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An analytical framework of a C-RAN supporting random, quasi-random and bursty traffic

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ABSTRACT

We consider a cloud radio access network (C-RAN) where the baseband signal processing servers, named baseband units (BBUs) are separated from the remote radio heads (RRHs). The RRHs form a single cluster while the BBUs form a pool of resources. Each RRH may accommodate random (Poisson) or quasi-random or bursty traffic. The latter is approximated via the compound Poisson process according to which batches of calls, with a generally distributed batch size, follow a Poisson process. A call requires a computational resource and a radio resource unit from the BBUs and the serving RRH, respectively. If any of the two units is unavailable, call blocking occurs. Otherwise, the new call is accepted in the RRH. We model this C-RAN as a loss system and study two different cases: i) all RRHs accommodate bursty traffic and ii) some RRHs accommodate random traffic, some quasi-random traffic and the rest RRHs accommodate bursty traffic. In both cases, we show that a product form solution exists for the steady state probabilities and propose efficient convolution algorithms for the accurate calculation of time and call congestion probabilities. The accuracy of these algorithms is verified via simulation.

1. Introduction

Teletraffic modelling is considered as a fundamental element of the information and communication technology infrastructure. The main task of teletraffic loss/queueing models is the determination of the essential quality of service (QoS) parameters including congestion probabilities and network resource utilization. This task is complicated in fifth generation (5G) networks because of the tremendous traffic growth, the necessity to support demanding applications (e.g., mobile cloud computing, mobile video streaming) [1] and the heterogeneity of traffic streams [2]. The latter requires research on call or packet-level teletraffic loss/queueing models based on traffic streams.

On call-level, the simplest arrival process, adopted in teletraffic theory, is the random or Poisson process since it results in efficient formulas for the computation of call blocking probabilities (CBP). The main disadvantage of this call-arrival process is that it cannot describe the smoother quasi-random process which is adopted when a finite number of sources (herein mobile users (MUs)) generates calls [3] and bursty traffic which will play a dominant role in 5G networks [4,5]. Bursty traffic can be well described via the compound Poisson process where batches of one or more calls, with a generally distributed batch size, arrive at time points that are exponentially distributed. For applications of this process in queueing or loss systems, the interested reader may resort to [6–13].

We consider the case of a cloud radio access network (C-RAN) that accommodates a mixture of random, quasi-random and compound Poisson traffic. The C-RAN architecture is a quite promising 5G network architecture [14]. It consists of distributed base stations (BSs) where the baseband signal processing servers, named herein baseband units (BBUs) are separated from the remote radio heads (RRHs). The RRHs are connected to the BBUs, which are organized as a pool of data center resources, via the common public radio interface (CPRI) with a fronthaul of high-capacity [15]. The BBUs are connected to the evolved packet core (EPC) via a backhaul connection (see Fig. 1). Generally speaking, BBU pooling not only supports upper layer functionalities and the dynamic allocation of the BBU processors (resources) among RRHs but also helps in the reduction of: a) the processors needed for baseband processing in comparison to the conventional RAN, b) capital and operational expenditure of mobile network operators and c) power consumption compared to conventional BSs [16,17].

We assume that BBU resources are virtualized (V-BBU) in order to benefit from the virtualization of the BBU functions [18]. A function that

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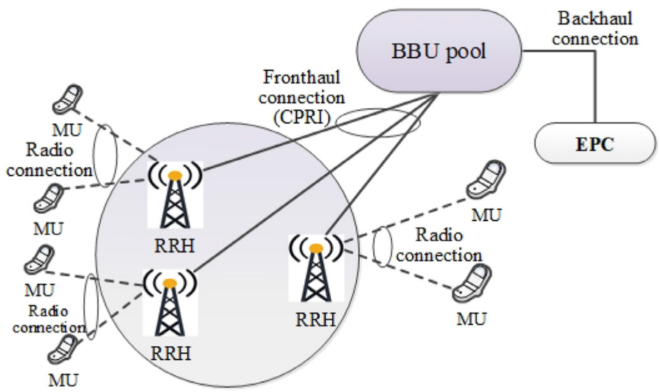

Fig. 1. The C-RAN architecture.

can be virtualized (as a virtual network function) is the radio resource management which is responsible not only for the allocation of radio resources but also for the call admission control (CAC) of MUs. CAC is a critical QoS mechanism that provides access to the resources required by MUs and ensures fairness among mobile applications that compete for available resources. By taking into consideration call-level traffic in the C-RAN, such a QoS mechanism is a resource sharing policy since it significantly affects CBP.

During the last few years various features of the C-RAN architecture have been studied including energy and cost saving issues [19–21], functional splits on the fronthaul network [22,23] and security issues [24,25]. However, very few papers exist in the literature that study CAC and propose efficient formulas for the CBP calculation in the C-RAN [26–30].

In the model proposed in [26], named single-class-single-cluster (SC-SC) model, the C-RAN services calls from a single service-class and the RRHs are grouped in a cluster. The adopted call arrival process in each RRH is the Poisson process. The acceptance of a new call in a RRH relies on the simultaneous availability of two different types of resources: i) a computational resource unit from the V-BBU and ii) a radio resource unit from the serving RRH. If these resources are unavailable, then the new call is blocked. Otherwise, the call remains in the serving RRH for a service time which is generally distributed. The analysis of the SC-SC model, although complex since the corresponding Markov chains are multidimensional, results in reversible Markov chains, a fact that is important in order to obtain the steady-state probabilities via a product form solution (PFS). The latter leads to an accurate determination of blocking probabilities either via recursive formulas or via the complex procedure of state space enumeration/processing. In [27,28], the SC-SC model is studied under the assumption that a finite number of MUs is serviced in each RRH. We name this model finite SC-SC (f-SC-SC) model. The extension of [26] that analyzes the case where the RRHs are grouped (in terms of their capacity in radio resource units) in two or more clusters is presented in [29].

In this paper, we initially extend the SC-SC model by considering that all RRHs serve bursty traffic modelled via the compound Poisson process. The proposed model is named compound SC-SC (c-SC-SC) model. Secondly, we generalize the SC-SC model by considering that a part of the single cluster consists of RRHs that serve Poisson (random) traffic, another part consists of RRHs that serve quasi-random traffic while the rest RRHs serve bursty traffic. We name the proposed model generalized SC-SC (g-SC-SC). More specifically, our contribution is the following: 1) we show that the proposed loss models (c-SC-SC and g-SC-SC) can be described via a continuous time Markov chain and that a PFS exists for the steady-state probability distribution, 2) we propose a brute force (BF) evaluation method for the congestion probabilities calculation in both models, 3) we propose an efficient convolution algorithm in order to determine the congestion probabilities in both models; such an algorithm

Table 1
List of abbreviations.

BBUs	Baseband units
BSs	Base stations
BF	Brute force
CAC	Call admission control
CBP	Call blocking probabilities
CC	Call congestion
CPRI	Common public radio interface
C-RAN	Cloud radio access network
c-SC-SC	Compound SC-SC
EPC	Evolved packet core
f-SC-SC	Finite SC-SC
FA	Fronthaul Aggregator
FAL	Fronthaul aggregated link
GB	Global balance
g-SC-SC	Generalized SC-SC
LB	Local balance
MUs	Mobile users
PFS	Product form solution
QoS	Quality of service
RRHs	Remote radio heads
SC-SC	Single-class-single-cluster
TC	Time congestion
V-BBU	Virtualized BBU

reduces the computational complexity of the models and therefore can be used in network planning procedures, 4) we compare the analytical results of the proposed models with those obtained via the SC-SC and the f-SC-SC models and verify, via simulation, the high accuracy of the proposed algorithms, 5) we include the constraint of the fronthaul capacity in the basic SC-SC model and provide formulas for the CBP determination.

The remainder of this paper is as follows: In Section 2, we present the related work for loss/queueing or simulation models applied in C-RAN. In Section 3, we propose the c-SC-SC model, provide a proof for the PFS of the steady-state probabilities (Section 3.1), a BF evaluation method (Section 3.2) for the determination of congestion probabilities and a convolution algorithm for the calculation of the various performance measures (Section 3.3). In Section 4, we propose the g-SC-SC model and provide the PFS for the steady-state probabilities (Section 4.1) and a BF evaluation method (Section 4.2) for the calculation of congestion probabilities. In Section 5, we propose a convolution algorithm for the calculation of the performance measures in the g-SC-SC model and also show the relationship between the g-SC-SC model and the SC-SC, f-SC-SC and c-SC-SC models. In Section 6, we present simulation and analytical results for the congestion probabilities of the proposed c-SC-SC and g-SC-SC models and compare them with the analytical results of the SC-SC and f-SC-SC models. In Section 7, we show how the additional constraint of the fronthaul capacity can be included in the basic SC-SC model. We conclude in Section 8. For the reader's convenience, we include in Table 1 the list of abbreviations used in this paper.

2. Related work

In the literature, there exist various analytical or simulation based models that study the C-RAN architecture from different aspects (see e.g., [30–42]). To briefly describe these models we classify them according to their main focus, in: a) models related to RRHs [30–32], b) models related to BBUs [33–39] and c) models related to the fronthaul network [40–42].

In [30,31], the SC-SC model is extended to include the analysis of overlapping cells. Such an analysis is based on the theory of a direct routing network [43]. The authors of [30,31] claim that their model has a PFS and propose a convolutional algorithm in order to decrease the complexity of the CBP determination. However, neither the PFS nor a detailed description of the convolution algorithm for their proposed C-RAN model is presented. In [32], it is assumed that Poisson arriving calls may wait to be served in RRHs. To this end, an analytical model is proposed for the computation of queueing delay and possible energy savings.

