Joint Optimization for Cell Configuration and Offloading in Heterogeneous Networks

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***Abstract*—To steadily gaining benefit from the exponential growth in mobile traffic, operators are eager to find solutions to maximize profits. Two very attractive strategies have been proposed to complement the existing macro cellular architecture: deploying low power bases stations and offloading data traffic to other networks. Each strategy has different costs and yields different benefits for operators. The offloading option could be cheaper in the short run; nevertheless, it might be more expensive in the long run than cell densification due to the varying cost. On the other hand, small cells, since having to be deployed in advance, may be underutilized or not fully meet future demands. In the latter case, offloading techniques can be used to increase capacity with additional costs. Further, uncertainty of future data demands and electricity prices also impact operators profitability, making the best network strategy difficult to achieve. To address such problem, an optimal cell configuration algorithm is proposed by formulating a stochastic programming model that considers both network design and data offloading. This algorithm can maximize the profit, under future demand and price uncertainty. Numerical studies are extensively performed in which the results show that operators' profits can be improved with our proposed algorithm.**

I. Introduction

The unprecedented explosion of mobile data traffic has brought mobile network operators (MNOs) substantial gains in profits. To continue achieving economical success, MNOs desire to find solutions for enhancing coverage, data rate, and quality of service (QoS) support in cellular wireless networks. Traditionally, operators consider improving cellular services through network expansion methods such as acquiring more spectrum licenses, deploying new macrocells, and upgrading technologies (e.g., from WCDMA to LTE/LTE-A). Most recently, two alternatives, i.e., small cell densification and mobile data offloading, appear to be promising for dealing with tremendous data usage increase for operators who rely on their existing macro cellular networks. In this respect, this paper develops a cellular network configuration framework that encompasses both network design and data offloading to optimize network operators' profits.

Heterogeneous networks (HetNets) have recently emerged as an attractive solution, where low power small cells such as micro, pico and femto are deployed as a way of increasing capacity and coverage beyond the initial deployment of macro cells. Incrementally deploying small cellular bases stations (BSs) is simpler than building out complex cell towers and macro BSs. Comparatively speaking, small cell densification offers reduced capital (e.g., hardware) and operating (e.g., electricity, backhaul and site lease) expenditures (CAPEX and OPEX), making it especially attractive to MNOs. As a result, a number of carriers in several countries (Sprint in the United States and Vodafone in the United Kingdom) have announced their plans for small-cell deployments in recent years [1], [2].

Another option, in response to the explosive of data traffic, is mobile data offloading through complementary network technologies such as a separate network's resources. It refers to the technique of routing the data traffic of a network operator to alternative networks run by cooperating operators. For example, with considering economic incentive a MNO is enabled to handle mobile data traffic through third party entities in a typical urban area supported by multiple MNOs with a variety of radio access technologies, some of which may be the small cell networks [3] or WiFi networks [4]. This strategy will allow to increase their network capacity on-demand, and save CAPEX and OPEX, while benefiting from increased revenue.

The topics of HetNets and traffic offloading, as a result, have sparked a tremendous interest and research endeavor. Placement and management problems in HetNets have been the center of the discussion on obtaining the most cost-effective or energy-efficient policy [5]. Specifically, since small cell planning and BS operation are greatly involved with infrastructure and energy costs, how MNOs design and manage networks impacts on their profitability and competitiveness. Similarly, offloading mechanisms bring MNOs the option that is less costly and time-consuming to fulfill requirements of enhancing QoS support. In a short run, following a offloading strategy reduces the infrastructure and operation costs incurred by adding small cells into cellular networks; nevertheless, independently it may not always provide the most profitable results in the long run due to its ad hoc nature and relying on third-party networks. While these two techniques become prominent in emerging wireless networks, there is little research conducted on cell configuration through joint consideration of network design and offloading. In particular, the problem of considering the optimal profit for a MNO to jointly consider both techniques has not been addressed.

The problem is challenging due to the following. For future usage in a certain time period, operators need to place a certain number of small cells in advance. As a result, the *overprovisioning problem* can occur if the BS resources are more than the actual demand, in which case part of the BS pool will be underutilized, incurring unnecessary operation costs.

On the other hand, the *underprovisioning problem* can occur if the available resources are unable to meet the demand due to inaccuracy in estimating traffic demands. Although with the offloading plan, the operators have the leeway to dynamically provision services at the moment when the resources are needed to fit the fluctuated and unpredictable demands, the cost is closely dependent on network design as well. Thus, offloading and cell deployment schemes should be incorporated in order to achieve a more efficient decision. Moreover, price fluctuation in electricity charged to MNOs has a profound impact on network operating costs and solution effectiveness. Without consideration of price variation, optimality of solutions cannot be guaranteed. To be able to adjust the tradeoff optimally, the demand uncertainty from mobile user side and price uncertainty from electricity retailers should be taken into account.

In this work, maximizing the profit, considering both underprovisioning and overprovisioning problems, of cell configuration is our motivation to explore an optimal strategy for the operators. The proposed cell configuration algorithm decides small cell deployment to a set of candidate locations, operation policy to layers of BSs, including active/sleep mode of operation and channel bandwidth allocation, and offloading strategies for BS traffic offloading. Meanwhile uncertainties of future data demands and prices of electricity are taken into account for optimal decisions. The decision made by the algorithm is obtained as the optimal solution from stochastic integer programming (SIP) formulation with multistage recourse [6]. Extensive numerical studies and simulation are performed to evaluate the effectiveness of our cell configuration algorithm. The results show that the algorithm can maximize the profit under uncertainty.

The rest of this paper is organized as follows: Related works are reviewed in Section II, and the system model and assumptions of cellular networks are described in Section III. In Section IV, the stochastic linear programming formulation of the cell configuration algorithm is presented, followed by experiments and simulations to evaluate the performance of the cell configuration algorithm in Section V. Finally, conclusions are stated in Section VI.

