Adaptive Admission Control in Interference-Coupled Wireless Data Networks: A Planning and Optimization Tool Set

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***Abstract*—Typically, wireless network performance decreases in high traffic regimes, e. g., at traffic hot spots and peak hours, since a large number of active users have to share limited radio resources. From a network perspective, even congestion may occur in some cells, which may lead to drastic deterioration of user throughputs. As a consequence, network operators employ admission control in their base stations in order to prevent congestion and enhance quality of experience. In this paper, we develop an effective network planning and optimization tool set, which considers the dynamic behavior of mobile traffic. The tool set allows for a more accurate prediction of data request blocking probabilities and data throughputs under admission control, since it explicitly considers the inter-cell interference coupled nature of frequency reuse one networks. This enables more reliable planning and (self-) optimization of wireless networks. We prove utility by applying the tool set to a traffic-adaptive admission control scheme and compare the resulting network performance with that of static admission control schemes under demands of high mobile data traffic. We find that the adaptive algorithm is able to exploit the trade-offs between blocking of requests, reduced interference, and guaranteed resources for individual data transmissions in each of the cells. Under high traffic conditions, it yields better performance compared to any other static scheme investigated.**

***Index Terms*—wireless network; network planning; network optimization; admission control; flow level modeling; queuing theory**

I. Problems due to High Base Station Utilization

It is common knowledge that wireless network performance experienced by mobile users decreases in high traffic regimes, i. e., when the base stations' utilization is high. The reason is that many users have to share limited time or bandwidth resources, as a result of which the data throughput of an individual user deteriorates. In order to understand and model related effects, and in order to develop effective planning tools and (self-) optimization algorithms, considering the dynamic behavior of traffic and inter-cell interference is inevitable [1], [2]. The fact that modern wireless technologies, such as Long Term Evolution (LTE), employ a frequency reuse factor of one confirms the need for more advanced inter-cell interference models.

A. Mobile Traffic Characteristics

Without doubt, mobile data traffic demand is increasing rapidly [3]. Moreover, mobile traffic is often characterized by strong heterogeneity both in time and space (hot spots), and by self-similarity characteristics in time [4]. Further, measurements reveal that traffic varies significantly over the course of a day [5].

Recently, many efforts have been undertaken to capture the dynamic behavior of data traffic and its impact on network performance, e. g., by using the notation of so-called sessions and elastic data flows, the arrival of which can be modeled by Poisson processes, see e. g., [1], [6], [7]. Since this results in a certain randomness in the number of active flows served by a base station, more often than not, the amount of resources per flow transmission is too low, thereby, delaying completion of data transfers and causing congestion in the cell.

B. Interference-Coupling Effect and Varying Cell Capacity

To cope with rising traffic demand, modern wireless technologies employ frequency reuse one and adaptive rate control. Since the traffic demand varies significantly with time, the resulting dynamic inter-cell interference affects the achievable rate per unit time or bandwidth resource, i. e., higher the interference, lower the rates achievable and higher the amount of resources necessary to serve a given traffic demand. This, in turn, increases the interference caused in neighboring cells, thereby, resulting in a further lowering of rates. In other words, we have to consider *time-varying* cell capacities that depend on the dynamic behavior of mobile traffic, and therefore, on the dynamic characteristic of inter-cell interference. For further characterization of the interference-coupling behavior, we refer to, e. g., [2], [8].