Contrary to the SC-SC model of [26], in [33], a statistical multiplexing gain analysis of the computational resource units based on a joint temporal-spatial traffic distribution model is proposed. More precisely, the authors consider that the mobile data traffic is distributed both in the space and time domains and propose a formula for the statistical multiplexing gain and an approximation of closed-form when the spatial traffic is lognormally distributed. However, the authors do not study the effect of their proposal in CBP and therefore do not provide formulas for the CBP determination. To overcome the limited number of BBUs, the authors of [34] study a scheduling mechanism in order to model the cooperation between the edge cloud and the remote (Internet) cloud which has sufficient computational resource units. To this end and assuming heavy traffic-load conditions, the local cloud executes delay-sensitive applications, while delay-tolerant applications are offloaded to the remote cloud. The BBUs are modeled as an $M/M/T$ system that incorporates preemptive priorities where T is the number of computational resource units. Regarding priorities, an application that requires smaller delay receives higher priority. A similar architecture is considered in [35], but the focus is given in the number of computational resource units that should be deployed in the edge cloud in order to maximize its profit. In [36], a scheme for evaluating the energy-efficiency of a C-RAN architecture is studied based on simulation. The authors focus on reducing the BBUs by matching the amount of baseband processing load with respect to the traffic load generated in each RRH. To this end, the baseband tasks from cells are mapped into computing processing in giga operations per second. Then, the computing resource requirement per user per task is determined according to the energy consumption model of [44]. The latter, provides energy modelling for macro, micro, pico and femto BSs. In [36], an RRH is represented via a micro BS. An extension of [36] where idle BBUs are switched off so as to reduce the overall network energy consumption is proposed in [37]. In [38] and [39], the concept of dividing 5G networks into slices and form isolated virtual networks, is studied. More precisely, in [38], slices service Poisson arriving calls of similar characteristics and therefore the dimensioning of each slice can be accomplished independently and appropriately to the accommodated streams. The analytical queueing/loss models proposed in [38] can be used for the determination of CBP (in each slice) as well as the average delay for service. In [39], a queueing model is proposed for the analysis of 5G network slicing. The model consists of three sequential queueing subsystems involving the C-RAN, a mobile edge computing, and a cloud data center. Each subsystem accommodates Poisson traffic under an exponentially distributed service time. In addition, each queueing subsystem has a finite buffer.

In [40,41], the notion of functional splits on the fronthaul network is considered. Functional split is a technique whereby the required fronthaul rate can be reduced by placing some network and baseband functions at RRHs. The cost of this technique is higher processing complexity and more energy consumption at RRHs. The authors of [40] study how to select the optimal functional split schemes, and the corresponding transmission duration and power of each scheme in order to maximize the throughput, given the average fronthaul rate in the C-RAN. In [41], an energy efficient mode switching mechanism with functional splitting is proposed. According to this mechanism, a controller decides the modes of the RRHs (sleep or active modes) together with the splitting level between the BBU and the RRH by taking into account the renewable energy levels and populations of RRHs. For a recent survey in functional splits the interested reader may resort to [23]. Finally, in [42], the concept of a fronthaul with variable rate is considered. The authors propose a mathematical model based on queueing theory for the determination of blocking probability at the fronthaul.

The abovementioned papers mainly consider the C-RAN architecture (either from an analytical or a simulation point of view) under the assumption of the classical Poisson arrival process. In this paper, we consider the co-existence of more complicated arrival processes such as the compound Poisson process and the quasi-random process and propose efficient convolution algorithms for the determination of congestion probabilities.

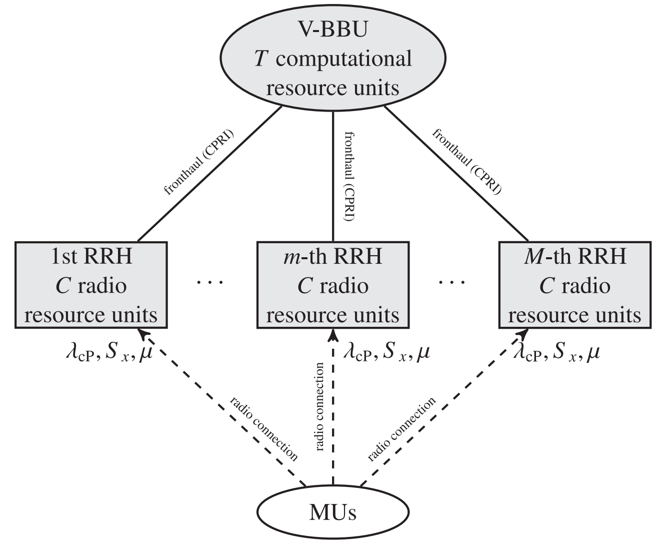

Fig. 2. The proposed c-SC-SC model.

3. The proposed compound poisson SC-SC model

3.1. The analytical model

In Fig. 2, we consider the C-RAN model where the V-BBU, which consists of T computational resource units, is separated from the M RRHs that accommodate compound Poisson traffic. Each RRH consists of C radio resource units. Both the computational and radio resource units are allocated to the accepted calls.

New batches of calls arrive in the C-RAN via a compound Poisson process with rate λ_{cP}. Assume that a new batch contains x ($x \geq 1$) calls and let S_x be the corresponding probability. Each of these calls is treated independently from the rest calls of the batch. This means that depending on the available computational and radio resource units, one or more of the x calls can be accepted in the serving RRH while the rest calls are blocked and lost. An arriving call requires a computational resource unit from the V-BBU and a radio resource unit from the serving RRH. If both resource units are available then the call can be accepted in the serving RRH for an exponentially distributed service time of mean μ^{-1}. Otherwise, the call is blocked and lost.

To analyze the proposed c-SC-SC model, we initially show that the steady-state probability distribution $P(\boldsymbol{n})$ has a PFS, where $\boldsymbol{n} = (n_1, \ldots, n_m, \ldots, n_M)$ is the steady-state vector that describes the number of calls in the M serving RRHs and n_m is the number of calls in the m-th RRH. Contrary to the SC-SC model of [26] where a PFS can be derived due to the fact that local balance (LB) exists between states $\boldsymbol{n}_m^- = (n_1, \ldots, n_m - 1, \ldots, n_M)$ and $\boldsymbol{n}$, in the c-SC-SC model the LB notion as adopted in [26] does not hold since calls arrive as batches. However, in the proposed model it can be shown that there exists a LB form across particular levels that leads to a PFS for the steady-state probability distribution $P(\boldsymbol{n})$.

To this end, for each state consider the level $L_{\boldsymbol{n}}^{(m)}$ which separates this state from the state $\boldsymbol{n}_m^+ = (n_1, \ldots, n_m + 1, \ldots, n_M)$ from $\boldsymbol{n}$. This level can be crossed either due to an arrival of a new batch of calls in the m-th RRH or because a call departs from the m-th RRH due to service completion. We start by considering the arrival of a batch of calls. Then,

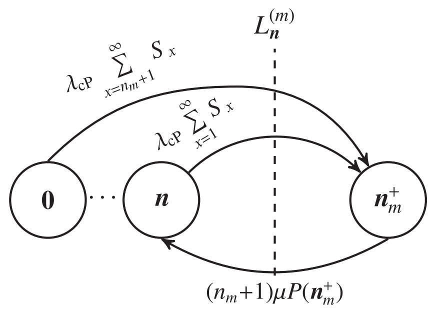

Fig. 3. LB in the c-SC-SC model.

the 'upward' probability flow across $L_{\boldsymbol{n}}^{(m)}$ is determined via

$$f^{(upw)}(L_{\boldsymbol{n}}^{(m)}) = \sum_{z=0}^{n_m} P(\boldsymbol{n}_m^{-z})\lambda_{cP} \sum_{x=z+1}^{\infty} S_x, \tag{1}$$

where $\boldsymbol{n}_m^{-z} = (n_1, \ldots, n_m - z, \ldots, n_M)$ and $P(\boldsymbol{n}_m^{-z})$ is the corresponding steady state probability.

Consider now that the system is in state $\boldsymbol{n}_m^+$ and examine the completion of a call in the m-th RRH. In that case, the 'downward' probability flow across $L_{\boldsymbol{n}}^{(m)}$ is determined via

$$f^{(dw)}(L_{\boldsymbol{n}}^{(m)}) = (n_m + 1)\mu P(\boldsymbol{n}_m^+). \tag{2}$$

Via (1) and (2), we obtain the LB equation across $L_{\boldsymbol{n}}^{(m)}$ for calls that are related to the m-th RRH (see also Fig. 3)

$$f^{(upw)}(L_{\boldsymbol{n}}^{(m)}) = f^{(dw)}(L_{\boldsymbol{n}}^{(m)}) \quad \text{or}$$

$$\sum_{z=0}^{n_m} P(\boldsymbol{n}_m^{-z})\lambda_{cP}\hat{S}_z = (n_m + 1)\mu P(\boldsymbol{n}_m^+), \tag{3}$$

where $\hat{S}_z = \sum_{x=z+1}^{\infty} S_x$ refers to the complementary batch size distribution.

By considering that state $\boldsymbol{n}$ is in the bound of the state space $\boldsymbol{\Omega}$, then the state $\boldsymbol{n}_m^+$ does not belong to $\boldsymbol{\Omega}$ and therefore both $f^{(upw)}(L_{\boldsymbol{n}}^{(m)})$ and $f^{(dw)}(L_{\boldsymbol{n}}^{(m)})$ are equal to zero.

Apart from the LB equation of (3), we also define the corresponding global balance (GB) equation for state $\boldsymbol{n}$ and the m-th RRH

$$f^{(upw)}(L_{\boldsymbol{n}_m^-}^{(m)}) + f^{(dw)}(L_{\boldsymbol{n}}^{(m)}) = f^{(upw)}(L_{\boldsymbol{n}}^{(m)}) + f^{(dw)}(L_{\boldsymbol{n}_m^-}^{(m)}). \tag{4}$$

The first (left) term of (4) refers to the 'upward' probability flow towards state $\boldsymbol{n}$ due to an arrival of a batch of calls. The next term refers to the 'downward' probability flow into state $\boldsymbol{n}$ (from state $\boldsymbol{n}_m^+$) due to a call departure. The third term refers to the 'upward' probability flow out of state $\boldsymbol{n}$ due to an arrival of a batch of calls. Finally, the fourth term of (4) refers to the 'downward' probability flow out of state $\boldsymbol{n}$ (towards state $\boldsymbol{n}_m^-$) due to a call departure.