II. Related Work

Only a few articles approach the joint problem of optimizing the network deployment and the energy-aware operation. The trade-off between deployment efficiency and energy efficiency is pointed out for the fundamental framework in green radio research in [7], while a static joint planning and management optimization approach is proposed in [8] to limit energy consumption and guarantee QoS while minimizing network operator costs. Much of current research focuses on energy-aware operation as a way to reduce network operator costs. Deterministic traffic variations over time are taken into account in [9], where the energy saved is characterized for different cell topologies by reducing the number of active access elements when they are not fully utilized. [10] uses cell-zooming techniques to adaptively adjust the cell size according to traffic load and to possibly switch off inactive cells. As for network planning, [11] measures the power efficiency of a large vs. small cell deployment on a service area; paper [12] evaluates the effectiveness of the joint deployment of macro cells and residential femtocells, while [13] investigates the cell layout impact on power consumption by varying the number of micro BSs per cell in addition to conventional macro sites.

A growing number of studies have been devoted to the potential performance benefits of mobile data offloading and the technologies to support it. Particularly, cooperating with third party networks through the market-based data offloading solution or usage-based charging model, MNOs can improve network throughput and overall network performance to increase their revenue and reduce CAPEX and OPEX [14]–[16]. However, the fundamentals of jointly optimizing cell configuration and offloading are not well understood. Moreover, none of these previous efforts considers uncertainty of future demands and prices, while the price fluctuations of electricity have been utilized as an important index for optimizing the operation, development, and scheduling in other areas [17]–[19]. Specifically, [20] studies the dynamic operation of cellular BSs with the consideration of the traffic and real-time electricity price; in contrast, our work considers also deployment and data offloading costs.

Stochastic programming has been developed to solve resource planning under uncertainty in various fields, e.g., production planning, financial management, and capacity planning [6]. For example, in [21] the authors applied the stochastic programming approach for cloud resource provisioning for reservation and on-demands plans while the demand uncertainty from cloud consumer side and price uncertainty from cloud providers are taken into account to adjust the tradeoff between the two costs. However, to the best of our knowledge, the application of stochastic programming to cell configuration has not been studied.

III. System Model and Assumption

We consider a simplified heterogeneous wireless network where the sets of deployed macro BSs and candidate locations for small cell deployment, denoted by $\mathcal{I}$ and $\mathcal{J}$, respectively, lie in the two-dimensional area $\mathcal{A} \subset \mathbb{R}^2$. Normally, a macro BS has a larger coverage radius (e.g., $\varphi_0 = 1$ km) while the micro and pico BSs have smaller coverage radius (e.g., $\varphi_1 =$ 200 m and 100 m, respectively). For simplicity of presentation, the area we consider for the deployment of small cell BSs is within macro cell regions[1].

A. Cell Configuration Plan

We devise three phases that compose the cell configuration plan: deployment, operation and offloading, as shown in Fig. 1. The three phases perform in different points of time (or events) with their actions discussed in the following. First, in the deployment phase, without knowing user demands and

[1]Without loss of generality, micro BSs are the only small cell type considered in this work; the model can be easily applied to scenarios with multiple types of small cells, and also macro cells.

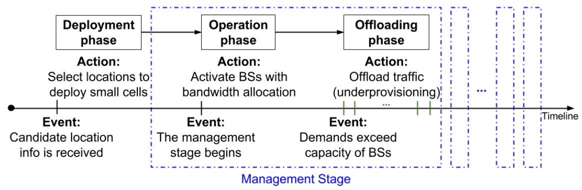


Fig. 1. Transition of phases and stages in the cell configuration plan.

electricity prices, the service provider deploys small cells in advance to increase network capacity beyond the initial deployment of macro cells. Then a management stage, consisting of an operation phase and an offloading phase, begins at BSs. Prior to the realization of demands and prices, at the beginning of a management stage, the service provider determines the operation mode of BSs (e.g., switch on or off) and the channel bandwidth allocated to BSs. In the remaining of the management stage, the price and demand are realized, and the switched-on BSs utilize the allocated resources to provision services to users. As a result, the BSs in operation can be underprovisioning or overprovisioning.

When the demand exceeds the capacity of allocated bandwidth (i.e., underprovisioning), the offloading phase starts. In this phase, small cells' traffic will be offloaded to the associated macrocell BS operated by the MNO, or the MNO can pay for offloading data traffic to other networks operated by cooperating third-party operators. We assume that there is no costs for offloading traffic between BSs under the same operator's mobile network. Also, we assume that the same observation area is served by multiple operators with agreements, meaning, it is always available to offload the traffic of one BS to a third-party mobile network. For example, [22] shows several operators provide coverage to the users in the same geographical area.

Within the cell configuration plan, multiple management stages can exist and are followed by one another. Between stages, BSs can switch between active and sleep mode, and be allocated with different channel bandwidth; therefore, the offloading decisions will vary. To obtain optimal decisions, uncertainty of prices and demands in stages are considered particularly. In addition, the duration of a management stage can differ from another (e.g., different number of hours or days). Based on the three phases, there are three costs associated with cell configuration: deployment, operation and offloading. The objective of a MNO is to maximize its profit by reducing all the above costs while demands at locations are met, using the cell configuration algorithm.

Given a set of small cell candidate locations, deployment costs, demand and price distributions at locations, the optimal solution of small cell deployment, HetNets operation and offloading is obtained by formulating and solving a SIP with multistage recourse (discussed in Section IV). There are two stages of decision making. The *first stage* defines the small cell deployment in deployment phase, while the *second stage* or *recourse* defines the network operation in operation phase, and the offloading policy in offloading phase. In the second stage the actual demands and prices are represented.