C. Trade-Off: Blocking Users vs. Guaranteeing Throughput

According to the previous paragraphs, two effects cause deterioration in user throughputs during high traffic demand: the fact that radio resources are shared among many users and that cell capacities decrease due to strong inter-cell interference. In order to tackle these issues, mobile network operators employ admission control mechanisms in their base stations that block single data transfer requests (flows) to guarantee minimum throughputs for ongoing transfers. Admission control, thereby, addresses both these issues: it limits the number of users served concurrently leading to a minimum amount of resources guaranteed for each user and the average base station

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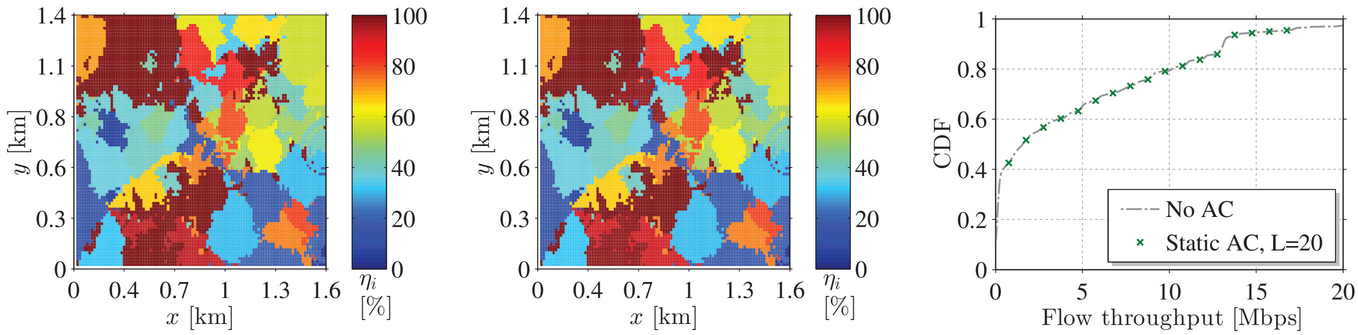


(a) (b) (c)

Fig. 1. (a) Base station utilizations without admission control, (b) with static admission control (max. 20 concurrent data transfers), and (c) throughput statistic comparison of both schemes. In order to illustrate the utilizations of individual base stations, the corresponding cell areas are color-coded.

utilization is reduced, which diminishes the interference issue. However, the gain in user throughput comes at the cost of blocked data requests. Here, the fundamental trade-off with regard to users' quality of service lies in balancing data request blocking probabilities and (cell edge) user throughput.

There has been substantial work with respect to call admission control, see, e. g., [9]. In most cases, quality of service-aware algorithms focusing on reducing call blocking and dropping rates in individual cells were employed [10]. However, we focus on characterizing the impact of admission control on the blocking rate and throughput of elastic data flows as well as its effect on inter-cell interference. This leads to a network-wide view (in the sense of multiple coupled cells) and centralized admission control algorithms, which will be elucidated later in this work.

D. Example Network Evaluation

We investigate an illustrative Long Term Evolution (LTE) network under with highly utilized base stations, i. e., under high traffic conditions. The network consists of 48 cells, of which 19 are pico cells deployed at traffic hot spots. The mean traffic demand is 102 Mbps/km^2, resulting in several overloaded and congested cells, see Fig. 1(a). The base station utilizations are denoted as $\eta_i \in [0, 1]$. Due to the high utilization, data throughputs at many locations in the network are very low. In order to guarantee some minimum throughput, one could employ an admission control scheme which permits at most 20 concurrent and individual data transfers in each of the cells. However, the average base station utilizations decrease only slightly, cell capacities remain almost the same, and an improvement in data throughputs is hardly distinguishable, see Figs. 1(b) and 1(c). Two questions come up:

1) How can an optimal configuration of *cell-individual* admission control parameters, which allows higher data throughputs depending on the current traffic situation, be obtained?
2) Can interference-coupling behavior be exploited in a way, such that admission control reduces the utilization of some overloaded base stations in order to relax the interference condition, and consequently, increase capacities of the other cells?

In the remainder of the paper, we answer these questions and build a planning and optimization tool set, which we use for developing traffic-adaptive admission control algorithms. We evaluate the algorithms' performance by applying them to the scenario described above.