Summing over all RRHs yields the GB equation for state $\boldsymbol{n}$

$$\sum_{m=1}^{M} \left[f^{(upw)}(L_{\boldsymbol{n}_m^-}^{(m)}) + f^{(dw)}(L_{\boldsymbol{n}}^{(m)}) \right] = \sum_{m=1}^{M} \left[f^{(upw)}(L_{\boldsymbol{n}}^{(m)}) + f^{(dw)}(L_{\boldsymbol{n}_m^-}^{(m)}) \right]. \tag{5}$$

The PFS that satisfies (4) and (5) is presented in the next theorem.

Theorem. The PFS of the steady-state probabilities in the c-SC-SC model is expressed via

$$P(\boldsymbol{n}) = G^{-1}\left(\prod_{m=1}^{M} P_{n_m}^{(m)}\right), \tag{6}$$

where $\boldsymbol{n} = (n_1, \ldots, n_m, \ldots, n_M)$, G is the normalization constant, $G = \sum_{\boldsymbol{n}\in\boldsymbol{\Omega}} \prod_{m=1}^{M} P_{n_m}^{(m)}$, $\boldsymbol{\Omega} = \{\boldsymbol{n} : 0 \le n_1, \ldots, n_M \le C, 0 \le \sum_{m=1}^{M} n_m \le T\}$, and

$$P_{n_m}^{(m)} = \begin{cases} \sum_{z=1}^{n_m} \frac{\alpha_{cP}}{n_m} P_{n_m-z}^{(m)} \hat{S}_{z-1}, & \text{for } n_m \ge 1 \\ 1, & \text{for } n_m = 0 \end{cases}, \tag{7}$$

where $\alpha_{cP} = \lambda_{cP}/\mu$ refers to the offered traffic-load (in erl) in every RRH.

Proof. For the m-th RRH, $1 \le m \le M$, and by assuming that $n_m \ge 1$ and $P_0^{(m)} = 1$ we can uniquely determine the values of $P_{n_m}^{(m)}$ via the formula $P_{n_m}^{(m)} = \sum_{z=1}^{n_m} \frac{\alpha_{cP}}{n_m} P_{n_m-z}^{(m)} \hat{S}_{z-1}$. If we take the product of $P_{n_m}^{(m)}$ for the M RRHs and normalize it, then we can easily verify that the result $P(\boldsymbol{n}) = G^{-1} \prod_{m=1}^{M} P_{n_m}^{(m)}$ satisfies $f^{(upw)}(L_{\boldsymbol{n}}^{(m)}) = f^{(dw)}(L_{\boldsymbol{n}}^{(m)})$ for all $\boldsymbol{n} \in \boldsymbol{\Omega}$. □

Having determined $P(\boldsymbol{n})$ via (6) and (7), the total time congestion probabilities (TC probabilities), B_{tot}^{TC}, can be calculated via

$$B_{tot}^{TC} = B_c^{TC} + B_r^{TC}, \tag{8}$$

where B_c^{TC}, B_r^{TC} refer to the TC events that are related to the insufficient computational and radio resource units, respectively.

Note that TC probabilities can be computed as the proportion of time that the C-RAN has no available resources for the batches of calls.

Based on the PFS of (6) and (7), we can determine B_{tot}^{TC} either via a BF evaluation method (presented in Section 3.2) or via a convolution algorithm (presented in Section 3.3) which is adopted in this paper.

3.2. The proposed BF evaluation method

The values of B_r^{TC} can be computed via the PFS of (6), (7) as

$$B_r^{TC} = \sum_{\boldsymbol{n}\in\boldsymbol{\Omega}_{<T}^{1,C}} P(\boldsymbol{n}), \tag{9}$$

where $\boldsymbol{\Omega}_{<T}^{1,C} = \{\boldsymbol{\Omega}_{<T} \cap \boldsymbol{\Omega}^{1,C}\}$, $\boldsymbol{\Omega}_{<T} = \{\boldsymbol{n} : n_1 + \cdots + n_M < T\}$ while $\boldsymbol{\Omega}^{1,C} = \{\boldsymbol{n} : n_1 = C\}$.

Note that the notation in (9) refers to the 1st RRH. However, since all RRHs have the same capacities C and offered traffic-load α_{cP}, (9) expresses the B_r^{TC} of every RRH.

By denoting as $\boldsymbol{\Omega}_{=T} = \{\boldsymbol{n} : n_1 + \cdots + n_M = T\}$, we can determine the values of B_c^{TC} via

$$B_c^{TC} = \sum_{\boldsymbol{n}\in\boldsymbol{\Omega}_{=T}} P(\boldsymbol{n}). \tag{10}$$

Eqs. (9) and (10) reveal that the determination of B_r^{TC} and B_c^{TC} can be quite complex via the BF evaluation method since it requires enumeration/processing of $\boldsymbol{\Omega}$ (in order to obtain the corresponding blocking states). For a system with many RRHs of large capacities C, the state space $\boldsymbol{\Omega}$ will be extremely large. Thus, the BF evaluation method is mainly useful for small (tutorial) examples.

3.3. The proposed convolution algorithm

Based on the fact that the c-SC-SC model has a PFS, we propose a convolution algorithm, for the efficient computation of congestion probabilities. The algorithm consists of the following 3 steps:

1st step

For the m-th RRH ($m = 1, \ldots, M$), determine the distribution of occupied resource units, $q_m(j)$, via

$$q_m(j) = \begin{cases} \sum_{l=1}^{j} \frac{\alpha_{cP}}{j} q_m(j-l)\hat{S}_{l-1}, & \text{for } j = 1, \ldots, C \\ 0, & \text{for } j > C \end{cases}. \tag{11}$$

Having obtained the values of $q_m(j)$, we normalize them via the constant $G_m = \sum_{j=0}^{C} q_m(j)$ and denote them as $q_m'(j) = q_m(j)/G_m$.

2nd step

Following a sequential convolution for all RRHs, apart from the first one, determine the occupancy distribution

$$Q_{(-1)} = q_2' * \cdots * q_m' * \cdots * q_M'. \tag{12}$$

Based on (12), the convolution operation of two normalized distributions q_u' and q_w', is given by

$$q_u' * q_w' = \left\{ \begin{array}{c} q_u'(0) \cdot q_w'(0), \sum_{x=0}^{1} q_u'(x) \cdot q_w'(1-x), \\ \ldots, \sum_{x=0}^{T} q_u'(x) \cdot q_w'(T-x) \end{array} \right\}. \tag{13}$$

The convolution operation of q'_u and q'_w may not lead to a normalized distribution. Thus, the normalization of the results of $q'_u * q'_w$ via the constant, $G_{u,w}$, is recommended.

3rd step

Based on the convolution operations of the previous step, calculate the values of B_{tot}^{TC} as follows:

$$B_{tot}^{TC} = B_r^{TC} + B_c^{TC} = \frac{1}{G}\left(q'_1(C) \sum_{z=0}^{T-C-1} Q_{(-1)}(z) + \sum_{x=0}^{T} Q_{(-1)}(x) q'_1(T-x) \right), \tag{14}$$

where $q'_1(C)$ (already determined in the 1st step) refers to the 1st RRH and the case where the occupied radio resource units equal C while the second term $\sum_{x=0}^{T} Q_{(-1)}(x) q'_1(T-x)$ expresses the (un-normalized) probability that no computational resource units are available. In addition, G refers to the normalization constant of the operation $Q_{(-1)} * q'_1$ determined in the 2nd step via (13).

Via (14), we determine the values of B_{tot}^{TC} for the first RRH. However, since all RRHs have the same capacities C and offered traffic-load α_{cP}, (14) expresses the B_{tot}^{TC} of every RRH.

With the aid of the convolution algorithm we can also determine the call congestion (CC) probabilities in the m-th RRH, $B_{CC}^{(m)}$, which express the proportion of new calls that is blocked in the m-th RRH due to lack of radio or computational resource units. As a general comment, the values of the CC probabilities are higher than those of the TC probabilities in the compound Poisson process. On the other hand, CC and TC probabilities coincide when the Poisson process is considered and are usually named CBP.

To obtain the values of $B_{CC}^{(m)}$, the following formula can be used

$$B_{CC}^{(m)} = \frac{\alpha_{\mathrm{cP}} \hat{S} - \bar{n}_m}{\alpha_{\mathrm{cP}} \hat{S}}, \tag{15}$$

where $\hat{S}$ refers to the average size of new batches that arrive in a RRH and can be determined via $\hat{S} = \sum_{x=1}^{\infty} x \hat{S}_x$, while $\bar{n}_m$ denotes the mean number of calls serviced in the m-th RRH.

As far as the batch size distribution is concerned, it is important to mention the geometric distribution which has the memoryless property as the discrete equivalent of the exponential distribution. In that case, $\hat{S} = (1-\beta)^{-1}$, where β is the parameter of the geometric distribution.

To determine the values of $\bar{n}_m$, we propose the formula

$$\bar{n}_m = \frac{1}{G} \sum_{j=1}^{C} y_m(j) q'_m(j) \sum_{l=0}^{T-j} Q_{(-m)}(l), \tag{16}$$

where $y_m(j)$ expresses the average number of calls of the m-th RRH in state j.