B. Capacity Model

A key challenge for the deployment of heterogeneous wireless networks is to cope with inter-layer and intra-layer interference when different layers of heterogeneous networks are deployed in one operator's spectrum band. A simple method is to do "frequency division", i.e., allocate orthogonal spectrum to different layers. Another method is to do "frequency sharing", i.e., keep the original spectrum band for macro layer as it is, and allocate a fraction of the spectrum to small cells. In this paper, we will focus on the first case. We assume small cells are deployed in macro cells in a sparse manner, i.e., there is no significant interference between small cells. We also assume that the radio spectrum access is based on the *Orthogonal Frequency-Division Multiple Access (OFDMA)* scheme, in which the total channel bandwidth B of BS i is divided in sub-channel of B^{sub} Hz each, and radio resources are allocated in the time/frequency domain, whereby each sub-channel is allocated to user terminals in slots (as 1 ms each in LTE networks, for instance).

The capacity of a BS depends on the bandwidth of channel and the SNR. The downlink data rate γ from a BS is computed using Shannon's capacity limit formula as:

$$\gamma = nB^{\text{sub}} \log(1 + \frac{pg}{\sigma^2}), \tag{1}$$

where n is the number of sub-channels allocated to the BS, and p is the BS transmit power; g is the channel gains of user of the BS, and σ^2 is noise power. Network throughput is the key measure of the revenue of wireless network service providers. In this work, network throughput is defined as the summation of the throughput of all BS sites within the considered network area, where the throughput of a BS site is the satisfied information bits from the data rate requirements for that BS site. We define network revenue as the network throughput multiplied by the revenue rate for a certain period.

C. Energy Model

In general, the energy consumption of a heterogeneous wireless network can be considered as the summation of the energy consumption of different classes of BS sites, i.e., $E^{\text{net}} = \sum_l N_l E_l^{\text{site}}$, where l is the class index, N_l and E_l^{site} are the number of BS sites and site energy consumption in class l, respectively. The latter is the accumulation of power consumption P^{site} over a certain time duration δ. Note that in this framework the power consumption of mobile terminals is not taken into consideration. Normally, the power consumption of a BS site includes power losses from circuit power of signal processing, radio frequency, A/D D/A converter, power supply, battery backup, antenna feeder, site cooling consumption, etc. It is shown in [23] that the relation between BS transmit power and BS site power consumption is nearly linear. Thus, the BS site power consumption can be approximated using the

TABLE I
POWER MODEL PARAMETERS FOR DIFFERENT BS CLASSES [24]

BS type	P^{base}	P^{sleep}	$P^{\max}$	λ
Macro	130 W	75 W	20 W	4.7
Micro	56 W	39 W	6.3 W	2.6

following linear model:

$$P^{\text{site}} = \begin{cases} P^{\text{sleep}}, & P^{\text{out}} = 0, \\ P^{\text{base}} + \lambda P^{\text{out}}, & P^{out} \in (0, P^{\max}], \end{cases} \quad (2)$$

where P^{out} is the BS transmit power, and P^{base} is the power consumption when BS transmits at the minimum non-zero power; λ is the slope of the traffic-dependent power consumption, which depends mostly on the power amplifier efficiency, i.e., BS transmit power and traffic have a near-linear relation. P^{sleep} is the sleep mode power consumption that is normally smaller than P^{base}.

Table I shows the reference values of $P^{\max}$, λ, P^{base}, and P^{sleep} for macro BSs and micro APs. Since in an LTE downlink, the BS load, defined by $\frac{P^{\text{out}}}{P^{\max}}$, is proportional to the amount of utilized resources, for both data and control signals, P^{out} can scale with the amount of assigned channel bandwidth a BS is operating on (nB^{sub}), that is,

$$P^{\text{out}} = \frac{nB^{\text{sub}}}{B} P^{\max}, \quad (3)$$

where B is the system bandwidth configuration and $P^{\max}$ denotes the maximum RF output power at maximum load.

D. Network Cost Model

In general, the total cost of a heterogeneous wireless network can be considered as the summation of the costs from different classes of BS sites c_l^{CO}, i.e., $C^{\text{net}} = \sum_l N_l c_l^{\text{CO}} = \sum_l N_l (C_l^{\text{Ca}} + C_l^{\text{Op}})$, where C_l^{Ca} and C_l^{Op} are BS site's CAPEX and OPEX, which can be further specified as

$$\begin{aligned} C_l^{\text{Ca}} &= c_l^{\text{BS}} + c_l^{\text{RNC}} + c_l^{\text{site}}, \\ C_l^{\text{Op}} &= c_l^{\text{PW}} + c_l^{\text{BT}} + c_l^{\text{lease}}, \end{aligned}$$

where c_l^{BS}, c_l^{RNC} and c_l^{site} represent the cost of BS equipments, radio network controller equipments, and BS site buildout of class l, respectively; c_l^{PW}, c_l^{BT} and c_l^{lease} are the expense related to BS operations, backhaul transmission leasing, and BS site leasing of class l, respectively.

Chen et al., model the annual average cell deployment cost (c^{CO}) as a function of the cell radius (φ) to compare the Macro ($\varphi \geq 0.5$ km) and Micro BS ($0.1 \leq \varphi < 0.5$ km) deployment options [25].

$$\begin{aligned} c^{\text{CO}}(\varphi) &= \frac{c^{\text{Ca}}(\varphi)}{T_{\text{lc}}(\varphi)} + c^{\text{Op}}(\varphi) \\ &= \begin{cases} 0.775 c_o + c_1 E^{\text{site}}(\varphi), & \varphi \geq 0.5, \\ 0.625 c_o + c_1 E^{\text{site}}(\varphi), & 0.1 \leq \varphi < 0.5, \end{cases} \end{aligned}$$

where c^{Ca} is the total CAPEX and c^{Op} is the annual OPEX; c_0 is the equipment cost of a macro BS, and c_1 is the electricity cost per Joule. E^{site} is the per-site energy consumption and the CAPEX weighting factors are based on a CAPEX and OPEX breakdown that considers nodes with different life-cycle (T_{lc}) for macro and micro BSs. To reflect the fact that the life-time of a macro BS is likely to be the double of the life-cycle of smell cells, we consider 10 and 5 years for the two types of BS, respectively.