II. Planning and Optimization Tool Set

To the best knowledge of the authors, current literature lacks an analytical investigation of the effects of admission control policies in interference-coupled wireless networks so far, except for the contribution in [11]. Here, we develop a tool set, which is based on the *average interference model* presented in [11]. From this model, we derive important network key performance indicators, illustrate fundamental trade-offs that occur using admission control mechanisms, and examine how they can be used in network planning and optimization.

A. Wireless Network Model

We model mobile traffic in terms of so-called elastic flows and sessions [1], where sessions are composed of a number of contiguous flows, e. g., data transfer requests by mobile users while browsing the Internet.

We assume that data flows are subject to *average interference* conditions [2], [11], such that their signal-to-interference and noise ratio (SINR) with respect to base station i and at location u becomes

$$\gamma_i(u, \eta) = \frac{p_i(u)}{\sum_{j \neq i} \eta_j p_j(u) + N_0}, \tag{1}$$

where $p_i(\cdot)$ and N_0 are the location-dependent but otherwise constant receive power and the noise power, respectively. The vector $\eta \in [0, 1]^N$ collects the utilizations η_i of N base stations. We model the achievable rate at location u by means of the Shannon capacity, i. e.,

$$c_i(u, \eta) := \min \left\{ aB \log_2 \left(1 + b\gamma_i(u, \eta)\right), c_{\max} \right\}. \tag{2}$$

The parameters $B, a, b, c_{\max}$ denote the system bandwidth, the bandwidth and SINR efficiencies [12], and the maximum rate achievable with the wireless access technology at hand, respectively.

Denoting the spatial mobile user distribution in a cell i by $\delta_i(u)$ with $\int_{\mathcal{L}_i} \delta_i(u)\,\mathrm{d}u = 1$ and cell area $\mathcal{L}_i$, the cell capacity C_i (in Mbps) is defined by the harmonic mean of the achievable data rates $c_i(u, \eta)$, i. e.,

$$C_i(\eta) := \left[\int_{\mathcal{L}_i} \frac{\delta_i(u)}{c_i(u, \eta)}\,\mathrm{d}u \right]^{-1}. \tag{3}$$

It becomes obvious that, in this model, the capacity C_i of a cell i depends on the utilizations of the surrounding base stations, and therefore, on the interference and mobile traffic situation. The higher the utilization of neighboring cells, lower the capacity and higher the utilization of base station i. This reflects the interference-coupled characteristic of frequency reuse one networks as described in Section I-B.

For more detailed information about the system model and aspects with regard to real networks (e. g., fast and slow fading and handover mechanisms), we refer to [11] and the references therein.

B. Wireless Network Key Performance Indicators

In addition to cell capacities, important key performance indicators are the probability $P_{\mathrm{b},i}$ that a flow in cell i is blocked by admission control and the flow throughputs r_i. In order to derive these quantities easily, we make the following simple, yet realistic, assumptions:

1) Flows with mean size Ω arrive at a cell i according to a Poisson process with intensity λ_i in s^{-1} [7],
2) Resources are shared equally among concurrent flows based on the egalitarian processor sharing (EPS) service discipline,
3) The admission control policy in cell i admits at most L_i concurrent flows and blocks all further requests.

With the resulting M/M/1/L EPS queuing model [13], it is now straightforward to compute the desired metrics. The cell load and the flow blocking probability are defined as

$$\rho_i(\eta) := \frac{\lambda_i \Omega}{C_i(\eta)}, \quad \text{and} \quad P_{\mathrm{b},i}(\eta) = \frac{(1-\rho_i(\eta))\rho_i(\eta)^{L_i}}{1-\rho_i(\eta)^{L_i+1}}, \tag{4}$$

respectively.

In order to compute base station utilizations, we have to subtract the blocked flows (or traffic) from the cell loads, i. e.,

$$\eta_i(\eta) = f_i(\eta) := \rho_i(\eta)(1 - P_{\mathrm{b},i}(\eta)). \tag{5}$$

Note that Eqn. (5) implicitly describes a system of equations since η is a vector of base station utilizations. This system of equations bearing the form $\eta = f(\eta)$, with vector function $f(\cdot) = \big(f_1(\cdot), \ldots, f_N(\cdot)\big)$, can be solved using a fixed point iteration (Theorem 1 in [11])).