The values of $y_m(j)$ can be computed via

$$y_m(j) = \frac{\alpha_{\mathrm{cP}}}{q'_m(j)} \sum_{l=1}^{j} q'_m(j-l) \hat{S}_{l-1}, \quad \text{for } j = 1, \ldots, C, \tag{17}$$

where $\hat{S}_{l-1} = \beta^{l-1}$ assuming the geometric distribution.

Another performance measure that can also be obtained via (18), is the distribution of the occupied computational resource units

$$\begin{aligned} q'(0) &= Q_{(-1)}(0) \cdot q'_1(0)/G, && j = 0 \\ q'(j) &= \sum_{z=0}^{j} Q_{(-1)}(z) \cdot q'_1(j-z)/G, && j = 1, \ldots, T, \end{aligned} \tag{18}$$

4. The proposed generalized SC-SC model

4.1. The analytical model

In the g-SC-SC model, let M_{inf}, M_{fin} and M_{cP} be the number of RRHs that accommodate Poisson, quasi-random and compound Poisson traffic, respectively. Also let, $M = M_{\mathrm{inf}} + M_{\mathrm{fin}} + M_{\mathrm{cP}}$.

In the case of the M_{inf} RRHs, new calls follow a Poisson process with rate λ_{P} in the m-th RRH, $m = 1, \ldots, M_{\mathrm{inf}}$, while the offered traffic-load is $\alpha_{\mathrm{P}} = \lambda_{\mathrm{P}}/\mu$. In the case of the M_{fin} RRHs, new calls arrive in the m-th RRH, $m = M_{\mathrm{inf}} + 1, \ldots, M_{\mathrm{inf}} + M_{\mathrm{fin}}$ following a quasi-random process with rate $\lambda_{m,\mathrm{F}} = (N_m - n_m)v_{m,\mathrm{F}}$, where N_m and n_m are the finite population of MUs and the number of calls serviced in the m-th RRH, respectively, while $v_{m,\mathrm{F}}$ is the (call) arrival rate per idle MU. The corresponding offered traffic-load per idle MU is $\alpha_{m,\mathrm{idle}} = v_{m,\mathrm{F}}/\mu$. Finally, in the case of the M_{cP} RRHs, new calls arrive as batches in the m-th RRH, $m = M_{\mathrm{inf}} + M_{\mathrm{fin}} + 1, \ldots, M$, via a compound Poisson process of rate λ_{cP} as already described in Section 3.

Regardless of the call arrival process, a new call requires a computational resource unit from the V-BBU and a radio resource unit from the serving RRH. If any of the two resource units is unavailable then call blocking occurs. Otherwise, the call is accepted in the serving RRH for an exponentially distributed service time with mean μ^{-1}.

Let $\boldsymbol{n} = (n_1, \ldots, n_{M_{\mathrm{inf}}}, n_{M_{\mathrm{inf}}+1}, \ldots, n_{M_{\mathrm{inf}}+M_{\mathrm{fin}}}, n_{M_{\mathrm{inf}}+M_{\mathrm{fin}}+1}, \ldots, n_M)$ be the vector of the number of calls serviced in the RRHs. The first part of the vector that ends with $n_{M_{\mathrm{inf}}}$ denotes the number of calls generated via a Poisson process. The part of the vector that starts with $n_{M_{\mathrm{inf}}+1}$ and ends with $n_{M_{\mathrm{inf}}+M_{\mathrm{fin}}}$ denotes the number of calls generated via a quasi-random process, while the last part of the vector that starts with $n_{M_{\mathrm{inf}}+M_{\mathrm{fin}}+1}$ and ends with n_M denotes the number of calls generated via a compound Poisson process. Also denote the steady-state vectors $\boldsymbol{n}_m^- = (n_1, \ldots, n_m - 1, \ldots, n_M)$, $\boldsymbol{n}_m^+ = (n_1, \ldots, n_m + 1, \ldots, n_M)$ and let $P_g(\boldsymbol{n}), P_g(\boldsymbol{n}_m^-), P_g(\boldsymbol{n}_m^+)$ be the corresponding probability distributions of states $\boldsymbol{n}, \boldsymbol{n}_m^-$ and $\boldsymbol{n}_m^+$, for the g-SC-SC model.

To analyze the proposed g-SC-SC model, we initially show that the steady-state probability distribution $P_g(\boldsymbol{n})$ has a PFS. Contrary to [26] where a PFS can be derived for the SC-SC model due to the LB between states $\boldsymbol{n}_m^-$ and $\boldsymbol{n}$, in the proposed g-SC-SC model the notion of LB (as expressed in [26]) does not hold. The reason is that in the g-SC-SC model new calls may arrive not only via a Poisson or a quasi-random arrival process but also in the form of batches. However, in the proposed model it can be shown that there exists a form of LB across certain levels that leads to a PFS for $P_g(\boldsymbol{n})$.

To this end, for each state $\boldsymbol{n}$ consider the level $L_{\boldsymbol{n}}^{(m)}$ which separates the state $\boldsymbol{n}_m^+ = (n_1, \ldots, n_m + 1, \ldots, n_M)$ from $\boldsymbol{n}$. This level can be crossed either: i) due to a Poisson arriving call, or ii) due to a call generated via a quasi-random process, or iii) due to a batch arrival in the m-th RRH or iv) because a call departs from the m-th RRH due to service completion.

Consider initially a Poisson arriving call. Then, the corresponding 'upward' probability flow across $L_{\boldsymbol{n}}^{(m)}$, for $m = 1, \ldots, M_{\mathrm{inf}}$ is expressed by

$$f^{(upw)}(L_{\boldsymbol{n}}^{(m)}) = \lambda_{\mathrm{P}} P_g(\boldsymbol{n}). \tag{19}$$

Consider now the completion of a call serviced in the m-th RRH ($m = 1, \ldots, M_{\mathrm{inf}}$). In that case, the 'downward' probability flow across $L_{\boldsymbol{n}}^{(m)}$ is expressed by

$$f^{(dw)}(L_{\boldsymbol{n}}^{(m)}) = (n_m + 1)\mu P_g(\boldsymbol{n}_m^+). \tag{20}$$

Via (19) and (20), we obtain the LB equation for the level $L_{\boldsymbol{n}}^{(m)}$ and calls that are related to the m-th RRH ($m = 1, \ldots, M_{\mathrm{inf}}$)

$$\lambda_{\mathrm{P}} P_g(\boldsymbol{n}) = (n_m + 1)\mu P_g(\boldsymbol{n}_m^+). \tag{21}$$

We continue by considering a quasi-random arriving call. Then, the corresponding probability flow across $L_{\boldsymbol{n}}^{(m)}$, for $m = M_{\mathrm{inf}} + 1, \ldots, M_{\mathrm{inf}} + M_{\mathrm{fin}}$, is given by

$$f^{(upw)}(L_{\boldsymbol{n}}^{(m)}) = (N_m - n_m) v_{m,\mathrm{F}} P_g(\boldsymbol{n}). \tag{22}$$

Consider now the completion of a call serviced in the m-th RRH ($m = M_{\mathrm{inf}} + 1, \ldots, M_{\mathrm{inf}} + M_{\mathrm{fin}}$). In that case, the corresponding probability flow across $L_{\boldsymbol{n}}^{(m)}$ is given by (20).

Via (22) and (20), we have the LB equation across $L_{\boldsymbol{n}}^{(m)}$ for calls that are related to the m-th RRH ($m = M_{\mathrm{inf}} + 1, \ldots, M_{\mathrm{inf}} + M_{\mathrm{fin}}$)

$$(N_m - n_m) v_{m,\mathrm{F}} P_g(\boldsymbol{n}) = (n_m + 1)\mu P_g(\boldsymbol{n}_m^+). \tag{23}$$

Finally, we consider the arrival of a batch. Then, the 'upward' probability flow across $L_{\boldsymbol{n}}^{(m)}$, for $m = M_{\text{inf}} + M_{\text{fin}} + 1, \ldots, M$ is expressed by

$$f^{(upw)}(L_{\boldsymbol{n}}^{(m)}) = \sum_{z=0}^{n_m} P_g(\boldsymbol{n}_m^{-z})\lambda_{\text{cP}} \sum_{x=z+1}^{\infty} S_x, \tag{24}$$

where $\boldsymbol{n}_m^{-z} = (n_1, \ldots, n_m - z, \ldots, n_M)$ and $P_g(\boldsymbol{n}_m^{-z})$ is the corresponding steady state probability.

Consider now the completion of a call serviced in the m-th RRH ($m = M_{\text{inf}} + M_{\text{fin}} + 1, \ldots, M$). In that case, the corresponding probability flow across $L_{\boldsymbol{n}}^{(m)}$ is given by (20).

Via (24) and (20), we have the LB equation across the level $L_{\boldsymbol{n}}^{(m)}$ for calls that are related to the m-th RRH ($m = M_{\text{inf}} + M_{\text{fin}} + 1, \ldots, M$)

$$\sum_{z=0}^{n_m} P_g(\boldsymbol{n}_m^{-z})\lambda_{\text{cP}}\hat{S}_z = (n_m + 1)\mu P_g(\boldsymbol{n}_m^{+}), \tag{25}$$

where $\hat{S}_z = \sum_{x=z+1}^{\infty} S_x$ refers to the complementary batch size distribution.

The PFS that satisfies (21), (23) and (25) has the form

$$P_g(\boldsymbol{n}) = \frac{1}{G}\left(\prod_{m=1}^{M_{\text{inf}}} \frac{\alpha_{\text{P}}^{n_m}}{n_m!} \prod_{m=M_{\text{inf}}+1}^{M_{\text{inf}}+M_{\text{fin}}} \binom{N_m}{n_m}\alpha_{m,\text{idle}}^{n_m} \prod_{m=M_{\text{inf}}+M_{\text{fin}}+1}^{M} P_{n_m}^{(m)}\right), \tag{26}$$

where $G = \sum_{\boldsymbol{n}\in\boldsymbol{\Omega}}\left(\prod_{m=1}^{M_{\text{inf}}} \frac{\alpha_{\text{P}}^{n_m}}{n_m!} \prod_{m=M_{\text{inf}}+1}^{M_{\text{inf}}+M_{\text{fin}}} \binom{N_m}{n_m}\alpha_{m,\text{idle}}^{n_m} \prod_{m=M_{\text{inf}}+M_{\text{fin}}+1}^{M} P_{n_m}^{(m)}\right)$, $\boldsymbol{\Omega}$ is the system's state space, $\boldsymbol{\Omega} = \{\boldsymbol{n} : 0 \le n_1, \ldots, n_M \le C, 0 \le \sum_{m=1}^{M} n_m \le T\}$ while the values of $P_{n_m}^{(m)}$ are given by (7).

