Optimized Small Cell Range Expansion in Mobile Communication Networks using Multi-Class Support Vector Machines

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***Abstract*—Heterogeneous cellular architectures are a promising technology direction for upcoming generations of wireless communication networks. Increasing performance requirements are fulfilled by utilizing a dense deployment of low-power small cells in addition to existing macro cells. In such dense cellular networks it is critical to prevent performance losses from increasing interferences and uneconomic operating costs caused by high power consumptions. These changes in the network architecture create the need for effective control mechanisms specifically designed for heterogeneous networks. Range expansion for small cells has been proposed and extensively researched to achieve load balancing between macro cells and small cells. In this work, we propose a decentralized approach for cell range expansion in small cell networks that in operation only requires very limited local interaction between neighboring cells. We use multi-class support vector machines as a classifier to select suitable parameters for each small cell. Experimental results show that the proposed decentralized approach achieves close to optimal load balancing performance.**

I. Introduction

As the current fourth generation of mobile communication networks reaches maturity, multiple technology directions are under investigation to fulfill the promises of higher performance set for the fifth generation (5G). State-of-the-art modulation and coding schemes push the achieved spectral efficiency to its theoretical limit. It becomes clear that more resources need to be utilized to increase the throughput of such networks. Possible approaches include drastically increasing the number of used antennas in Massive-MIMO systems, using additional frequency bands in the millimeter-wave spectrum, or increasing the number and density of mobile cells especially in urban environments [1], [2]. The latter approach involves supplementing the existing and established network of high-power macro cells (MC) with a high number of so-called ”small cells” (SC). These SCs can be deployed in critical areas such as hotspots with a high density of users, or along the edges of the coverage area of MCs [3]–[5].

The resulting network is commonly called ”Heterogeneous Network” or in short ”HetNet”. As a major challenge for such dense networks, the load experienced by both macro cells and small cells needs to be balanced to avoid a decrease in the experienced quality of service caused by dropped connections. The two main challenges for deployment of dense HetNets are the increased interferences, which sets an upper bound on the achievable data rates through densification [6], and the high cumulative power consumption of small cells deployed in huge numbers, which can render the network operation uneconomical for the operator [7]. Developing effective control schemes that coordinate and optimize the network resources is critically important to mitigate the aforementioned drawbacks and to enable the success of HetNets in 5G.

In addition to the correct placement of SCs [8], the optimized allocation of users to MCs or SCs is a subject of current research [9]–[11]. The allocation can be optimized while the network is in operation, or optimized allocation rules can be devised before, based on demand forecasts. Most prominently, small cell range expansion has been proposed as an effective way to move users from the typically overloaded MCs to the less utilized SCS. This is achieved by introducing a so-called *bias* to the signal power report received by the user node, where the user is typically allocated to the cell providing the strongest reported signal power value. For the allocation decision with range expansion however, the signal power from small cells is increased with a bias value. This leads to more users being allocated to SCs, which corresponds to an increased coverage area. The main parameter to be optimized for range expansion is the bias value for each SC, for which optimized allocation schemes have been proposed [10], [12]. The common drawback of these schemes is that they require extensive knowledge about the channel conditions and the state of each network entity to perform the bias value and allocation optimization, which is carried out either centrally or using consensus algorithms [13].

In this work, we propose a mixed-integer linear program (MILP) approach to solve the range expansion problem optimally. We obtain the MILP from a nonlinear formulation that is linearized in a lifting procedure. To mitigate the aforementioned problem of high communication and coordination overhead with established methods, we also introduce a learning-based approach for optimized range expansion in heterogeneous wireless communication networks. Our method relies on the optimal bias values from MILP solution of the