The throughput of a flow at location u, if connected to base station i, can be calculated by

$$r_i(u, \eta) = \frac{\eta_i c_i(u, \eta)}{n_i(\eta)} \tag{6}$$

with n_i being the mean number of active flows in cell i, i. e.,

$$n_i(\eta) = \frac{\rho_i(\eta)}{1-\rho_i(\eta)} - \frac{(L_i+1)\rho_i(\eta)^{L_i+1}}{1-\rho_i(\eta)^{L_i+1}}. \tag{7}$$

In the remainder, we use the overall network flow blocking probability

$$P_{\mathrm{b}} = \frac{\sum_{i=1}^{N} \lambda_i P_{\mathrm{b},i}}{\sum_{i=1}^{N} \lambda_i} \tag{8}$$

and the 5$^{\text{th}}$ percentile R_5 of the throughputs r_i for network evaluation and optimization. For other performance metrics computable such as flow sojourn times that can be computed, we refer to [2] and the references therein.

C. Tool Set Use Cases and Basic Admission Control Findings

1) Network Planning: Similar to planning call centers using Erlang's formulae for telephone call blocking probabilities and waiting times [14], the tool set enables dimensioning wireless networks more accurately, e. g., in terms of maximum data request blocking rates or minimum cell edge throughputs (5$^{\text{th}}$ percentiles). Since it explicitly takes the dynamic behavior of mobile traffic and inter-cell interference into account, over- and under-provisioning can be avoided by choosing more appropriate bandwidths, base station densities, cell sizes, etc.

2) Network Optimization: Mobile traffic demand varies greatly on different time scales. Therefore, it seems natural to adapt network control parameters, such as antenna tilt settings, transmit power, small cell on/off states, offloading, or cell range expansion schemes, to current traffic situations dynamically. The tool set presented is a perfect basis for developing reliable and robust self-organizing network (SON) algorithms. See [15] for an effective application of the flow level model without admission control to SON.

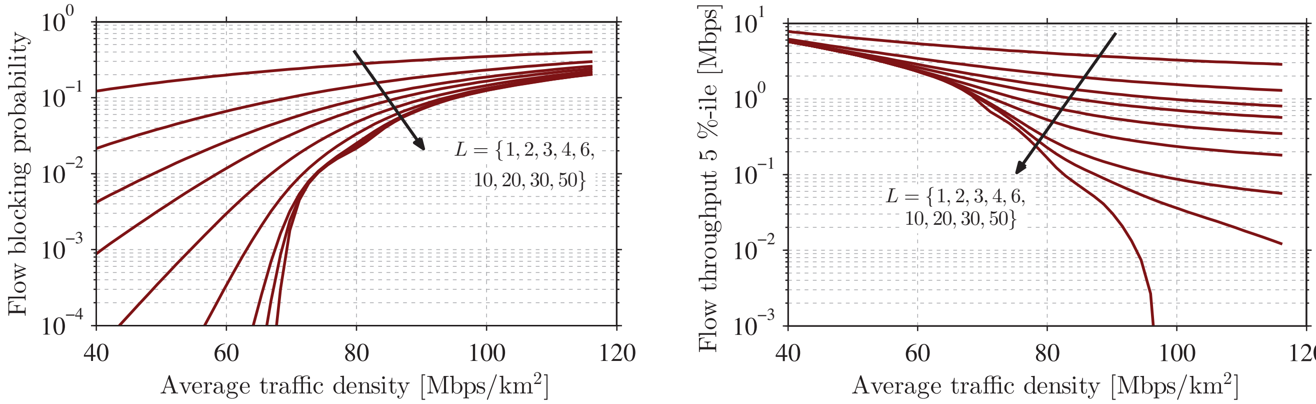
3) Admission Control: Fig. 2 depicts the data flow blocking probability and cell edge throughput for increasing traffic demand and varying admission control parameter L applied to all base stations. In the low traffic regime ($<$ 70 Mbps/km^2), for decreasing L, there is only a small increase in flow throughput but a relatively strong decrease in flow blocking probability such that admission control can be used to reduce blocking rates. In the high traffic regime ($>$ 70 Mbps/km^2), the opposite behavior can be observed. Here, an adaptive admission control may increase the throughputs at a relatively low cost of increased blocking probabilities. These findings indicate a great potential for the optimization of traffic-adaptive admission control schemes, which we investigate in the next section.