Having obtained $P_g(\boldsymbol{n})$, the TC probabilities in the m-th RRH ($m = 1, \ldots, M$), $B_{tot,m}^{TC}$, can be calculated via

$$B_{tot,m}^{TC} = B_c^{TC} + B_{r,m}^{TC}, \tag{27}$$

where B_c^{TC}, $B_{r,m}^{TC}$ refer to the TC events that are related to the insufficient computational resource units in the V-BBU and radio resource units in the m-th RRH, respectively

Based on the PFS of (26), we can calculate $B_{tot,m}^{TC}$ either via a BF method (presented in Section 4.2) or via a convolution algorithm (presented in Section 5) which is adopted in this paper.

4.2. The BF evaluation method

The values of $B_{r,m}^{TC}$, $m = 1, \ldots, M$, can be computed via (26) as follows

$$B_{r,m}^{TC} = \sum_{\boldsymbol{n}\in\boldsymbol{\Omega}_{<T}^{m,C}} P_g(\boldsymbol{n}), \tag{28}$$

where $\boldsymbol{\Omega}_{<T}^{m,C} = \{\boldsymbol{\Omega}_{<T} \cap \boldsymbol{\Omega}^{m,C}\}$, $\boldsymbol{\Omega}_{<T} = \{\boldsymbol{n} : n_1 + \cdots + n_M < T\}$ while $\boldsymbol{\Omega}^{m,C} = \{\boldsymbol{n} : n_m = C\}$.

Similarly, we can determine the values of B_c^{TC} via

$$B_c^{TC} = \sum_{\boldsymbol{n}\in\boldsymbol{\Omega}_{=T}} P_g(\boldsymbol{n}), \tag{29}$$

where $\boldsymbol{\Omega}_{=T} = \{\boldsymbol{n} : n_1 + \cdots + n_M = T\}$.

Eqs. (28) and (29) show that the determination of $B_{r,m}^{TC}$ and B_c^{TC} can be quite complex via the BF method since enumeration/processing of $\boldsymbol{\Omega}$ is required.

5. The proposed convolution algorithm for the generalized SC-SC model

Since the g-SC-SC model has a PFS, we propose a convolution algorithm, for the efficient computation of congestion probabilities. The algorithm consists of the following 3 steps:

1st step

a) For every RRH that services Poisson traffic, compute the distribution of occupied resource units, $q_{g,m}(j)$, where $m = 1, \ldots, M_{\text{inf}}$ and $j = 1, \ldots, C$, via

$$q_{g,m}(j) = \frac{\alpha_{\text{P}}^{j}}{j!} q_{g,m}(0). \tag{30}$$

b) For every RRH that services quasi-random traffic, compute $q_{g,m}(j)$, where $m = M_{\text{inf}} + 1, \ldots, M_{\text{inf}} + M_{\text{fin}}$ and $j = 1, \ldots, C$, via

$$q_{g,m}(j) = \binom{N_m}{j}\alpha_{m,\text{idle}}^{j} q_{g,m}(0). \tag{31}$$

c) For every RRH that services compound Poisson traffic, compute $q_{g,m}(j)$, where $m = M_{\text{inf}} + M_{\text{fin}} + 1, \ldots, M$ and $j = 1, \ldots, C$, via

$$q_{g,m}(j) = \sum_{l=1}^{j} \frac{\alpha_{\text{cP}}}{j} q_{g,m}(j - l)\hat{S}_{l-1}. \tag{32}$$

Note that $q_{g,m}(0) = 1$, $q_{g,m}(x) = 0$ for $x < 0$ or $x > C$, while the values of $q_{g,m}(j)$ can be normalized by $G_{g,m} = \sum_{j=0}^{C} q_{g,m}(j)$. The normalized values are expressed as $q'_{g,m}(j) = q_{g,m}(j)/G_{g,m}$, $m = 1, \ldots, M$.

2nd step

Following a sequential convolution for all RRHs, apart from the m-th RRH, determine the occupancy distribution

$$Q_{g,(-m)} = q'_{g,1} * \cdots * q'_{g,m-1} * q'_{g,m+1} * \cdots * q'_{g,M}. \tag{33}$$

Based on (33), the convolution operation of two normalized distributions $q'_{g,u}$ and $q'_{g,w}$ is expressed by

$$q'_{g,u} * q'_{g,w} = \left\{ \begin{array}{c} q'_{g,u}(0) \cdot q'_{g,w}(0), \sum_{x=0}^{1} q'_{g,u}(x) \cdot q'_{g,w}(1 - x), \\ \ldots, \sum_{x=0}^{T} q'_{g,u}(x) \cdot q'_{g,w}(T - x) \end{array} \right\}. \tag{34}$$

The convolution operation of $q'_{g,u}$ and $q'_{g,w}$ may not lead to a normalized distribution. Thus, the normalization of the results of $q'_{g,u} * q'_{g,w}$ via the constant, $G_{g,u,w}$, is recommended.

3rd step

Based on the convolution operations of the previous step, calculate the values of $B_{tot,m}^{TC}$ as follows

$$B_{tot,m}^{TC} = B_{r,m}^{TC} + B_c^{TC}$$
$$= \frac{1}{G_g}\left(q'_{g,m}(C) \sum_{z=0}^{T-C-1} Q_{g,(-m)}(z) + \sum_{x=0}^{T} Q_{g,(-m)}(x) q'_{g,m}(T - x)\right), \tag{35}$$

where $q'_{g,m}(C)$ (determined in the 1st step) refers to the case where no radio resource units are available in the m-th RRH while the second term $\sum_{x=0}^{T} Q_{g,(-m)}(x) q'_{g,m}(T - x)$ express the (un-normalized) probability that all computational resource units are occupied. In addition, G_g refers to the normalization constant of the operation $Q_{g,(-m)} * q'_{g,m}$ determined via (34).

To obtain the values of the CC probabilities, $B_{CC}^{(m)}$, for a new call in the m-th RRH that serves quasi-random traffic (i.e., $m = M_{\text{inf}} + 1, \ldots, M_{\text{inf}} + M_{\text{fin}}$), we can use the previous 3-step algorithm for a system with $N_m - 1$ sources. Note that, TC probabilities are slightly higher than CC probabilities in quasi-random models, especially when the number of sources is high.

To obtain the values of $B_{CC}^{(m)}$, for a new call in the m-th RRH that serves Poisson or compound Poisson traffic we can use (36) and (15), respectively

$$B_{CC}^{(m)} = \frac{\alpha_{\text{P}} - \bar{n}_m}{\alpha_{\text{P}}}, \quad m = 1, \ldots, M_{\text{inf}}, \tag{36}$$

where $\bar{n}_m$ is the mean number of calls serviced in the m-th RRH.

To determine the values of $\bar{n}_m$ we propose the formula

$$\bar{n}_m = \frac{1}{G_g} \sum_{j=1}^{C} y_{g,m}(j) q'_{g,m}(j) \sum_{l=0}^{T-j} Q_{g,(-m)}(l), \tag{37}$$

where G_g is the normalization constant of the operation $Q_{g,(-m)} * q'_{g,m}$ determined via (34), while $y_{g,m}(j)$ is the average number of in-service calls of the m-th RRH in state j.

The values of $y_{g,m}(j)$ can be determined via (38) and (17) for the m-th RRH that accommodates Poisson or compound Poisson traffic, respectively

$$y_{g,m}(j) = \frac{\alpha_{\text{P}} q'_{g,m}(j - 1)}{q'_{g,m}(j)}, \quad \text{for } j = 1, \ldots, C. \tag{38}$$

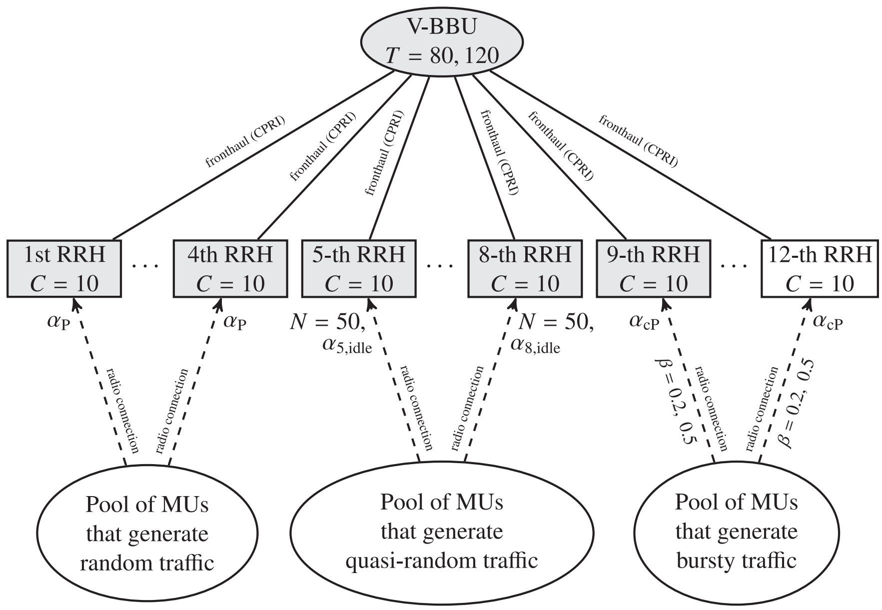

Fig. 4. The application example of the g-SC-SC model.