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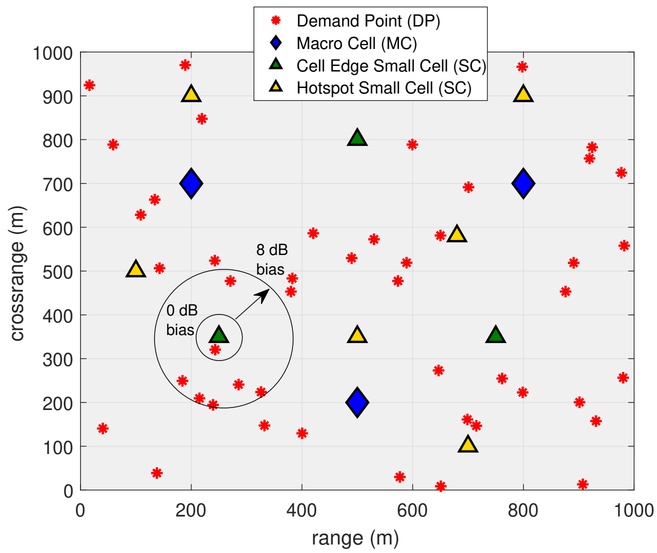

Fig. 1. Illustration of the wireless network scenario

range expansion problem obtained from historical network data. We extract attributes of the network state that are easily accessible to each small cell, such as its own load levels and that of neighboring macro cells. The small cell attributes and the optimal MILP results are used to train a classifier based on multi-class support vector machines. This classifier is then applied locally in each SC to find its optimal bias value in new network scenarios. Using machine learning classifiers as improvised resource allocation schemes in wireless communication networks is only being considered recently, and to the best of our knowledge comparable methods have not been introduced.

The remainder of the paper is organized as follows: In Sec. II, we introduce the system model for the considered wireless communication network. The proposed methods for load balancing are explained in Sec. III. In Sec. IV we provide simulation results and an evaluation of the algorithms performance, followed by a final summary and conclusion in Sec. V.

Notation: We use normal letters for scalars, bold lowercase letters for column vectors and bold uppercase letters for matrices. We further indicate with $||\cdot||$ the Euclidean norm of a vector, and with $\cdot^T$ the vector transpose.

II. System Model

The elements of a heterogeneous mobile communication network are illustrated in Fig. 1. We consider a network containing K cells, each formed by a base station with respective transmit power p_k, $k = 1, \ldots, K$. We denote as $\mathcal{C}^{\text{MC}}$ and $\mathcal{C}^{\text{SC}}$ the sets of all base stations that correspond to macro cells and small cells, respectively. Additionally the network contains M demand points (DP) with a respective data demand d_m in bits per second, with $m = 1, \ldots, M$. These demand points may represent single users or the aggregated demand of multiple users in close proximity, for example in a mobile hotspot. The attenuation factor of the wireless link between cell k and DP m resulting from antenna gains and path loss is in the following denoted as g_{km}. The signal-to-interference-plus-noise-ratio of cell k serving DP m can be defined as

$$\gamma_{km} = \frac{p_k g_{km}}{\sum_{j=1, j \neq k}^{K} p_j g_{jm} + \sigma^2} \tag{1}$$

where σ^2 represents the power of additive white Gaussian noise. The transmission link between cell k and DP m has a bandwidth efficiency η_{km}^{BW}, and the total available system bandwidth is denoted as W. We assume that cell k needs to utilize the fraction

$$\Phi(k, m) = \frac{d_m}{\eta_{km}^{\text{BW}} W \log_2(1 + \gamma_{km})} \tag{2}$$

of its available resources to satisfy the data demand of DP m. The binary matrix $\boldsymbol{A} \in \{0, 1\}^{K \times M}$ indicated the allocation of DPs to cells. Element A_{km} set as $A_{km} = 1$ if DP m is allocated to cell k, and $A_{km} = 0$ otherwise. In order to quantify the data demand of all its allocated users, the ratio of total used and total available resources for cell k can be determined as

$$\rho_k(\boldsymbol{A}) = \sum_{m=1}^{M} A_{km} \Phi(k, m). \tag{3}$$

We introduce a set of available nonnegative bias values $\mathcal{S} = \delta_1, \ldots, \delta_S$. The K-element vector of the selected bias values for all cells is denoted as $\boldsymbol{\lambda}$ with the elements $\lambda_k \in \mathcal{S}_k$. For example, if SCs operate with any of the available bias values and MCs would not be biased, we would have $\lambda_k = 1 \; \forall k \in \mathcal{C}^{\text{MC}}$ and $\lambda_k \; \in \mathcal{S} \; \forall k \in \mathcal{C}^{\text{SC}}$ According the the general allocation procedure in 4G 3GPP networks we assume that a DP m is allocated to the cell k providing the highest product of received transmit power and bias value. Thus the resulting allocation rule used to determine $\boldsymbol{A}$ can be formulated as

$$A_{km} = \begin{cases} 1 & \text{if} \lambda_k p_k g_{km} \geq (1 - A_{jm}) \lambda_j p_j g_{jm} \; \forall \; j, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