III. A Two-Step Adaptive Admission Control

In the following, we demonstrate the utility of the proposed tool set by developing traffic-adaptive admission control schemes and by applying them to the network model presented in Section I-D.

A. Algorithm Description

The purpose of the admission control (AC) schemes is to find a trade-off between overall network flow blocking probability and cell edge user throughputs depending on the traffic



(a) (b)

Fig. 2. (a) Flow blocking probability and (b) flow throughput percentiles for increasing traffic demand and various (global) admission control parameters L.

demand. We consider two different (traffic-) adaptive admission control schemes, prerequisites for which are knowledge of receive powers $p_i(\cdot)$ and the traffic distributions $\lambda_i \Omega \delta_i(\cdot)$. The two schemes are

a) Equal adjustment of the AC parameters of all base stations, i. e., all base stations apply the same value L,
b) Cell-individual adjustment of the AC parameters L_i.

Algorithm a) is realized by sweeping over the global parameter L and by choosing the configuration that minimizes a cost function Φ. Algorithm b) uses the output of algorithm a) as the starting point and employs a coordinate-wise search procedure to obtain an (possibly locally) optimal configuration for the parameters L_i, for all cells i. The 2-step procedure, which uses the taxi-cab search method (as a version of Powell's method [16]), is sketched in the Appendix. We choose the cost function Φ to be

$$\Phi(P_b, R_5) = 400 \cdot \exp(0.3 \cdot P_b) + 1/R_5, \tag{9}$$

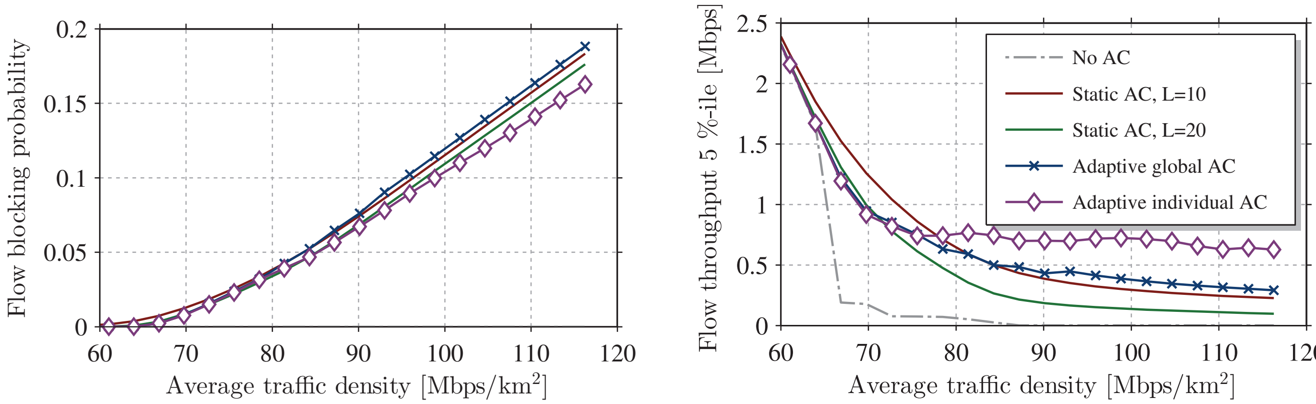
such that the overall cost increases significantly for blocking probabilities P_b greater than 0.05 and for cell edge user throughputs R_5 less than 1 Mbps. Note that the cost function Φ can be chosen according to the operators' needs, e. g., focusing more strongly on reducing the blocking probability, or taking cell-individual performance metrics into account.

