Radio Access Network Energy Minimization in Multi-Layer Heterogeneous Wireless Systems

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***Abstract*—The energy consumption reduction in cellular systems is important from both economic and environmental perspectives. Nearly 80% of the energy in cellular systems is consumed by the Radio Access Network (RAN). In recent years, much research has been done to reduce the energy consumption in the RAN. However, existing models fail to capture the spatio-temporal variability of traffic demands, bit rate and power requirements, as well as the peculiarities in the energy consumption from different hardware components in a base station (BS). In this paper, a new RAN energy consumption model for multi-layer infrastructure-based heterogeneous wireless systems (IbHWS) is proposed. It captures all the aforementioned factors and accurately addresses the characteristics of IbHWS, where cellular systems are a particular case. A low-complexity algorithm is proposed to minimize the RAN's energy consumption, and to satisfy all traffic demands in space and time. Based on extensive simulation results across a wide range of scenarios, the energy savings from this algorithm were on average 26%.**

I. Introduction

Energy consumption reduction in cellular systems provides benefits from both environmental and operational perspectives. Cellular systems account for nearly 60 billion kWh per year, roughly 0.33% of all electricity consumption worldwide. In cellular systems, the RAN represents the highest energy consumption, over 80% [1]. Thus, electricity is a significant part of the RAN's operational expenses (OPEX). From the environmental point of view, the corresponding CO_2 emissions account for nearly 64 million tons per year, and are expected to triple by 2020 [2].

In recent years, energy consumption in cellular systems has gained a lot of attention due to its economic and environmental impact. For instance, since its Rel-10, 3GPP began working on standardizing the support for automated energy savings management features [3]. This is part of the self-organizing network (SON) paradigm that allows for dynamic network adjustments with minimum human intervention [4]. The main motivation behind SON is to address the increasing complexity and heterogeneity of cellular systems. Such systems are composed of many types of base stations (e.g. femto-, pico-, micro-, macrocell), with different capabilities, features, energy consumption levels, and overlapping coverage areas. Thus, energy-saving algorithms must be developed with this framework in mind.

Several methods already exist to tackle the energy consumption reduction in the RAN, particularly in the BS. One approach is to increase the energy efficiency of the major hardware components of the BS [5] [6]. For example, with new technologies, power amplifiers can achieve efficiency levels of at least 70% instead of the typical 20% to 40% range [5]. Baseband microprocessors are also open to energy-saving innovations, such as new heterogeneous multi-core architectures [6]. Another approach to reducing the energy consumption is to dynamically reconfigure the RAN. This involves satisfying the traffic demands and serving each area by using the lowest amount of energy possible. In some cases this may allow turning-off some BSs in the network. This paper focuses on the second approach.

In the related literature, several studies discuss the reduction of energy consumption through network reconfiguration. A common approach defines thresholds necessary to satisfy upon reconfiguring the network. These thresholds may be in terms of service outage probability [7], traffic in terms of Erlangs [8], a percent of the peak traffic [9], and minimim SINR [10], among others. However, they fail to address the unique spatio-temporal variability of the traffic demands. In [11], the space variability is captured in terms of a non-homogeneous Poisson point process, but the time variability is not considered. Furthermore, the above approach also fails to address that the RF energy consumption highly depends on the data rate, the session duration, and the location of traffic demands. In addition, these sources oversimplify the energy consumption of the BS. First, they tend to view this consumption as the sum of a traffic-dependent dynamic part and a traffic-independent minimum part. However, this is incomplete since many of the BS components, such as air conditioners, contain additional energy consumption parameters. Second, these sources assume that all BSs in the heterogeneous systems belong to a single layer. This assumption recognizes that the coverage area of each BS is different and may be redefined to accommodate energy-saving algorithms. However, it ignores the possibility of having multiple layers with overlapping coverage areas working simultaneously.

In this paper, we address the most important aspects of modeling and reducing the RAN's energy consumption in a multi-layer infrastructure-based heterogeneous wireless system

(IbHWS), where cellular systems are a particular case. Our contributions can be summarized as follows:

- We model the traffic demands (TDs) not only considering bit rate requirements, but also the spatio-temporal variability of the arrival rate and session duration.
- We characterize the RF energy required by a BS according to the TDs properties, as well as the locations that requested them.
- We analyze the total energy consumption of a BS by developing models for the major types of energy-consuming hardware components that reside in it.
- We propose a low-complexity energy-saving algorithm that satisfies all TDs in the network, while reducing the energy consumption.