E. Uncertainty of Parameters

The optimal solution is obtained from the algorithm based on stochastic integer programming. Stochastic programming takes a set of uncertainty parameters (called *scenarios*), described by a probability distribution [6]. Let Ω denote the set of scenarios for all management stages and Ω_t the set of all scenarios in management stage t. Set Ω is defined as the Cartesian product of all Ω_t, namely $\Omega = \prod_{t \in \mathcal{T}} \Omega_t = \Omega_1 \times \Omega_2 \times \cdots \times \Omega_{|\mathcal{T}|}$. It is assumed that the probability distribution of Ω has *finite support*, i.e., set Ω has a finite number of scenarios with respective probabilities $p(\omega) \in [0, 1]$, where ω is a composite variable defined as $\omega = (\omega_1, \cdots, \omega_{|\mathcal{T}|}) \in \Omega$. In this paper, demands and prices are considered as scenarios in Ω whose probability distribution is assumed to be available. The actual scenarios of uncertainty parameters after they are observed are called realization.

The demands at locations are not exactly known when the deployment and operation decisions are made. Let $\mathcal{D}_k^t = \{d_{k1}^t, d_{k2}^t, \cdots, d_{k|\mathcal{D}_k^t|}^t\}$ denote the set of possible demands of BS $k \in \mathcal{K} = \mathcal{I} \cup \mathcal{J}$ in management stage t. The set of all possible demands of all BSs in a management stage can be obtained from the Cartesian product as follows: $\mathcal{D}^t = \prod_{k \in \mathcal{K}} \mathcal{D}_k^t = \mathcal{D}_1^t \times \mathcal{D}_2^t \times \cdots \times \mathcal{D}_{|\mathcal{K}|}^t$. Similarly, the price of electricity for BS operation could be random. Let $\mathcal{C}_t^{(o)}$ denote the set of possible prices in management stage t. Assuming the locations in the interested area $\mathcal{A}$ are under the same price fluctuation, the set of all possible prices in all stages can be obtained as $\mathcal{C}^{(o)} = \prod_{t \in \mathcal{T}} \mathcal{C}_t^{(o)} = \mathcal{C}_1^{(o)} \times \mathcal{C}_2^{(o)} \times \cdots \times \mathcal{C}_{|\mathcal{T}|}^{(o)}$. Then, $\Omega_t = \mathcal{D}^t \times \mathcal{C}_t^{(o)}$. We assume that probability distributions for both demands in $\mathcal{D}^t$ and prices in $\mathcal{C}^{(o)}$ are known; the distributions can be obtained by using a established statistical process to analyze historical data or forecasting technique.

IV. STOCHASTIC PROGRAMMING MODEL

In this section, the stochastic programming with two-stage recourse is presented as the core formulation of the proposed algorithm. First, the original form of stochastic integer programming formulation is derived; then the formulation is transformed into the deterministic equivalent formulation (DEF), which can be solved by well-developed software packages.

A. Stochastic Integer Programming

The general form of SIP of the cell configuration algorithm is formulated in (4)–(7). The objective function (4) is to maximize the mobile operator's profits by configuring cells in both of the stages or equivalently in all phases. The binary decision variable d_j indicates whether candidate location j is chosen for small cell deployment, and $c_j^{(d)}$ is the deployment cost of small cell[2] j. h_{kt} represents the BS status (active or sleep), and n_{kt} denotes the amount of channel bandwidth, for BS k in management stage t. The first stage decides where small cells should be placed in deployment phase, while the second stage defines which BSs should be switched on/off and the number of allocated subchannels of BSs in operation phase, and in offloading phase, the bandwidth for offloaded traffic to the third-party network and associated macro BSs. The second stage shows the actual data demands and electricity prices.

Maximize:

$$-\sum_{j\in\mathcal{J}} c_j^{(d)} d_j + \mathbb{E}_\Omega[\mathcal{Q}(d_j, h_{kt}, n_{kt}, \omega)], \tag{4}$$

Subject to:

$$d_j \in \{0,1\}, \quad j \in \mathcal{J}, \tag{5}$$

$$h_{kt} \in \{0,1\}, \quad k \in \mathcal{K},\ t \in \mathcal{T}, \tag{6}$$

$$n_{kt} \in \{0,1,\ldots\}, \quad k \in \mathcal{K},\ t \in \mathcal{T}, \tag{7}$$

The expected profit under the uncertainty is defined as the function $\mathbb{E}_\Omega[\mathcal{Q}(d_j, h_{kt}, n_{kt}, \omega)]$, where $\Omega = \prod_{t\in\mathcal{T}} \mathcal{D}^t \times \mathcal{C}_t^{(o)}$ denotes the set of possible demands and prices in all management stages (called *realizations*, in general) observed in the second stage. For a given realization $\omega \in \Omega$, the recourse function $\mathcal{Q}(d_j, h_{kt}, n_{kt}, \omega)$ can be expressed as follows:

$$\mathcal{Q}(d_j, h_{kt}, n_{kt}, \omega) = \max_{Y=(y_{kt}(\omega), x_{ijt}(\omega))} \mathcal{F}(Y), \tag{8}$$

where $Y \in \Upsilon(d_j, h_{kt}, n_{kt}, \omega)$. In (8), the objective of $\mathcal{Q}(d_j, h_{kt}, n_{kt}, \omega)$ is to maximize the profit under uncertainty given ω, d_j, h_{kt} and n_{kt}. $\mathcal{F}(\cdot)$ denotes the utility function in the second stage and is defined as follows, where the revenue is generated through satisfying traffic demands of BSs multiplied by $e^{(v)}$, which is the revenue rate.