In order to compare the adaptive AC performance, we derive the metrics for systems

c) Without AC ($L_i \to \infty$),
d) With static AC ($L = 10$), and
e) With static AC ($L = 20$).

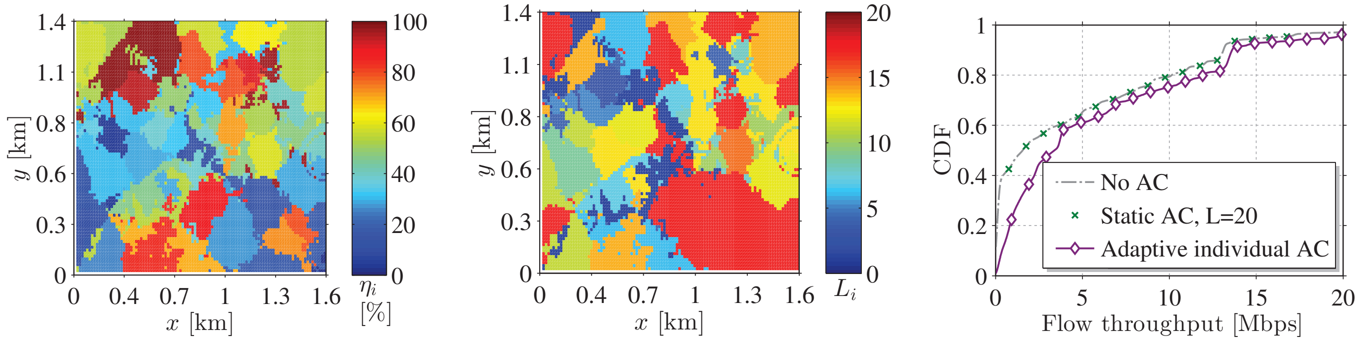
B. Scenario Setup

The test scenario is the model of a heterogeneous network located in a large North-American city, with 29 macro and 19 pico base stations deployed in traffic hot spot areas. Each base station uses the same frequency band of width B = 10 MHz. Receive powers p_i are computed with the COST-Hata model [17] with a carrier frequency of 2.6 GHz. Additionally, receive powers are affected by slow fading with clutter-dependent standard deviations ranging from 1 dB to 9 dB. Since, according to the previous findings, cell edge throughput improvements are expected in the very high traffic regimes, we investigate the trade-off and algorithm performance for mean traffic densities between 60 and 120 Mbps/km^2.



(a) (b)

Fig. 3. (a) Flow blocking probabilities and (b) flow throughput 5-percentiles for increasing traffic demand and for different admission control schemes.



(a) (b) (c)

Fig. 4. (a) Base station utilizations with adaptive, cell-individual admission control, (b) parameters L_i, and (c) throughput statistic comparison of the schemes presented.

C. *Algorithm Performance*

It can be observed from Fig. 3(b) that, if no AC scheme is applied, the cell edge user throughput decreases drastically with increasing traffic demand and eventually reaches 0 Mbps. Then congestion occurs in some of the cells, such that the number of users (or active flows) increases indefinitely and the users' throughput tends to zero in the long run.

In order to guarantee a minimum throughput for cell edge users, choosing finite values for L_i yields a certain flow blocking probability in the overall network, see Fig. 3(a). Although the static AC schemes cause slightly lower blocking probabilities than adaptive AC with global parameter L, the cell edge user throughput is higher for traffic densities larger than 85 Mbps/km^2 for the adaptive scheme. Further, the flow blocking probabilities are relatively insensitive to adjusting the parameter(s) L in the high traffic regime.