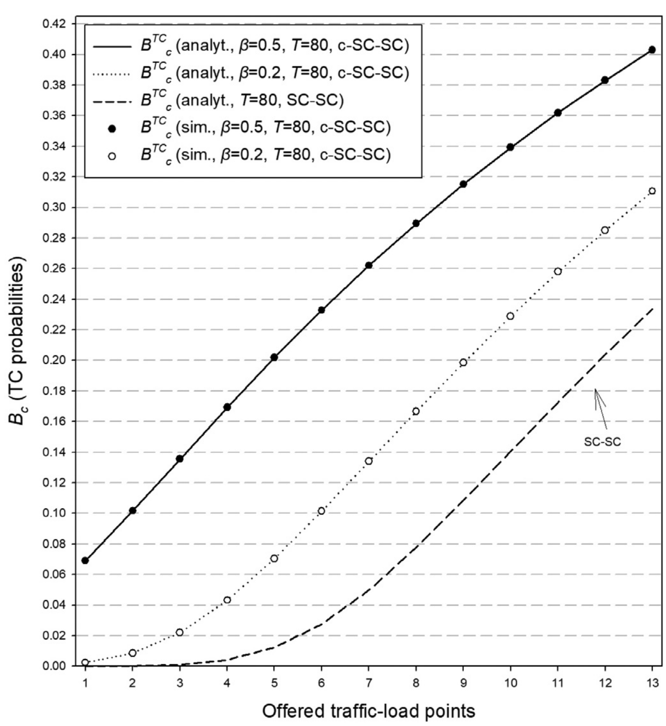

Fig. 5. TC probabilities (B_c^{TC}) for the c-SC-SC and the SC-SC models.

Regarding the occupancy distribution of the computational resource units, it can be determined via

$$q'_g(0) = Q_{g,(-m)}(0) \cdot q'_{g,m}(0)/G_g, \qquad j = 0$$
$$q'_g(j) = \sum_{z=0}^{j} Q_{g,(-m)}(z) \cdot q'_{g,m}(j-z)/G_g, \qquad j = 1, \dots, T, \tag{39}$$

where G_g is the normalization constant of $Q_{g,(-m)} * q'_{g,m}$ determined via (34).

The proposed g-SC-SC model leads to the SC-SC model of [26] if: a) $N_m \to \infty$, for $m = M_{\text{inf}}+1, \dots, M_{\text{inf}}+M_{\text{fin}}$, and the total offered traffic-load is constant, and b) $S_x = 1$ for $x = 1$ and $S_x = 0$ for $x > 1$ and $m = M_{\text{inf}} + M_{\text{fin}} + 1, \dots, M$. In both cases (a) and (b), the call arrival process becomes Poisson. In particular, in case (b) each arriving batch (that follows the Poisson process) contains only one call.

In order to determine the values of B_{tot}^{TC} of the SC-SC model via the proposed convolution algorithm, the only change is in the 1st step where only (30) is considered (for $m = 1, \dots, M$).

Similarly, the proposed g-SC-SC model leads to the f-SC-SC model of [27] if all RRHs accommodate calls from finite number of sources. In that case, the determination of B_{tot}^{TC} in the f-SC-SC model, via the proposed convolution algorithm, requires only the use of (31) for $m = 1, \dots, M$.

6. Numerical results

In this section, we consider a C-RAN example and provide simulation and analytical TC and CC probabilities results of the proposed c-SC-SC and g-SC-SC models as well as the corresponding analytical TC probabilities of the existing SC-SC and f-SC-SC models. The simulation model is based on Simscript III [45], while the simulation results presented in this section are mean values of seven runs. In each run, the system generates two hundred million calls. The first 5% of them do not affect the determination of the TC and CC probabilities in order to consider a warm-up period. The choice of 5% is based on the visual inspection of the simulation output and depends on the application example presented herein. The interested reader may resort to [46,47] for particular methods used for the selection of a warm-up period in a simulation model. In addition, since reliability ranges are less than two order of magnitudes, they are not presented in the following figures.

In our example, we study a C-RAN architecture of $M = 12$ RRHs. Each RRH consists of $C = 10$ resource units. As far as the computational resource units are considered, we consider the values: 1) $T = 80$ and 2) $T = 120 = M \cdot C$. Regarding the g-SC-SC model, let the RRHs numbered 1 to 4 serve Poisson traffic, the RRHs numbered 5 to 8 serve quasi-random traffic and the RRHs numbered 9 to 12 serve compound Poisson traffic (see Fig. 4). Regarding the number of finite sources for the RRHs 5 to 8, we consider the value of $N = 50$ sources. In each of these four RRHs, the offered traffic-load per idle MU is $\alpha_{m,\text{idle}} = \alpha_m/N$ where α_m refers to the value of the Poisson traffic. Initially, we consider that $\alpha_m = 4.2$ erl for $m = 1, \dots, 12$. Regarding the distribution of the batch size, we consider the geometric distribution with parameters $\beta = 0.2$ or $\beta = 0.5$, common for the RRHs 9 to 12. Depending on the value of β, the average number of calls in a new batch is 1.25 and 2.0, respectively. In the x-axis of

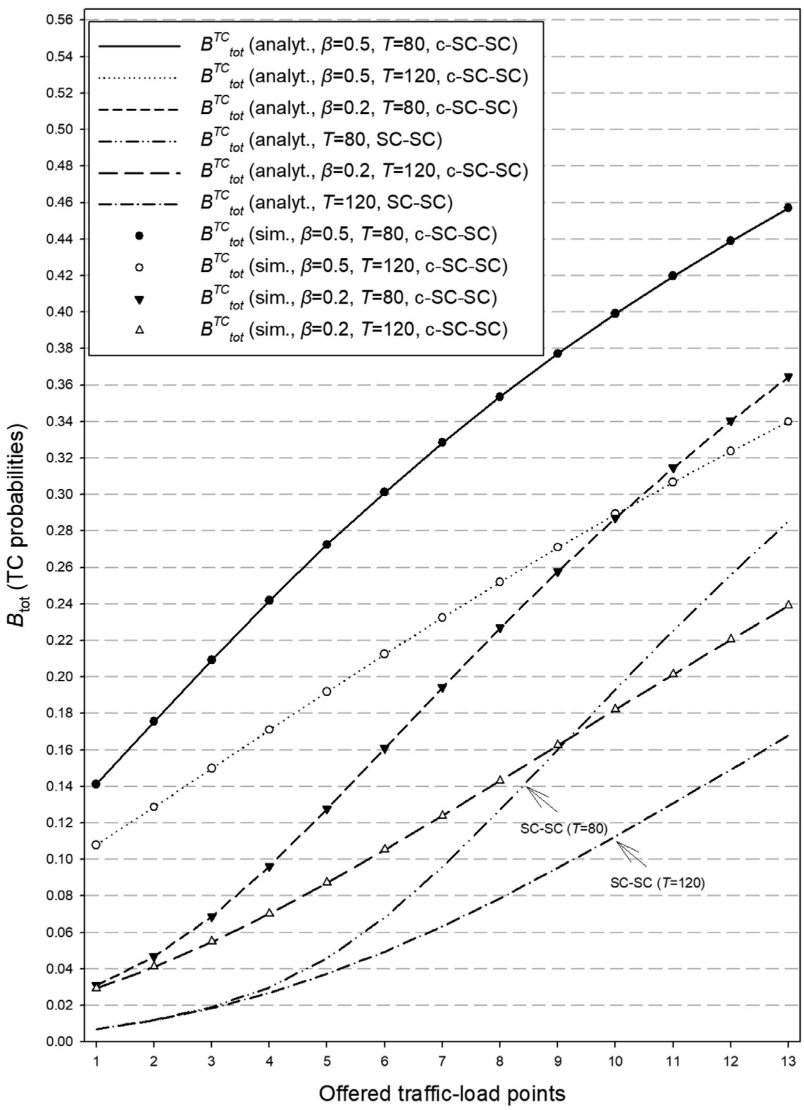

Fig. 6. TC probabilities (B^{TC}_{tot}) for the c-SC-SC and the SC-SC models.

Figs. 5-10, α_m increases in steps of 0.4 erl. Thus, in point 13 the value of α_m is 9.0 erl for each RRH.

In Fig. 5, we present simulation and analytical results of the TC probabilities B_c^{TC} for the c-SC-SC model, assuming $T = 80$ and $\beta = 0.2$ or $\beta = 0.5$. For comparison, we show the corresponding results of the SC-SC model. In Fig. 6, we show the TC probabilities B_{tot}^{TC} for both models and both values of T. In Fig. 7, we provide the corresponding CC probabilities. According to Figs. 5 to 7, we observe that: i) Even a slight increase in the value of β (a value of $\beta = 0.2$ means that the average batch size is 1.25 calls, slightly higher than that of the SC-SC model (1 call per arrival due to the Poisson process)) may substantially increase TC (Figs. 5 and 6) and CC probabilities (Fig. 7). As an example, consider point 13 of Fig. 5 and let the reference value be that of the SC-SC model. Then, the relative increase of B_c^{TC} is 32.96% when $\beta = 0.2$ and 72.56% when $\beta = 0.5$. Similarly, consider point 13 of Fig. 7. The relative increase of B_{CC} for $T = 80$ is 123% when $\beta = 0.5$ and 48.05% when $\beta = 0.2$. The corresponding values for $T = 120$ is 214.7% when $\beta = 0.5$ and 74% when $\beta = 0.2$. ii) The SC-SC model fails to capture the behavior of the proposed model in all cases. This is also quantitatively explained in the previous point. iii) An increase in T decreases the values of the TC (Fig. 6) and CC probabilities (Fig. 7), iv) CC probabilities are much higher than the TC probabilities B_{tot}^{TC} (compare Figs. 6–7) in the c-SC-SC model since calls arrive in the network as batches. v) Analytical and simulation results of the c-SC-SC model are almost identical. Note that an increase in T from 80 to 120 resource units significantly decreases the values of B_c^{TC} and therefore these values are not presented in Fig. 5. As an example, in point 13 (where $\alpha_m = 9.0$ erl), the values for the c-SC-SC model are: $B_c^{TC} = 2.38 \times 10^{-6}$ for $\beta = 0.5$ and $B_c^{TC} = 3.5 \times 10^{-8}$ for $\beta = 0.2$. The corresponding value for the SC-SC model is 5.04×10^{-10} (compare with Fig. 5).