$$\mathcal{F}(Y) = \sum_{t\in\mathcal{T}} \sum_{k\in\mathcal{K}} (e^{(v)} r_{kt}(\omega) - c_t^{(o)}(\omega) s_{kt} - c^{(b)} y_{kt\omega}), \tag{9}$$

In (9), $c_t^{(o)}$ is the electricity cost rate, and s_{kt} represents the energy consumption in management stage t for BS operation from set $\mathcal{K}$, which is expressed as: $s_{kt} = \delta_t\big(P_k^{\text{sleep}}(1-h_{kt}) + P_k^{\text{base}} h_{kt} + P_{kt}^{\text{out}}\big)$, where δ_t is the time duration of management stage t. P^{sleep}, P^{base} are discussed in (2), and as mentioned in (3), $P_{kt}^{\text{out}} = \lambda_k P_k^{\max} h_{kt} \frac{n_{kt} B^{sub}}{B}$.

Composite variable Y representing the solution of $\mathcal{Q}(d_j, h_{kt}, n_{kt}, \omega)$ consists of the variables, $x_{ijt}(\omega)$ and $y_{kt}(\omega)$, which denote the amount of traffic to be offloaded to associated macro cells and the cooperating third-party network in offloading phase, respectively. Set $\Upsilon(d_j, h_{kt}, n_{kt}, \omega)$ controls the relationship among the variables in the first and second stages by constraints expressed in (10)–(21). Constraints (10) and (11) guarantee that a small cell is placed only if the cell site will be active in any of the following stages, while (12) and (13) impose switching on the BS if the number of allocated channels is not 0, where M is a large constant (i.e., the Big M method). In (14) and (15), the allocation of channel bands to the macro BS and any of its small cell BSs must not exceed the channel bandwidth available to the operator, and all the available subchannels are allocated among BSs.

The demand under a realization ω is governed by the constraints in (16)–(19), where $r_{kt}(\omega)$ denotes the amount of traffic demand in the second stage to cell k. Variables $x_{ijt}(\omega)$ and $y_{it}(\omega)$ denote the traffic offloaded to its macro cell, and to the cooperating third-party network, respectively. The constraints in (16) and (17) ensure that the amount of bandwidth provisioned is sufficient, where the capacity, γ is defined in (1). Since the small cells are overlapping with associated macro ones, traffic can be offloaded to macrocellular network layer as well; in (17), the traffic of a small cell can be met by the associated macro cell and the third-party operator. Constraints (18) and (19) state the amount of traffic being offloaded does not exceed the capacity offered by macro cells and the third-party, respectively. Constraints (20) and (21) indicate that variables take the values from a set of nonnegative numbers (i.e., $\mathbb{R}$).

$$d_j \geq h_{jt}, \quad j \in \mathcal{J},\ t \in \mathcal{T}, \tag{10}$$

$$d_j \leq \sum_{t\in\mathcal{T}} h_{jt}, \quad j \in \mathcal{J},\ t \in \mathcal{T}, \tag{11}$$

$$n_{kt} \leq M h_{kt}, \quad k \in \mathcal{K},\ t \in \mathcal{T}, \tag{12}$$

$$n_{kt} \geq h_{kt}, \quad k \in \mathcal{K},\ t \in \mathcal{T}, \tag{13}$$

$$n_{it} + n_{jt} \leq \frac{B}{B^{sub}}, \quad i \in \mathcal{I}, \quad j \in \mathcal{U}_i,\ t \in \mathcal{T}, \tag{14}$$

$$n_{it} + \sum_{j\in\mathcal{U}_i} n_{jt} \geq \frac{B}{B^{sub}}, \quad i \in \mathcal{I},\ t \in \mathcal{T}, \tag{15}$$

$$r_{it}(\omega) \leq \gamma_{it} + y_{it}(\omega) + \sum_{j\in\mathcal{U}_i} x_{ijt}(\omega), \quad i \in \mathcal{I},\ t \in \mathcal{T}, \tag{16}$$

$$r_{jt}(\omega) \leq \gamma_{jt} + y_{jt}(\omega) + x_{ijt}(\omega), \quad i \in \mathcal{I},\ j \in \mathcal{U}_i,\ t \in \mathcal{T}, \tag{17}$$

$$\gamma_{it}(\omega) \geq \sum_{j\in\mathcal{U}_i} x_{ijt}(\omega), \quad i \in \mathcal{I},\ j \in \mathcal{U}_i,\ t \in \mathcal{T}, \tag{18}$$

$$y_{it}(\omega) + \sum_{j\in\mathcal{U}_i} y_{jt}(\omega) \leq l_i, \quad i \in \mathcal{I},\ t \in \mathcal{T}, \tag{19}$$

$$x_{ijt}(\omega) \geq 0, \quad i \in \mathcal{I},\ j \in \mathcal{U}_i,\ t \in \mathcal{T}, \tag{20}$$

$$y_{kt}(\omega) \geq 0, \quad k \in \mathcal{K},\ t \in \mathcal{T}. \tag{21}$$

B. Deterministic Equivalent Formulation

The SIP formulation defined in (4)–(21) can be transformed into a deterministic integer program called *deterministic equivalent formulation*. The deterministic equivalent SIP is expressed in (22)–(29). When demands and prices are realized in management stages, $y_{kt\omega}$ and $x_{ijt\omega}$ denote the amount of bandwidth offered to BS k by the other provider, the traffic in small cell j offloaded to the associated macro BS i, respectively. The recourse cost is defined after $r_{kt\omega}$, $c_{t\omega}^{(o)}$

[2] Since this paper focuses on providing the solution for the small cell deployment problem, the respective deployment cost of macro BSs is not considered; however, it is straightforward how the model can be modified for the consideration of macro BS deployment.

are observed in t.