In the following we denote the $\boldsymbol{A}$ obtained from applying (4) with $\lambda_k = 1 \; \forall k$ (no bias) as $\tilde{\boldsymbol{A}}$. Similarly we define $\boldsymbol{A}^0$ as the allocation result according to Eq. (4) for $\lambda_k = 1 \; \forall k \in \mathcal{C}^{\text{MC}}$ (no bias) and $\lambda_k = 0 \; \forall k \in \mathcal{C}^{\text{SC}}$ (bias). We further define κ_k^{P} and κ_k^{S} as the indices of the two cells which provide the strongest and second strongest signal in the location of cell k, other than cell k itself.

III. Load Balancing

A. Optimal MILP

In the following we introduce a scheme to find the optimal bias values for each cell that minimize the maximum load of any cell in the network. These optimal bias values are obtained as the optimal solution of a mixed integer problem. We assume that $\lambda_k \in \mathcal{S}_k \; \forall k \in \mathcal{C}^{\text{SC}}$ and $\lambda_k = 1 \; \forall k \in \mathcal{C}^{\text{MC}}$, which means that SCs can operate with any of the available bias values

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and MCs operate without bias. The proposed problem can be formulated as follows:

$$\underset{\alpha,\boldsymbol{A},\boldsymbol{\lambda}}{\text{minimize}} \quad \alpha \tag{5a}$$

$$\text{subject to} \quad \alpha \geq \sum_{m} A_{km}\Phi(k,m) \tag{5b}$$

$$\sum_{k} A_{km}\lambda_k p_k g_{km} \geq (1-A_{jm})\lambda_j p_j g_{jm} \; \forall j,m \tag{5c}$$

$$\sum_{k=1}^{K} A_{km} = 1 \; \forall m \tag{5d}$$

$$\alpha \in \mathbb{R}_{0+} \tag{5e}$$

$$A_{km} \in \{0,1\} \; \forall k,m \tag{5f}$$

$$\lambda_k \in \mathcal{S}_k \; \forall k \in \mathcal{C}^{\text{SC}}, \lambda_k = 1 \; \forall k \in \mathcal{C}^{\text{MC}} \tag{5g}$$

In problem (5), constraints (5d) force each DP to be allocated to exactly one cell. Contraints (5c) represent a reformulation of the allocation rule introduced in Eq. (4). Problem (5) is a mixed-integer nonlinear problem (MINLP) because of the bilinear product terms $A_{km}\lambda_k$. We will in the following convert this problem into a mixed integer linear problem (MILP) using a lifting strategy in a Big-M approach [14]. Let the constant

$$\overline{\lambda} = \underset{s,k}{\arg\max} \quad \delta_{s,k} \tag{6}$$

denote the largest bias value. We introduce an auxiliary parameter Λ_{km}, for which we enforce $\Lambda_{km} = A_{km}\lambda_k \; \forall k,m$ using the following linear inequalities:

$$\Lambda_{km} \leq A_{km}\overline{\lambda} \tag{7a}$$

$$\Lambda_{km} \leq \lambda_{km} \tag{7b}$$

$$\Lambda_{km} \geq \lambda_{km} - (1-A_{km})\overline{\lambda} \tag{7c}$$

$$\Lambda_{km} \geq 0 \tag{7d}$$

Problem (5) can be reformulated as the following:

$$\underset{\alpha,\boldsymbol{A},\boldsymbol{\lambda},\boldsymbol{\Lambda}}{\text{minimize}} \quad \alpha \tag{8a}$$

