce the overall system throughput. However, existing Markov models are unable to characterise such time-varying contention behaviour.

We developed an embedded Markov model to characterise the time-varying contention behaviour caused by the bursty MTC traffic. We then presented, modelled and validated three possible solutions to reduce the temporary high contention: increasing the contention window for the IoT devices; scheduling the accesses of the IoT devices through TDMA over the Idle Period; and randomly spreading the MTC accesses over the Idle Period. The first solution increased the total system throughput, but at the cost of significant MTC data loss. The second solution improved both the Wi-Fi and MTC throughput, but required a centralised scheduling, which is impractical. The third, random spreading, solution was a practical distributed scheme. It achieved an increase in system throughput of almost as much as the TDMA scheme. The proposed random spreading solution produced a 25% reduction in collision probability and a 25% lift to the instantaneous network throughput for a typical setting of 10 saturated Wi-Fi stations and 20 active IoT devices. The proposed solution achieves up to 13% system throughput gain for the coexistence of Machine type communications with Wi-Fi data traffic under Frame-based LBT.

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