In Fig. 8, we present simulation and analytical results of the TC probabilities B_c^{TC} for the g-SC-SC and the c-SC-SC models, assuming $T = 80$ and $\beta = 0.2$. For comparison, we show the corresponding results of the SC-SC and the f-SC-SC models. In Fig. 9, we provide the corresponding TC probabilities B_{tot}^{TC} for all models. In Fig. 8, we show the corresponding CC probabilities. According to Figs. 8–10, we observe that: i) The c-SC-SC and the f-SC-SC models can be an upper and a lower bound for the TC and CC probabilities of the proposed g-SC-SC model, but they cannot capture the behavior of the g-SC-SC model. As an example, consider point 13 of Fig. 8 and let the reference value be that of the f-SC-SC model. Then, due to the g-SC-SC model, the relative increase of B_c^{TC} is 52.60%. On the same hand, the relative increase of B_c^{TC}, due to the c-SC-SC model is 101.69%, a fact that shows that the results obtained via the existing f-SC-SC model cannot approximate those of the proposed c-SC-SC model. ii) The CC probabilities of the c-SC-SC model are higher than the (corresponding) TC probabilities due to the compound Poisson

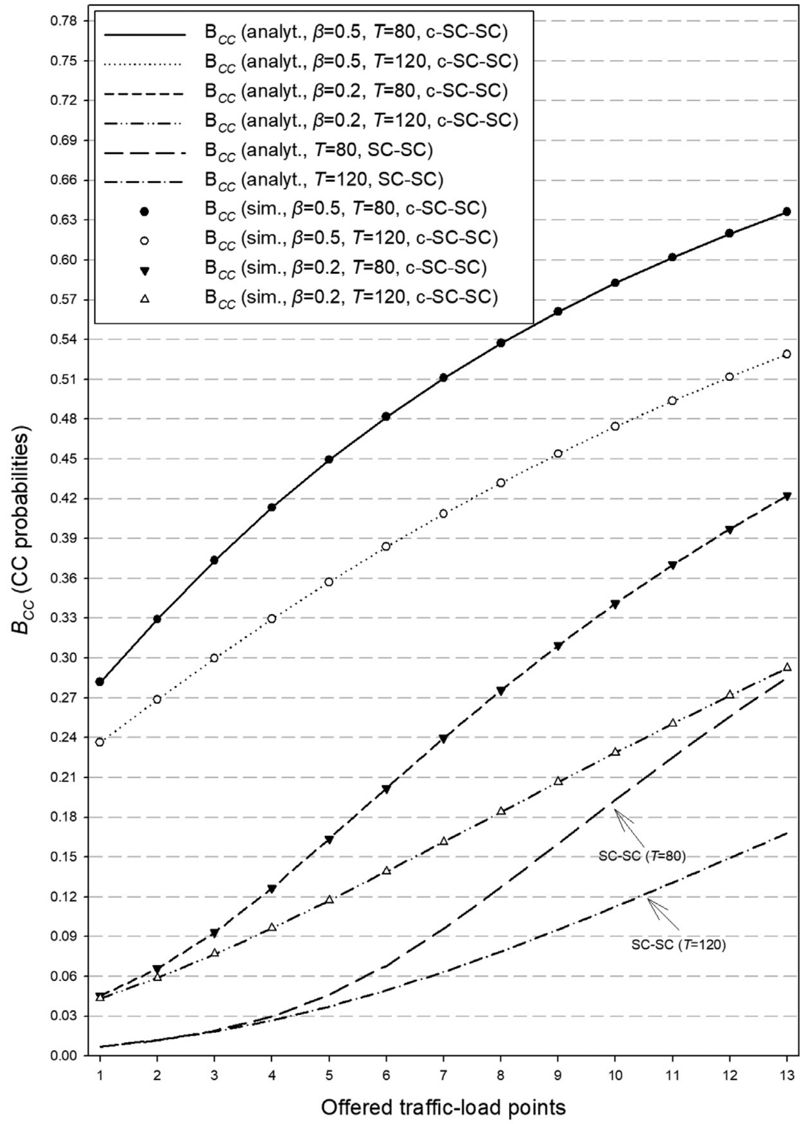

Fig. 7. CC probabilities for the c-SC-SC and the SC-SC models.

call arrival process (compare Figs. 9 and 10). iii) The CC probabilities of the f-SC-SC model are slightly lower compared to the corresponding TC probabilities since calls are generated via a finite number of MUs (compare Fig. 9 and Fig. 10). iv) Analytical and simulation results are almost identical. Note that in Fig. 8, the values of the SC-SC model are closer to those of the g-SC-SC model but this is mainly due to the small value of $\beta = 0.2$ and the mixture of traffic selected for this example (four RRHs serve Poisson traffic, four RRHs serve compound Poisson traffic and four RRHs serve quasi-random traffic). Different values of β and a different mixture of traffic will result in different TC probabilities for these models.

The results presented in this section show that particular attention is required when we want to determine congestion probabilities in a network that accommodates calls which follow different arrival processes. A model that is based on the classical Poisson process (such as the SC-SC model) may be simpler but will fail to capture the behavior of smoother or burstier call arrival processes. To this end, our work can be helpful to telecom engineers who are responsible for network planning and dimensioning procedures. The latter should adopt not only efficient teletraffic models but also models that approximate (as much as possible) the call-level network conditions.

7. Incorporating the fronthaul capacity in the SC-SC model

Consider the C-RAN model of Fig. 11, where the V-BBU which consists of T computational resource units is separated from the M_{inf} RRHs that accommodate Poisson traffic. Each RRH consists of C radio resource units and transmits data to the V-BBU via the CPRI links. These links are aggregated to form a fronthaul aggregated link (FAL) with the aid of a fronthaul aggregator (FA). Let the FAL capacity be equal to C_{FAL} resource units.

A Poisson arriving call requires a computational resource unit from the V-BBU, a resource unit from the FAL and a radio resource unit from the serving RRH. If these resource units are available then the call can be accepted in the serving RRH for a generally distributed service time of mean μ^{-1}. Otherwise, the call is blocked and lost.

Let $P(\boldsymbol{n})$ be the steady-state probability distribution where $\boldsymbol{n} = (n_1, \dots, n_m, \dots, n_M)$ is the steady-state vector that describes the number of calls in the M_{inf} serving RRHs and n_m is the number of calls in the m-th RRH. The extended SC-SC model has a PFS of the form:

$$P(\boldsymbol{n}) = G^{-1}\left(\prod_{m=1}^{M_{\text{inf}}} \frac{\alpha_{\text{P}}^{n_m}}{n_m!}\right), \tag{40}$$

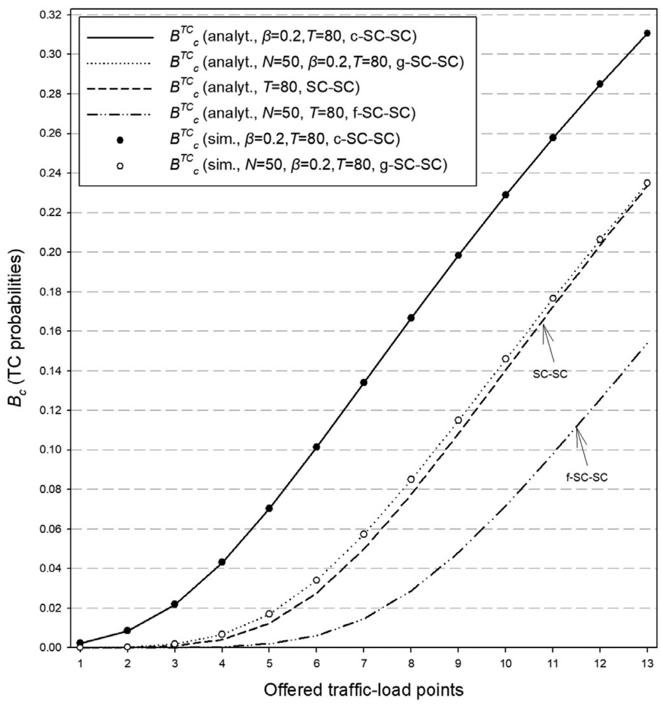

Fig. 8. TC probabilities (B_c^{TC}) for the g-SC-SC, the c-SC-SC, the SC-SC and the f-SC-SC models.