To the best of our knowledge, this is the first RAN model that accurately captures the energy consumption as a function of the rate requirements of TDs, their spatio-temporal variability, and different types of energy-consuming hardware components inside the BSs.

The rest of the paper is organized as follows. In section II we describe the model for an IbHWS, including the RF and BS energy models. In section III we present an efficient algorithm to reduce the energy consumption of the IbHWS. Simulation parameters and results are given in section IV, and conclusions are drawn in section V.

II. Network and Energy Consumption Models

In this section, we describe the models to capture the characteristics of an IbHWS, the TDs, RF energy consumption, and BS energy consumption.

A. Network Model

We model the IbHWS as a set $\mathcal{A}$ of layers. Each layer $a \in \mathcal{A}$ contains a set $\mathcal{B}_a$ of BSs. Each BS $b \in \mathcal{B}_a$ is deployed in a coordinate $x_b \in \mathbb{R}^3$. In addition, we presume there is no inter-layer interference, which matches existing deployment approaches used in cellular systems. Also, to make the formulation tractable, we consider the expected intra-layer interference to be known or managed through techniques, such as enhanced inter-cell interference cancellation (eICIC).

In general, a TD is characterized by the sessions arrival rate and an average file size [11]. However, this approach is inaccurate because the energy consumption depends on each sessions duration and power requirements. For wireless systems, the RF power is a function of the bit rate (bits per seconds) that is requested. Unlike the typical approach that completely ignores the bit rate of the TD, we take it into account in our model.

We consider the network to be able to serve sessions that have different QoS requirements. These are defined in terms of bit rates, allowing us to estimate the power needed to serve each session. Here, $\mathcal{Q}$ denotes the set of QoS requirements that the network supports. We also consider the total service area to be divided into locations $u \subset \mathbb{R}^3$. These locations are non-overlapping and each one can generate sessions of any QoS. The set of all locations of interest is denoted by $\mathcal{U} = \bigcup u$.

For each time interval Δt_j and location u, the session arrival rate of QoS $q \in \mathcal{Q}$ is denoted by $\lambda_{u,q}(\Delta t_j)$, and the session average duration is denoted by $1/\mu_{u,q}(\Delta t_j)$. We consider the function $\lambda_{u,q}(\Delta t_j)$ to follow an inhomogeneous Poisson arrival process distribution in time and space. However, during any time interval Δt_j, we consider such distribution to be homogeneous in time, but not necessarily in space.

B. RF Energy Model

We focus on the model that addresses the RF energy requirements for the traffic demands a BS must satisfy. Consider a BS b that serves a set of locations $\mathcal{G} \subset \mathcal{U}$. The total RF power radiated by b is

$$P_{RF}(t) = \operatorname{tr}\left(N(t)P^T(t)\right), \tag{1}$$

where **tr** denotes the trace of a matrix. $N(t)$ and $P(t)$ are matrices whose elements $N_{\omega,\tau}(t)$ and $P_{\omega,\tau}(t)$ denote (at a time t and location $u_\omega \in \mathcal{G}$) the number of sessions with QoS q_τ, and the amount of power to satisfy one session of QoS q_τ, respectively. The total RF energy radiated by b during Δt_j is

$$E_{RF}(\Delta t_j) = \int_{\Delta t_j} P_{RF}(t)\mathrm{d}t = \int_{\Delta t_j} \operatorname{tr}\left(N(t)P^T(t)\right)\mathrm{d}t. \tag{2}$$

The expected value of this energy is

$$\mathbb{E}[E_{RF}(\Delta t_j)] = \int_{\Delta t_j} \operatorname{tr}\left(\mathbb{E}\left[N(t)P^T(t)\right]\right)\mathrm{d}t. \tag{3}$$

By assuming that $N(t)$ and $P(t)$ are uncorrelated, we obtain

$$\mathbb{E}[E_{RF}(\Delta t_j)] = \int_{\Delta t_j} \operatorname{tr}\left(\mathbb{E}\left[N(t)\right]\mathbb{E}\left[P^T(t)\right]\right)\mathrm{d}t. \tag{4}$$

For current wireless systems, this assumption implies that the power required to serve a user at a specific rate is uncorrelated with the number of users that are served by the BS. Thus, this assumption can hold for existing systems. For example, in OFDMA-based systems such as LTE, once the subcarriers are allocated to a user, the power required to serve the user is independent of the number of users served by the BS. In UMTS/WCDMA, this assumption generally does not hold due to the orthogonality factor greater than zero. However, the expression can still apply if the power is calculated considering an expected level of intra-cell interference.