However, the two-step adaptive AC algorithm with cell-individual parameters L_i yields the lowest flow blocking probabilities, while guaranteeing a minimum cell edge throughput, which is significantly higher than the throughputs obtained by using the other approaches proposed. For very high traffic demand of around 110 Mbps/km^2, it is approximately a 7-fold increase compared with the static scheme ($L = 20$), and a two fold increase compared with the adaptive scheme with global parameter L.

Fig. 4 depicts the scenario from Section I-D after the AC parameters L_i have been adjusted by the adaptive, cell-individual AC schemes. The algorithm tends to choose smaller values for L_i in highly loaded cells, such that more flows are blocked and the base station utilization is reduced, compare Figs. 1(b) and 4(a). This relaxes the interference situation in the entire network, and hence, cell capacities increase. As a consequence, non-blocked flows experience higher throughputs, see Fig. 4(c). It can be concluded that the adaptive algorithm exploits the trade-offs between blocking of flows, increased cell capacities, and guaranteed resources for individual flows in each of the cells resulting in better performance under high traffic compared to any static scheme investigated.

IV. Summary

Usually, network operators employ admission control in their base stations in order to prevent congestion and user throughput deterioration, which typically occurs during time intervals of very high traffic demand. In this paper, we develop an effective network planning and optimization tool set which considers the dynamic behavior of mobile traffic. The tool set allows more accurate prediction of data request blocking probabilities and data throughputs under admission control, since it considers the inter-cell interference coupling nature of frequency reuse one networks explicitly. This enables more reliable planning and (self-) optimization of wireless networks. We prove its utility by applying the tool set to a traffic-adaptive admission control scheme and compare the resulting network performance with static admission control schemes under high mobile data traffic demand. We find that the adaptive algorithm is able to exploit trade-offs between blocking of requests, reduced interference, and guaranteed resources for individual flows in each of the cells, which yields better performance under high traffic compared with any other static scheme investigated.

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Appendix

The 2-step adaptive admission control algorithm is given in pseudo code in Algorithm 1. In the first step (ll. 1-6), a common AC parameter L for all cells is chosen, which minimizes the cost function Φ. Possible values for the configuration range from 1 to 100. Algorithm a) terminates here.

In step two, the configuration from step one is used as starting point (l. 8). Then, the algorithm iterates three times over all cells (l. 9). For each cell i, the costs for different values for its AC parameter L_i are computed. The value that minimizes the cost is chosen and applied to the cell. The search range for a new value L_i is chosen here from $L_i - 3$ to $L_i + 3$, i. e., around the old value L_i.

After three iterations have finished, the optimized AC parameters L_i are returned. Note that the number of iterations over all cells, as well as, the search range for values L_i can be chosen according to individual preferences. The trade-off here is a balance between computational effort and optimization gain; however, the configuration presented here, already achieves satisfactory results.

Algorithm 1 2-Step Adaptive Admission Control

Input: $p_i(u)$, $\lambda_i \Omega \delta_i(u)$
for all $L \in \{1, 100\}$ **do**
  $L_i := L, \forall i$
  solve $\eta = f(\eta)$
  compute $P_b(\eta), R_5(\eta),$ and $\Phi(P_b, R_5)$
end for
choose and apply L that minimizes Φ
$k := 0$
$L_i := L, \forall i$
while $(k < 3)$ **do**
  for all (cells i) **do**
    for all $L'_i \in \{L_i - 3, \ldots, L_i + 3\}$ **do**
      $L_i := L'_i$
      solve $\eta = f(\eta)$
      compute $P_b(\eta), R_5(\eta),$ and $\Phi(P_b, R_5)$
    end for
    choose and apply L_i that minimizes Φ
  end for
  $k := k + 1$
end while
return $L_i, \forall i$

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