$$\text{subject to} \quad \alpha \geq \sum_{m} A_{km}\Phi(k,m) \tag{8b}$$

$$\sum_{k} \Lambda_{km} p_k g_{km} \geq (\lambda_j - \Lambda_{jm}) p_j g_{jm} \; \forall j,m \tag{8c}$$

$$\text{(5d)}, \text{(7)} \; \forall k,m \tag{8d}$$

$$\alpha \in \mathbb{R}_{0+} \tag{8e}$$

$$A_{km} \in \{0,1\} \; \forall k,m \tag{8f}$$

$$\lambda_k \in \mathcal{S}_k \; \forall k \in \mathcal{C}^{\text{SC}}, \lambda_k = 1 \; \forall k \in \mathcal{C}^{\text{MC}} \tag{8g}$$

$$\Lambda_{km} \in \mathbb{R}_{0+} \tag{8h}$$

Problem (8) is linear in all optimization variables and therefore classifies as a MILP, which can be solved using conventional state-of-the art solvers. Even though problem (8) is capable of obtaining the optimal bias values, the network needs to gather all information about SINR-levels, user demands etc. centrally to solve the problem. In the following we introduce a learning-based decentralized approach.

B. SVM-based optimization

We denote as $\boldsymbol{\lambda}^*$ the optimal bias values for a given network scenario obtained by solving problem (8). We compute a vector of class labels $\boldsymbol{y}$ with its elements $y_k = \{s|\lambda_k = \delta_s\}$. In the following we design suitable attributes for each small cell that are being mapped to corresponding features to be used in the proposed classification scheme.

We define the attribute $\alpha(k)$ which is determined as $\alpha(k) = 1$ if small cell k is deployed on the edge of the coverage areas between two macro cells, and $\alpha(k) = 0$ otherwise, which is illustrated in Fig. 1. Which of these roles a small cell fulfills is known to the operator from the network architecture.

For the second set of attributes, let us define the index set

$$\mathcal{M}_k^{\{s\}} = \{m|\delta_s p_k g_{km} \geq p_j g_{jm} \forall j \in \mathcal{C}^{\text{MC}}\} \tag{9}$$

of DPs connected to cell k if bias value δ_s is used, for which we compute the expected load of cell k as

$$\beta(k,s) = \sum_{m \in \mathcal{M}_k^{\{s\}}} \Phi(k,m). \tag{10}$$

Similarly we compute the expected sum load that DPs in the coverage area of SC m operating with bias δ_s causes to the first and second neighboring cell in the allocation defined by $\boldsymbol{A}^0$:

$$\epsilon^{\text{P}}(k,s) = \sum_{m \in \mathcal{M}_k^{\{s\}}} A^0_{\kappa_k^{\text{P}} m}\Phi(\kappa_k^{\text{P}}, m) \tag{11}$$

and

$$\epsilon^{\text{S}}(k,s) = \sum_{m \in \mathcal{M}_k^{\{s\}}} A^0_{\kappa_k^{\text{S}} m}\Phi(\kappa_k^{\text{S}}, m), \tag{12}$$

respectively. The aforementioned attributes are combined into the following $(3S+1)$-element attribute vector:

$$\boldsymbol{x}_m = [\alpha(k), \beta(k,1), \ldots, \beta(k,S), \epsilon^{\text{P}}(k,1), \ldots, \epsilon^{\text{P}}(k,S), \epsilon^{\text{S}}(k,1), \ldots, \epsilon^{\text{S}}(k,S)]^T \tag{13}$$

We assume that for the training of the classifier, N network scenarios each with $||\mathcal{C}^{\text{SC}}||$ small cells are being used, such that a total of $T = N||\mathcal{C}^{\text{SC}}||$ datasets are available. In the following we refer to the t-th class label and attribute vector as y_t and $\boldsymbol{x}_t$ respectively, with $t = 1, \ldots, T$.