Maximize:

$$\sum_{\omega\in\Omega}\sum_{t\in\mathcal{T}}\sum_{k\in\mathcal{K}} p(\omega)(e^{(v)}r_{kt\omega} - c^{(o)}_{t\omega}s_{kt} - c^{(b)}y_{kt\omega}) - \sum_{j\in\mathcal{J}} c^{(d)}_j d_j, \tag{22}$$

Subject to: (10)–(15), (23)

$$r_{it\omega} \le \gamma_{it} + y_{it\omega} + \sum_{j\in\mathcal{U}_i} x_{ijt\omega}, \quad i\in\mathcal{I},\, t\in\mathcal{T},\, \omega\in\Omega, \tag{24}$$

$$r_{jt\omega} \le \gamma_{jt} + y_{jt\omega} + x_{ijt\omega}, \quad i\in\mathcal{I},\, j\in\mathcal{U}_i,\, t\in\mathcal{T},\, \omega\in\Omega, \tag{25}$$

$$\gamma_{it\omega} \ge \sum_{j\in\mathcal{U}_i} x_{ijt\omega}, \quad i\in\mathcal{I},\, t\in\mathcal{T},\, \omega\in\Omega, \tag{26}$$

$$y_{it\omega} + \sum_{j\in\mathcal{U}_i} y_{jt\omega} \le l_i, \quad i\in\mathcal{I},\, t\in\mathcal{T},\, \omega\in\Omega, \tag{27}$$

$$x_{ijt\omega} \ge 0, \quad i\in\mathcal{I},\, j\in\mathcal{U}_i,\, t\in\mathcal{T},\, \omega\in\Omega, \tag{28}$$

$$y_{kt\omega} \ge 0, \quad k\in\mathcal{K},\, t\in\mathcal{T},\, \omega\in\Omega. \tag{29}$$

To solve the DEF, probability distributions of must be available, i.e., in Section III-E. Then, the DEF can be solved by using basic optimization solvers. In this work, the formulation is implemented using Java, and solved by IBM ILOG CPLEX Optimizer [26].

V. Performance Evaluation

Numerical studies are performed to evaluate the performance of the proposed approach. The real historical data of demands and prices are used in the evaluation. We assume that operators are able to observe and analyze the traffic load profile, and traffic distributions can be modeled in time periods (this is common assumption in network resource management [27]). Essentially, probabilities are characterized to represent levels of data traffic being requested. The load profiles for our experiments are reported in Fig. 2(a) and have been used in other study [27]. This real traffic traces consist of normalized cellular traffic collected in a metropolitan urban area over a span of one week [28]. In the experiments, within the considered area for the deployment, each location presents one of the five traffic variation behaviors. We also assume the electricity price distribution is available to operators. For example, the distributions can be obtained by statistically analyzing historical data or forecasting electricity prices [29]. The price variations in our experiments are reported in Fig. 2(b), which are based on hourly day-ahead marginal pricing from the PJM [30], where data sets are widely used for electricity price forecasting.

Our algorithm optimizes the profit of network operators for the period of a week. Namely, the whole week are split in management stages, each of which gathers intervals (hours) in which the demands and prices are fluctuated with probabilities. To simplify the evaluation, demands and prices are redefined in each management stages, and the probabilities are generated accordingly based on the available data. Without loss of generality, we assume that all the macro BSs and all the micro cells are identical, and the cooperating third-party operator shares same coverage area. The values of experimental parameters are reported in Table II.

TABLE II
Experimental Settings

Parameter	Value
Channel bandwidth of BS (B)	20 MHz
Sub-channel bandwidth (B^{sub})	180 kHz
Noise power	-104.5 dBm
Installation cost of d_j ($c^{(d)}_j$)	\$ 230 (based on [24])
Power consumption for k	Table I
Offloading cost ($c^{(b)}$)	\$ 15/500 MB (as overage in [31])
Revenue rate ($e^{(v)}$)	\$ 75/2 GB (as in [31])
Third-party offload capacity	105 Mbps

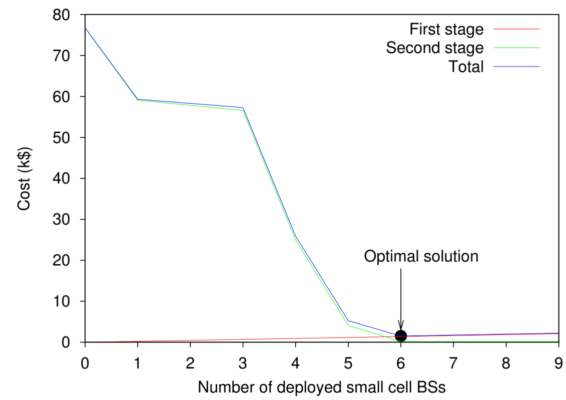
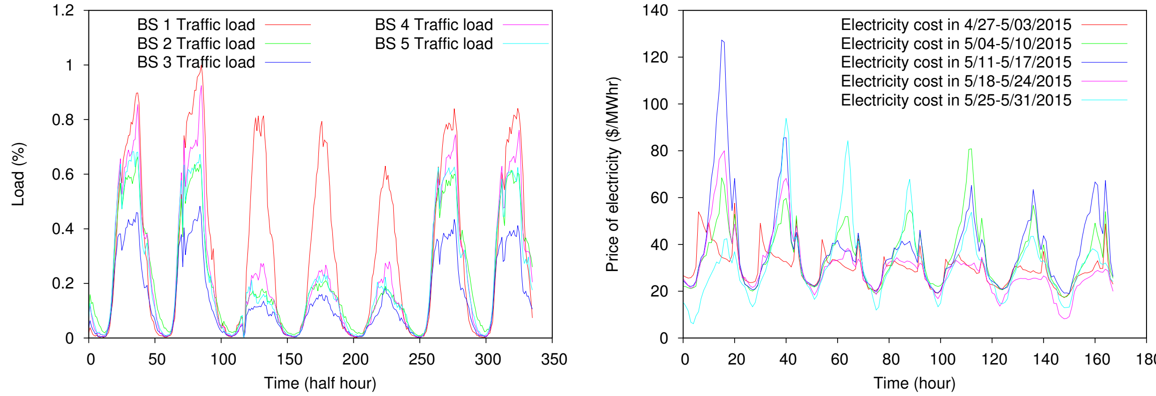


Fig. 3. The optimal solution in a simple cell configuration environment.