We can further simplify this expression by treating $N(t)$, $P(t)$, or both, as first-order stationary (FOS). In the case that both are FOS, we get

$$\mathbb{E}[E_{RF}(\Delta t_j)] = \Delta t_j \operatorname{tr}\left(\mathbb{E}\left[N\right]\mathbb{E}\left[P^T\right]\right), \tag{5}$$

where the time dependency of N and P has been removed to reflect the first-order stationarity of each random process.

In section II-C we obtain the amount of energy consumed by the BS to produce the energy described by $\mathbb{E}[E_{RF}(\Delta t_j)]$.

C. Base Station Energy Consumption Model

Consider the components $c \in \mathcal{C}$ to represent the major energy-consuming elements in a BS, such as the feeder, power amplifier (PA), baseband microprocessor (BuP), power supply (PS), and air conditioner (A/C). Each one can be either *on* (with load), *on* (with no load), or *off*. When a component is *off*, its energy consumption in a time interval Δt_j is

$$E_{off}(\Delta t_j) = P_{off}\Delta t_j, \tag{6}$$

where P_{off} is the standby power. For passive components $P_{off} = 0$, and for non-passive components $P_{off} > 0$.

When a component is *on*, it consumes a minimum amount of energy that is independent of its load. For example, a BuP has to process control channels even if no users are connected to the BS. We model the minimum energy consumption as:

$$E_{on,min}(\Delta t_j) = P_{on,min}\Delta t_j, \tag{7}$$

where $P_{on,min}$ denotes power consumed with no load. For passive components $P_{on,min} = 0$, and for non-passive components $P_{on,min} > 0$.

For the dynamic part of the energy consumption when a device is *on*, we define two types of models. The dynamic energy required at the input $E_{on,dyn}(\Delta t_j)$ of a Type A component (e.g. PA) is

$$E_{on,dyn}(\Delta t_j) = \int_{\Delta t_j} \frac{1}{\alpha(t)} P_{out}(t)\mathrm{d}t, \tag{8}$$

where $\alpha(t)$ is the power efficiency of the device, and $P_{out}(t)$ is the power that it needs to produce at its output. For most components, $\alpha(t)$ can be assumed to be a constant. So, taking the expected value, we obtain

$$\mathbb{E}[E_{on,dyn}(\Delta t_j)] = \frac{1}{\alpha}\mathbb{E}[E_{out}(\Delta t_j)]. \tag{9}$$

The dynamic energy required at the input $E_{on,dyn}(\Delta t_j)$ of a Type B component (e.g. BuP) depends on the traffic load in the BS rather than on output RF energy of the BS:

$$E_{on,dyn}(\Delta t_j) = \int_{\Delta t_j} (P_{on,max} - P_{on,min}) h(\mathrm{load}(t))\mathrm{d}t, \tag{10}$$

where $P_{on,max}$ is the maximum power, and $0 \leq h(\mathrm{load}(t)) \leq 1$. By assuming that h is linear in the load, and that the load is FOS, the expected value of the dynamic energy becomes

$$\mathbb{E}[E_{on,dyn}(\Delta t_j)] = \frac{\Delta t_j (P_{on,max} - P_{on,min})}{\mathrm{load}_{max}}\mathbb{E}[\mathrm{load}]. \tag{11}$$

$\mathbb{E}[\mathrm{load}]$ can be expressed as $\mathrm{tr}\left(\mathbb{E}\left[\mathrm{N(t)R^T}\right]\right)$, where R is a matrix in which (i) all rows are equal, and (ii) the values in a row represent the bit rate associated with each $q \in \mathcal{Q}$. Assuming FOS for $N(t)$, we obtain

$$\mathbb{E}[E_{on,dyn}(\Delta t_j)] = \frac{\Delta t_j (P_{on,max} - P_{on,min})}{\mathrm{load}_{max}} \mathrm{tr}\left(\mathbb{E}[N]R^T\right). \tag{12}$$