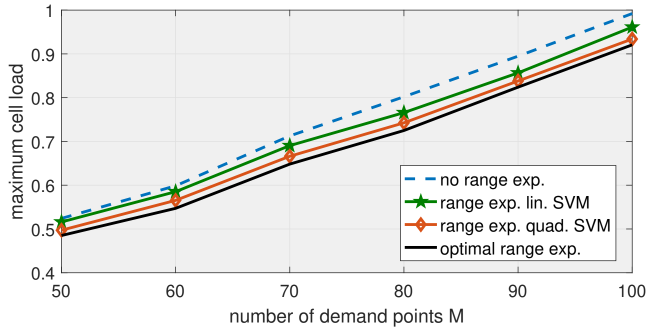

Fig. 2. Maximum cell load over number of users M

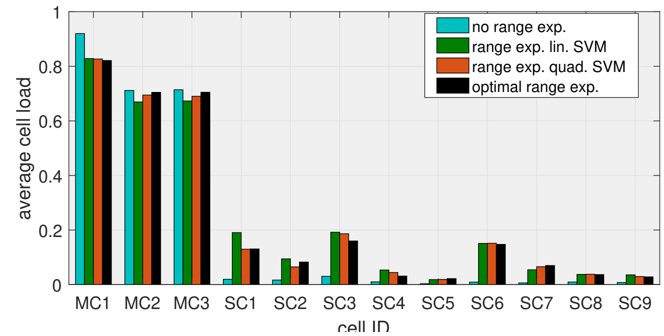

Fig. 3. Average cell load over cell ID

We solve the following optimization problem to train an SVM that classifies between classes i and j [15], [16]:

$$\underset{\boldsymbol{w}^{\{ij\}}, b^{\{ij\}}, \boldsymbol{\xi}^{\{ij\}}}{\text{minimize}} \quad \frac{1}{2}(\boldsymbol{w}^{\{ij\}})^T \boldsymbol{w}^{\{ij\}} + C \sum_t \xi_t^{\{ij\}} \tag{14a}$$

$$\text{subject to} \quad (\boldsymbol{w}^{\{ij\}})^T \phi(\boldsymbol{x}_t) + b^{\{ij\}} \geq 1 - \xi_t^{\{ij\}} \text{ if } y_t = i \tag{14b}$$

$$(\boldsymbol{w}^{\{ij\}})^T \phi(\boldsymbol{x}_t) + b^{\{ij\}} \leq \xi_t^{\{ij\}} - 1 \text{ if } y_t = j \tag{14c}$$

$$\xi_t^{\{ij\}} \geq 0 \tag{14d}$$

$$\boldsymbol{w}^{\{ij\}} \in \mathbb{R}^{L \times 1}, b^{\{ij\}} \in \mathbb{R}, \boldsymbol{\xi}^{\{ij\}} \in \mathbb{R}^{L \times 1} \tag{14e}$$

The function $\phi(\boldsymbol{x}_t)$ in problem (14) maps the $(3S+1)$-dimensional attribute vector $\boldsymbol{x}_t$ onto the L-dimensional feature space. In this feature space polynomial combinations of the attributes are used as training features. In order to evaluate a "one-vs.-one" majority vote between the trained SVMs, we introduce a voting parameter

$$z_t^{\{ij\}} = \begin{cases} 1 & \text{if } (\boldsymbol{w}^{\{ij\}})^T \phi(\boldsymbol{x}_t) + b^{\{ij\}} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

which is used to determine the estimated class

$$\hat{y}_t = \arg\max_i \sum_{j=1}^{S} z_t^{\{ij\}} \tag{16}$$

Multiclass SVM training problems like (14) are typically solved with high computational efficiency in their Lagrange dual formulation using kernel functions [17]. This functionality is included in common machine learning software tools [18], [19].