A. Cost Structure

First, the cost structure is studied. To ease the illustration, a simple cell configuration environment is considered which consists of only one management stage, i.e., $|\mathcal{T}| = 1$. We consider a deployment and operation hierarchy that encompasses a single macro site (i.e., $|\mathcal{I}| = 1$) and a set of 9 candidate locations for the small cell deployment (i.e., $|\mathcal{J}| = 9$). The traffic demands are varied, and two sets of demands and probabilities are selected for individual cells. In Fig. 3, for different number of deployed small cells, *first stage cost* (which is actually deployment cost), *second stage cost* (including operation and offloading costs), and total cost, are presented. As expected, the first stage cost increases, as the number of deployed small cells increases. However, the second stage cost decreases after the demand is realized, since the network operator needs a smaller amount of data traffic provisioned by offloading plan. In this case, the optimal number of deployed small cells can be determined to be 6, which is the point of the minimum total cost. Clearly, even in this small setting (one management stage and two possibilities for demands and prices), the optimal solution is not trivial to obtain due to the uncertainty of demands and prices. Therefore, the proposed algorithm would be required to guarantee the minimum cost to the operator.



(a) Traffic load curves for the BSs

(b) Energy cost curves for the operators

Fig. 2. Traffic load and electricity price curves for the experimental scenarios.

Another experiment is conducted to compare optimal profits of different cell deployment schemes. The results are illustrated in Fig. 4, in which ”with optimal deployment” optimizes cell deployment, ”without optimal deployment” deploys cells at all candidate locations, and ”without deployment” considers no small cell deployment. Without the cell deployment, no deployment costs but macro cell operational and offloading costs are incurred. Here we consider 5 candidate locations in 1 macro cellular BS under demand uncertainty for one management stage, and the optimal solution deploys 4 small cells at the locations. Fig. 4 presents scenarios with different demands (or realizations of mobile network traffic) from low to high. Without the optimal deployment, although it is near-optimal, the best profit cannot be achieved. The profit without cell deployment is higher than the other two deployment schemes until a certain level of total demands, which is the effective deployment point. The fact indicates that even if with the optimal deployment, it cannot guarantee the best profit in all realizations of observed parameters. However, the expected profit of the optimal deployment is the greatest (shown as optimal value in the figure). Therefore, the effective way to tackle the uncertainty is not to search for the best solution for every possible situation happening in the future, but to obtain the solution which is to maximize the expected profit while the uncertainty is carefully considered.

B. Cell Configuration in Different Stages

To show how demand uncertainty affects operation decisions under an optimal deployment, we compare costs in different management stages. We proceed by splitting the traffic load curve of each BS displayed in Fig. 2(a) into 4 management stages with same time duration. Note that no time gap is admitted between adjacent management stages, and the summed duration of all stages is equal to the number of hours in a week. Each location is characterized with a different demand mean and variance. Fig. 5 shows the cost in different management stages, where second-stage cost is the summed cost of operation and offloading cost. Given the optimal deployed small cells, the demand varies from stages to stages; the mean is lowest in stage 2 and highest in stage 1 (i.e., 1.5 times), and the mean in the other 2 stages are close (i.e., 2% difference). As a result, the offloading cost is the highest in stage 1 and lowest in stage 2. Although an offloading cost increases since more capacity is required, the solution ensures that the cost is not too high.

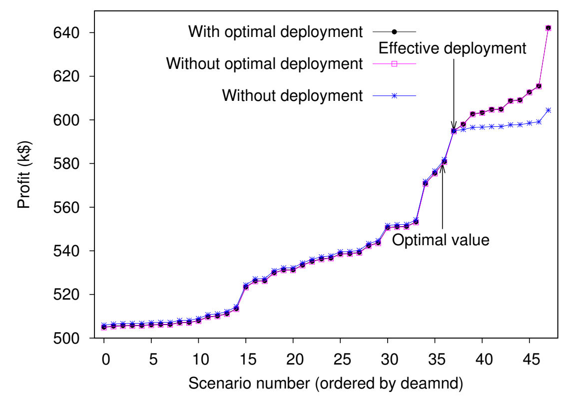


Fig. 4. Profit comparison among different deployment strategies.

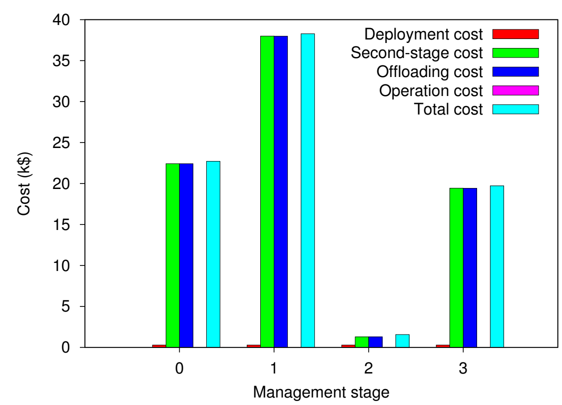


Fig. 5. Cost in different management stages.