For all the previous expressions, $\mathbb{E}[N]$ can be defined as the matrix whose elements $N_{\omega,\tau}$ are:

$$N_{\omega,\tau} = \lambda_{u_\omega,q_\tau}(\Delta t_j)/\mu_{u_\omega,q_\tau}(\Delta t_j). \tag{13}$$

The total energy consumption $\hat{E}_b(\Delta t_j)$ of a BS b in time interval Δt_j can now be expressed as

$$\hat{E}_b(\Delta t_j) = \begin{cases} \hat{E}_{off}(\Delta t_j) & \text{if } b \text{ is } \textit{off} \\ \hat{E}_{on,min}(\Delta t_j) + \hat{E}_{on,dyn}(\Delta t_j) & \text{if } b \text{ is } \textit{on} \end{cases} \tag{14}$$

where $\hat{E}_{off}(\Delta t_j)$ represents the total energy consumption of b when it is *off*. $\hat{E}_{on,min}(\Delta t_j)$ and $\hat{E}_{on,dyn}(\Delta t_j)$ represent the total minimum and dynamic energy consumption when b is *on*. Exact expressions for these variables will not only depend on N, P, R and Δt_j, but also on the specific set $\mathcal{C}$ of components present in b and how they are interconnected. For example, even if no users are connected to b, the PS is *on* (with load) since it provides the power to all components.

III. ENERGY SAVING

For every Δt_j, to achieve the maximum energy saving in the RAN can be represented by the following objective function:

$$\min \sum_{a\in\mathcal{A}} \sum_{b\in\mathcal{B}_a} \mathbb{E}\left[\hat{E}_b(\Delta t_j)\right], \tag{15}$$

s.t.:

$$\sum_{a\in\mathcal{A}} \sum_{b\in\mathcal{B}_a} \phi_b(\Delta t_j, u) = 1, \forall u \in \mathcal{U}, \tag{16a}$$

$$\sum_{u\in\Psi_b(\Delta t_j)} \sum_{q\in\mathcal{Q}} \mathbb{E}\left[N_{u,q}\right] R_{u,q} \leq \Upsilon_b, \forall a \in \mathcal{A}, \forall b \in \mathcal{B}_a, \tag{16b}$$

where $\phi_b(\Delta t_j, u)$ is an indicator function equal to 1 when b serves u, $\Psi_b(\Delta t_j)$ is the set of users served by b, and Υ_b is the maximum load supported by b. Constraint (16a) indicates that each u is served by a single b, while (16b) indicates that the total load in each BS should be below the maximum it can support. This problem is in general non-convex and not-solvable through standard optimization methods. Hence, we propose a low complexity heuristic algorithm to tackle it:

Algorithm 1 Energy Saving

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∀u,∀a : Find argmin_{b∈B_a} χ(b,u).
Create partition Γ of U such that
    ∀a,∀b ∈ B_a : ∃Ω_b ⊆ Γ | ψ_b = ⋃_{γ∈Ω_b} γ, and |Γ| is minimum.
∀a,∀b ∈ B_a,∀γ ∈ Ω_b : Ê_{on,dyn}(γ).
repeat
    repeat
        Find γ_v = argmax_{a∈A,b∈B_a,γ∈Ω_b} Ê_{on,dyn}(γ) + E_{OH}(γ).
        Find b_v = argmin_{a∈A,b∈B_a} Ê_{on,dyn}(γ_v) + E_{OH}(γ_v).
        Assign γ_v to b_v.
    until Each γ has been assigned to a b.
    ∀a,∀b ∈ B_a : Calculate and apply energy overhead to
    each γ served by b.
    Calculate total energy of new configuration.
until No further energy savings.
```

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Bandwidth	3.84 MHz
BS Max. bit rate	14.4 Mbps
QoS Rates	[1,20,80,200]*15kbps
Time intervals	24 (1 hr each)
Total Coverage Radius	2500 m
Number of Locations	500
Altitude of Locations	1.5 m
Number of Layers	3
Type of BSs (per layer)	[macro,pico,pico]
Number of BSs (per layer)	[7,15,25]
Altitude of BSs (per layer)	[25,20,10]m

TABLE II
BS COMPONENTS AND PARAMETERS, PER LAYER

Component	P_{off}(W)	$P_{on,min}$(W)	α	$P_{on,max}$(W)
Feeder	[2,0,0]	[0,0,0]	[1,0,0]*0.63	-
PA	[1,1,1]*0.25	[4,1,0.25]	[2,1,1]*0.2	-
BBuP	[1,1,1]	[4,2,2]	-	[2,1,1]*6
A/C	[3,3,-]	[1,1,-]*0.9	[3,3,-]	-
PS	[1,1,1]*0.9	[1,1,1]*0.1	[1,1,1]*0.9	-

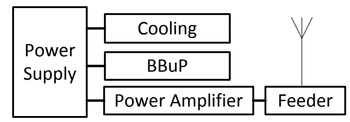


Fig. 1. Interconnections of BS components

$\chi(b,u)$ represents the pathloss between b and u, ψ_b represents the set of locations that b could serve, $\hat{E}_{on,dyn}(\gamma)$ denotes the total dynamic energy required by a BS b to serve γ, and $E_{OH}(\gamma)$ denotes the energy overhead for γ. The concept is summarized as follows: each location u finds, per layer, the best BS that could serve it (based on path loss). The set of users $\mathcal{U}$ is partitioned into groups to reduce the complexity. Then, the total dynamic energy required to serve each group is calculated, per layer. Groups get assigned to BSs as to minimize the maximum required energy, accounting for an energy overhead due to $\hat{E}_{on,min}$. For m layers, up to n BSs per layer, and p locations, the overall complexity is $O\left(mp\max(n,p)\right)$.

IV. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the proposed energy-saving algorithm in a IbHWS.

A. Simulation Setup

Simulation parameters for the IbHWS are shown in Table I. BSs per layer and locations are uniformly distributed across the coverage area. The IbHWS is setup to satisfy the needs of capacity and coverage, using three layers. TDs are generated so that the second layer (L2) is able to satisfy the peak TD at any time and location, providing the minimum required capacity. To capture the spatio-temporal variability, each L2 BS is setup to experience the peak TD at different times.

The previous formulation also has consequences in the other layers. L1 cannot satisfy all traffic demands, since it has less BSs than L2. Consequently, L1 is meant for coverage. On the other hand, L3 has excess capacity to satisfy all TDs. As such, it is meant to enhance capacity. Therefore, this formulation allows to capture operators' objectives of satisfying and enhancing capacity and coverage.

In Table II, the BSs' components and parameters are listed. We assume the BSs in L3 require no A/C due to a low expected value of power consumption. The interconnection among these elements is shown in Fig. 1. E_{RF} is the output energy of the feeder. The energy received at the input of the feeder comes from the PA, whose power is mainly drawn from the PS. The BBuP's energy is also provided by the PS. The A/C needs to compensate the energy dissipated by all the previous elements, and the energy it needs is drawn from the PS. Based on these relations and the energy models, we obtain the energy used by each BS.

B. Simulation Results

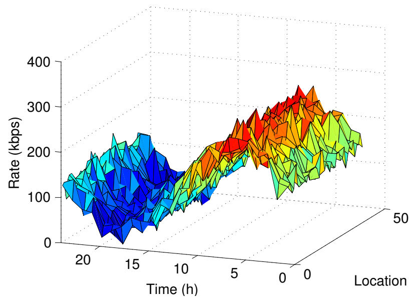