IV. Simulation Results

We carry out simulations of a wireless network with the parameters listed in Table IV and the locations of 3 MCs and 6 SCs as depicted in Fig.1. We solve the MILP (8) using the CVX toolbox for MATLAB [21] with the Gurobi solver [22], and we perform the training of the multiclass SVM classifier (14) by using the Machine Learning Toolbox for Matlab [19]. For the function $\phi(\cdot)$ in problem (14) we consider

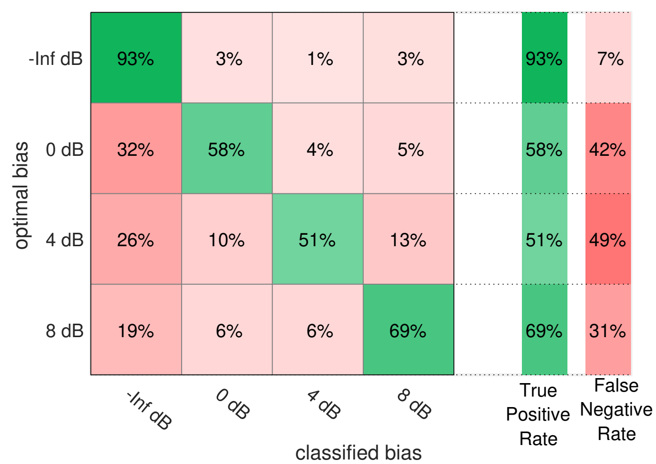

Fig. 4. Confusion matrix for SVM with quadratic feature mapping

a linear mapping of attributes to features, and the mapping to quadratic features. We refer to these two methods as "lin. SVM" and "quad. SVM", respectively. Multiple network scenarios, each with randomly distributed DPs, are used for the SVM training and testing phases. For the SVM training, we use $N = 250$ network scenarios for a total of $T = 2250$ training datapoints. To test the performance of the SVM-based classifier as a parameter optimization scheme, we use 100 new

TABLE I
LTE NETWORK SIMULATION PARAMETERS

Area size	1000×1000 m
Noise power	-145 dBm/Hz
System bandwidth W	20 MHz
MC transmit power p_k	46dBm
MC antenna gain	15dB
SC transmit power p_k	36dBm
SC antenna gain	5dB
DP antenna gain	0dB
Propagation loss	3GPP TS 36.814 [20]
Bandwidth efficiency η^{BW}	0.8
Bias values $\mathcal{S}$	0, 1, 4dB, 8dB

network scenarios in a Monte-Carlo evaluation and compute the average achieved cell loads as performance metrics.

As a benchmark to evaluate the performance of the proposed scheme, we use a network with SCs operating without range expansion and DP allocation according to the strongest received signal [12], in the following referred to as "no range exp.". This approach minimizes the load incurred for each connection of DP to cell. The upper bound performance benchmark is given by the optimal bias selection obtained from solving problem (8). Fig.2 shows the average maximum load over the evaluated network scenarios for an increasing number of users with a data demand of 1 MBit/s each. As observable, the quadratic SVM achieves close to optimal performance, while the linear SVM causes slightly higher cell load, with both approaches showing lower load levels than without range expansion for all M. This underlines the stability of the proposed scheme and the suitability of the selected SC features.

The load of individual cells for a simulation of 100 network scenarios with 100 DPs with 0.8 MBit/s data demand each is shown in Fig. 3. The load of MC1 without range expansion is the critical one to be minimized for the load balancing scheme to be successful. All proposed methods achieve decreased load for MC1, with the SVM-based approaches being only slightly worse than the optimum. The highest load of any SC is about 20%, which is a large increase relative to the load level without range expansion.

The confusion matrix of optimal bias levels and classified bias levels for the quadratic SVM is shown in Fig. 4. The classifier shows very good performance with 93% accuracy in detecting which small cells, according to the optimal solution of the MILP, do not serve any DPs.Mainly for the bias values 0dB and 4dB, the accuracy is decreased. The most common error made by the classifier, with respect to the optimal MILP solution, is to not allocate users to SCs that for the optimal solution actually had users allocated to them. The good performance in load balancing however, as discussed for Fig. 2, suggests that these wrong classifications do not occur in critical scenarios.

V. Conclusion

We introduced a scheme for optimized small cell range expansion for small cells in heterogeneous wireless communication networks. The proposed method relies on training a classifier based on support vector machines using historical network data. This classifier is then used by each SC in operation of the network to set an optimized bias parameter for range expansion, such that the maximum load of any cell in the network is minimized. The attributes to be extracted by each small cell only require local interaction with the neighboring macro cells. Simulation results show that the proposed method achieves close to optimal performance especially if support vector machines with quadratic feature mapping are being used.

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