TABLE III
CELL CONFIGURATION RESULT

	Stage 0			Stage 1			Stage 2		
Cell	Subchannel	Net. offload	BS offload	Subchannel	Net. offload	BS offload	Subchannel	Net. offload	BS offload
0	79	0.0015	N/A	64	0	N/A	76	0.0002	N/A
1	32	0.1261	347393	27	0	194699	35	0	246559
2	32	0.0665	143204	0	0	125025	28	0.0018	134358
3	32	0.2040	496424	0	0	211232	35	0	235969
4	32	0.0849	260342	20	0	224700	17	0	557777

C. Impact of Variance in Random Price

The effect of randomness in electricity prices is investigated. For Fig. 6, the distribution variance for the electricity price is varied from 9 to 714; the mean of the distribution is fixed to \$26 per Megawatt-hour. Here, since the demand is constant, only the electricity price and offloading rate affect the profit. We observe that the variance of profit is not as in large degree as the electricity price, as a result of the fixed mean. Also the effect of different prices of offloading traffic in offloading phase is presented in Fig. 6. Three prices of offloading traffic in offloading phase is considered, i.e., normal price (1x), decuple price (10x), and centuple price (100x). The last two prices are calculated by multiplying the normal price by coefficients of 10 and 100, respectively. We observe that with higher price of traffic offloading, the profit of network service providers is lower. This result is due to the fact that the cost in the small cell deployment becomes relatively cheaper.

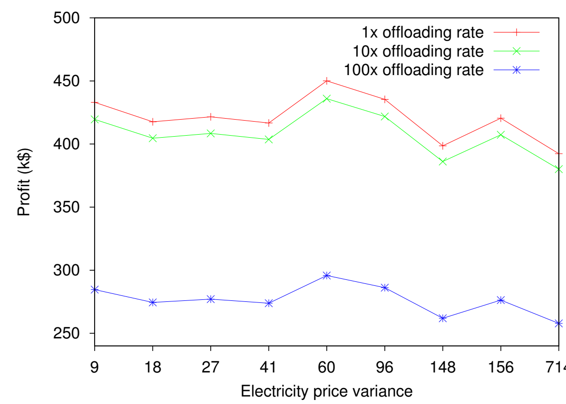


Fig. 6. Total cost under different price variances and offloading rates.

TABLE IV
COMPARISON AMONG DIFFERENT CELL CONFIGURATION ALGORITHMS

	SIP	NoOff	2-step	EVF	DE
Profit (k\$)	761.594	761.387	761.387	728.657	761.961
CAPEX (k\$)	1.84	2.07	2.07	1.38	1.48691
Energy (kWh)	473.828	487.274	477.270	451.788	450.098
OPEX (k\$)	0.00528	0.00541	0.00529	0.00507	0.00506
Offload (k\$)	0.02302	0	0	33.4203	0.01084

D. Example of Cell Configuration

To illustrate how our proposed solution works and what configuration structures may form with it, we present in Table III the some detailed results for a scenario where 1 macro BS exists in the network, and 4 locations are deployed with small cells. The whole considered week is separated into three 56-hour management stages, and the algorithm is run prior to the first stage. The columns of the table display, respectively, the cell index (expressed in number, 0 is the macro cell), the number of allocated subchannel, network offload (offloading expenses paid to the cooperating operator, expressed in k\$ based on the cost of \$ 15/500 MB), and BS offload (traffic offloaded to the macro, expressed in MB). Every column within the three management stages presents the corresponding expected values. It is shown in the table how the cell configuration differs as moving through management stages, how the operation changes (cell is off when no channels are allocated), and how the number varies (traffic of some cells are only offloaded to the macro one).

E. Comparison with Other Configuration Algorithms

The comparison between configuration algorithms is performed, including the proposed (SIP), nonoffloading (NoOff), 2-step, expected-value formulation (EVF), and deterministic (DE) algorithm. NoOff enables no offloading mechanism to other networks, while 2-step decomposes the cell configuration problem (SIP) into 2 optimization problems, where the deployment problem is solved first, and then the problem of operation and offloading is solved together. EVF uses the average values of uncertainty parameters and solves them by a traditional deterministic program. The following entries are reported in Table IV: profit, CAPEX, energy requirements, OPEX, offloading costs.

The DE algorithm perfectly knows the demands and prices in advance, and, hence, it achieves the highest profit, while SIP algorithm achieves the solution which are close to the DE solution. Since it generates the maximum expected profit under uncertainty, the SIP algorithm cannot achieve the efficient in some cases. Since NoOff dose not consider offloading traffic to the cooperating network, it costs more CAPEX and OPEX to meet the demand. 2-step deploys more small cells than SIP when solving the deployment problem, but later optimizes the energy cost for operation, compared with NoOff. Since EVF cannot adopt to changes in demands and prices, it cannot guarantee the highest profit. We also implement two other algorithms. Due to space limitations, the resulting numbers are not included. Nonoperation constantly turns on deployed cells, while nondeploying does not deploys any small cells and performs the worst. For both, SIP also outperforms them.

VI. Conclusion

Although network operators have increased their revenues for the boosted traffic demand, it is also underlined that the network operators' growing needs for cost-effective solutions to improve cellular services. The heterogeneity and offloading are set to play an important role in emerging wireless networks. To the best of our knowledge, the presented work is the first to study the profit maximization problem in the context of an integrated network design and traffic offloading framework for mobile networks. This framework is based on the model where three phases are devised, i.e., deployment, operation, and offloading phase. Within every phase, specifical decision is made to maximize the profit of the network operator. The algorithm obtains optimal solutions by formulating and solving the stochastic integer programming problem with multistage recourse under uncertainty of price and demand. The performance of the proposed algorithm is evaluated by numerical studies and simulations. From the results, the algorithm can optimally adjust the tradeoff among small-cell deployment, BS operation and traffic offloading costs. Comparing to other algorithms, our algorithm can achieve the highest profit, considering the stochastic environment.

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