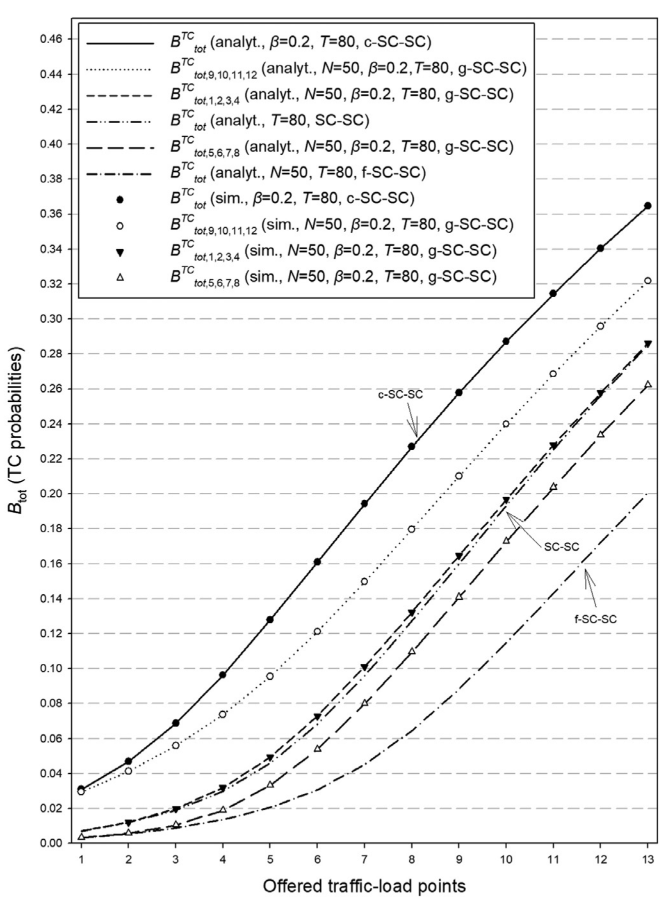

Fig. 9. TC probabilities (B_{tot}^{TC}) for the g-SC-SC, the c-SC-SC, the SC-SC and the f-SC-SC models.

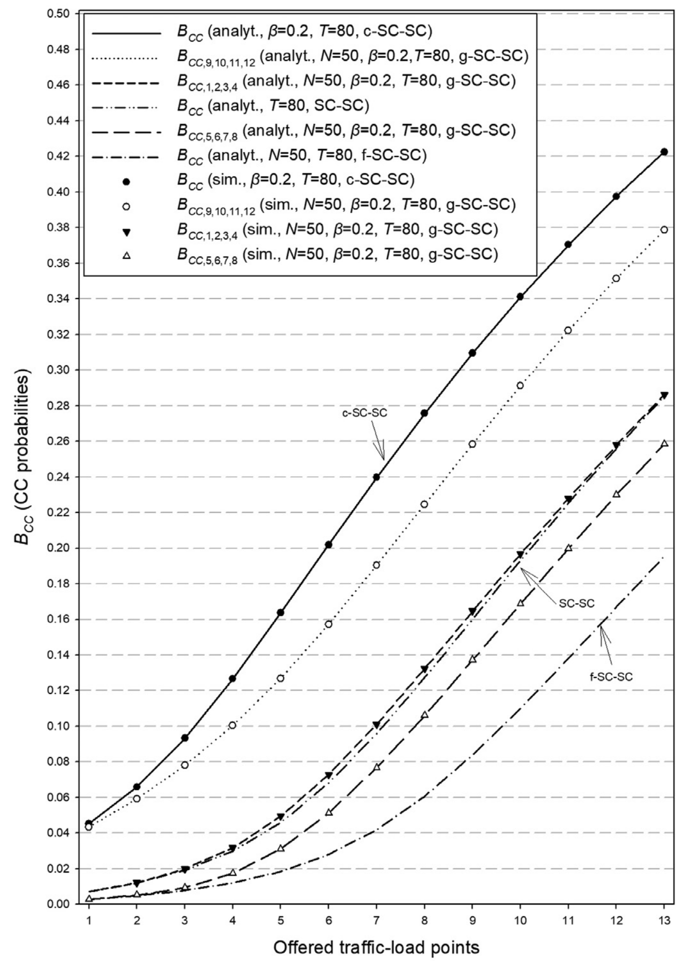

Fig. 10. CC probabilities for the g-SC-SC, the c-SC-SC, the SC-SC and the f-SC-SC models.

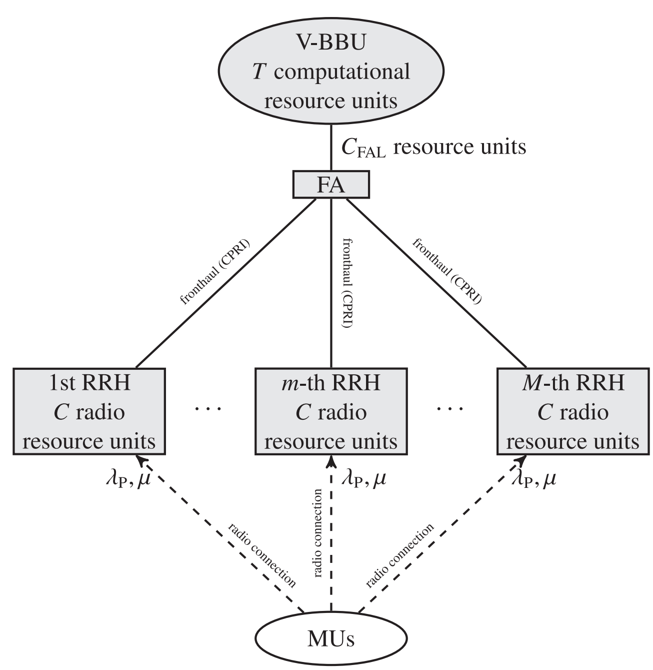

Fig. 11. The SC-SC model including a FAL.

where $\alpha_{\mathrm{P}} = \lambda_{\mathrm{P}}/\mu$ is the offered traffic-load in each RRH, $G = \sum_{\boldsymbol{n}\in\boldsymbol{\Omega}} \prod_{m=1}^{M_{\inf}} \alpha_{\mathrm{P}}^{n_m}/n_m!$ and $\boldsymbol{\Omega}$ is the system's state space given by: $\boldsymbol{\Omega} = \{\boldsymbol{n} : 0 \le n_1, \ldots, n_M \le C, 0 \le \sum_{m=1}^{M_{\inf}} n_m \le C_{\mathrm{FAL}}, 0 \le \sum_{m=1}^{M_{\inf}} n_m \le T\}$.

Based on the PFS of (40), we can adopt the following convolution algorithm for the determination of B_{tot}:

1st step

For every RRH, compute the occupancy distribution $q_m(j)$, where $m = 1, \ldots, M_{\inf}$ and $j = 1, \ldots, C$, via

$$q_m(j) = \frac{\alpha_{\mathrm{P}}^j}{j!} q_m(0). \tag{41}$$

The normalized values are expressed as $q'_m(j) = q_m(j)/G_m$, $m = 1, \ldots, M_{\inf}$ and $G_m = \sum_{j=0}^{C} q_m(j)$.

2nd step

Following a sequential convolution for all RRHs, apart from the m-th RRH, determine the occupancy distribution

$$Q_{(-m)} = q'_1 * \cdots * q'_{m-1} * q'_{m+1} * \cdots * q'_M, \tag{42}$$

where the convolution operation of q'_u and q'_w is expressed by

$$q'_u * q'_w = \left\{ \begin{array}{c} q'_u(0) \cdot q'_w(0), \sum_{x=0}^{1} q'_u(x) \cdot q'_w(1-x), \\ \ldots, \sum_{x=0}^{\min(T, C_{\mathrm{FAL}})} q'_u(x) \cdot q'_w(\min(T, C_{\mathrm{FAL}}) - x) \end{array} \right\}. \tag{43}$$

At this step, it is recommended to normalize the results of $q'_u * q'_w$ via $G_{u,w}$.

3rd step

Based on the convolution operations of the previous step, calculate the values of B_{tot} as follows

$$B_{tot} = \frac{1}{G_g} \Bigg(q'_m(C) \sum_{z=0}^{\min(T, C_{\mathrm{FAL}})-C-1} Q_{(-m)}(z) + \sum_{x=0}^{\min(T, C_{\mathrm{FAL}})} Q_{(-m)}(x) q'_m(\min(T, C_{\mathrm{FAL}}) - x) \Bigg), \tag{44}$$

where $q'_m(C)$ (determined in the 1st step) refers to the case where no radio resource units are available in the m-th RRH while the second term $\sum_{x=0}^{\min(T, C_{\mathrm{FAL}})} Q_{(-m)}(x) q'_m(\min(T, C_{\mathrm{FAL}}) - x)$ expresses the (un-normalized) probability that all computational or FAL resource units are occupied, depending on the minimum value between T and C_{FAL} which expresses the bottleneck. In addition, G refers to the normalization constant of the operation $Q_{(-m)} * q'_m$ determined via (43).

8. Conclusion

In this paper we propose two loss models for the call-level analysis of a C-RAN that services either compound Poisson traffic (c-SC-SC model) or a mixture of compound Poisson, random and quasi-random traffic (g-SC-SC model). The compound Poisson process is burstier than the Poisson process since calls arrive in the C-RAN as batches whose size is generally distributed. On the other hand, the quasi-random traffic refers to the case where calls are generated by a finite number of MUs, contrary to random (Poisson) traffic which is generated by an infinite number of MUs. As far as the steady state probabilities is concerned, we show that the proposed models have a PFS and propose BF evaluation methods and convolution algorithms for the determination of TC and CC probabilities. The accuracy of the proposed algorithms is verified via simulation. As a future work, we intend to study various call arrival processes in a C-RAN that accommodates elastic traffic. By the term "elastic traffic", we refer to calls whose occupied resource units may fluctuate between a minimum and a maximum value [48–51]. In addition, we intend to study the call-level peculiarities of the 3-layer C-RAN architecture in which the radio, the distributed and the central units are introduced [52].

Declaration of Competing Interest

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.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at10.1016/j.comnet.2020.107410.

CRediT authorship contribution statement

Iskanter-Alexandros Chousainov: Conceptualization, Methodology, Software, Validation, Writing - review & editing. **Ioannis Moscholios:** Conceptualization, Methodology, Software, Validation, Writing - review & editing. **Panagiotis Sarigiannidis:** Conceptualization, Writing - review & editing. **Alexandros Kaloxylos:** Conceptualization, Writing - review & editing. **Michael Logothetis:** Conceptualization, Writing - review & editing.

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