The amount of energy savings that can be achieved depends on the specific layout of the network, locations, and traffic demands. First, we present the results obtained from a single scenario generated with the previous parameters. Then, we provide values for average achievable energy savings across multiple scenarios.

As mentioned previously, traffic is generated using L2 as reference. In Fig. 2a we show the average rate requested per time interval for all locations associated with a single BS of L2. There is an overall trend in how the average rate of each location evolves in time. However, each location still has its own variability. Each L2 BS has a similar behavior, but they experience the peak rate at different times. Fig. 2b shows the different trend seen by a L3 BS. This occurs because a L3 BS may serve locations whose traffic followed the trend from different L2 BSs. As such, the locations served by a L3 BS may generate more traffic than the capacity of the L3 BS. In terms of RF energy, Fig. 2c shows the amount required to satisfy the TDs of Fig. 2a. This shows that the energy consumption trend may be completely different from the TDs' trend. This reinforces the value of an accurate mapping from TDs to RF energy consumption.

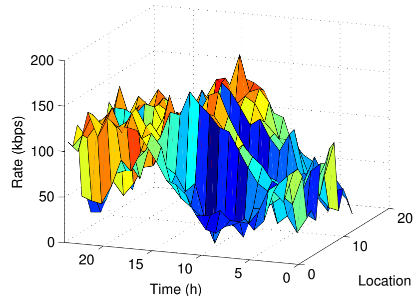
Fig. 3 shows the total energy consumed per layer, in the configuration of energy saving. Even though the energy consumptions are quite similar among the layers, we identified that L3 was taking care of nearly 72% of all locations. This strongly suggests that L3, the layer with smallest cells, is energy efficient in satisfing most locations, but not all.

To evaluate the efficiency of the proposed algorithm, we generated 1000 different scenarios using the parameters shown in Table II. Fig. 4 shows the distribution of the percent of energy savings that were achieved across all scenarios and all time intervals. The mean value of energy savings is 26.04%, and the standard deviation is 8.26.

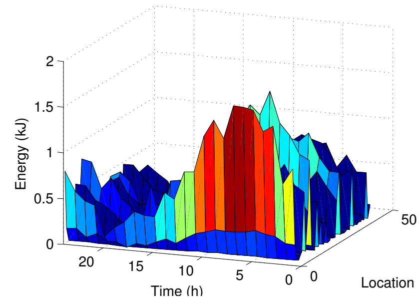
It is important to remember that during periods of peak TD, the values of achievable energy savings are low. Furthermore,



(a) Average rate for a BS in layer 2



(b) Average rate for a BS in layer 3



(c) Average RF energy for a BS in layer 2

Fig. 2. Average rate and RF energy

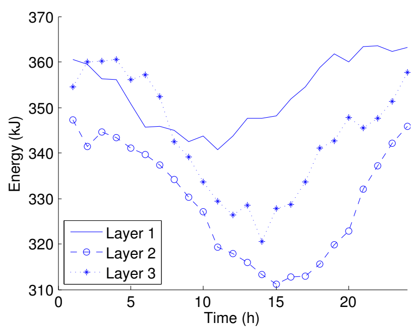


Fig. 3. Total energy consumption per layer

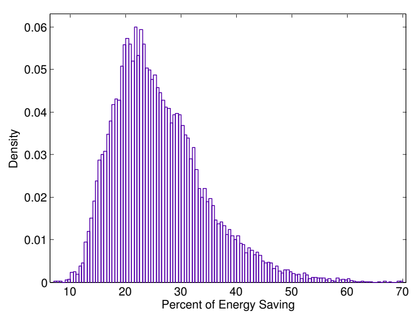


Fig. 4. Probability density function of the percent of energy saving

even during time instants of low TDs, BSs that enter into the *off* state would still consume standby energy, further reducing the amount of achievable energy savings. Taking this into account, the amount of energy savings that we can achieve with our low complexity algorithm allows operators to maximize the energy efficiency of their networks while satisfying the time-varying and space-varying TDs.

V. Conclusions

Due to their environmental and economic impact, energy savings in cellular systems have drawn significant amount of attention. However, existing models characterizing the energy consumption in the RAN have severe limitations. In this paper, we have accurately captured the energy consumption in the RAN, and tackled the said limitations. We developed a model that addresses traffic demands considering not only their spatio-temporal variability, but also QoS requirements. We derived the amount of RF energy required by BSs deployed in a multi-layer infrastructure-based heterogeneous wireless system, in order to satisfy the traffic demands. In addition, the model describes the peculiarities in the energy consumption from various BS hardware components, such as the power amplifier and the A/C. Our model also presents the energy consumption of the BS in terms of its overall load and RF energy. Finally, we introduced a low-complexity algorithm that achieves on average 26% energy savings in the RAN across several scenarios. Future work will address the issue of limited knowledge of traffic demands' properties.

Acknowledgment

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