Multilayer Optimization of Heterogeneous Networks Using Grammatical Genetic Programming

Michael Fenton, David Lynch, Stepan Kucera, Holger Claussen, and Michael O'Neill

ABSTRACT

Wireless communications networks are a global trillion dollar industry, where small improvements can scale to provide significant cost savings to networks operators. In a field full of NP-hard optimisation problems, heuristic optimisation techniques such as Evolutionary Computation offer a means to provide bespoke, scalable solutions. Grammatical Genetic Programming is applied to optimise three aspects of an LTE Heterogeneous Network: setting optimal Small Cell powers and biases, Macro Cell ABS patterns, and Small Cell scheduling. The evolved heuristics yield minimum downlink rates three times greater than a baseline technique, and twice that of a state-of-the-art industry standard benchmark. This work appears in full in Fenton *et al.*, "Multilayer Optimization of Heterogeneous Networks using Grammatical Genetic Programming", *IEEE Transactions on Cybernetics*, 2017. DOI: 10.1109/TCYB.2017.2688280.

KEYWORDS

Evolutionary Computation, Grammatical Genetic Programming, Wireless Communications Networks

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1 INTRODUCTION

Wireless communications networks are a global trillion dollar industry, where small improvements can scale to provide significant cost savings to networks operators. With the advent of the internet of things and the exponential increase in the number of connected devices, operators are struggling to meet demand. Under the 3$^{\text{rd}}$ Generation Partnership Project - Long Term Evolution (3GPP-LTE) [1], Heterogeneous Networks (HetNets) have been proposed as a relatively cheap, scalable means by which to ease congestion and increase capacity. HetNets are multi-tier cellular communications networks, where existing high-powered Macro Cells (MCs) are supplemented in areas of high congestion by lower-powered Small Cells (SCs). Since bandwidth is scarce and expensive, all tiers operate on the same bandwidth in a co-channel deployment. This multi-tier co-channel implementation introduces a number of challenges for network operators.

User Equipments[1] (UEs) greedily attach to and receive data from whichever cell provides the strongest signal strength. Since MCs transmit at a much higher power than SCs, the SC tier is typically underutilized even though SCs can vary their power output and so increase their operational range. As such, provision has been made in recent 3GPP releases for a mechanism known as Cell Selection Bias (CSB), whereby SCs can artificially increase their operational range by broadcasting an optional non-negative bias β_s [1]. UEs factor this bias into their cell attachment decisions, thereby allowing the SC tier to offload more UEs from the MC tier, thus easing congestion. The extra coverage area leveraged by SCs as a result of this bias is termed the "expanded region"

An issue arises with the use of non-negative bias values, however. Any UE attached to a SC who is in the expanded region of that SC will necessarily receive greater signal strength in the form of interference from the neighboring MC than from their hosting SC. To combat this, an enhanced Inter Cell Interference Coordination (eICIC) mechanism has been proposed [1]. eICIC allows macro cells to periodically "mute" their transmissions in order to allow neighboring SCs to transmit to interference-prone UEs with reduced interference. These muting periods are known as Almost Blank Subframes (ABSs). Note that the setting of optimal ABS patterns has been shown to be NP-hard, even for simple networks with a single MC and multiple SCs [2].

Cells transmit data to all attached UEs during 1 ms timeframes known as "subframes" (f). The downlink rate of a UE u attached to a cell i during a subframe f is calculated through Shannon's equation for the transmission of wireless data in the presence of noise [6]:

$$R_{ui,f} = \frac{B}{N_{i,f}} \times \log_2(1 + SINR_{ui,f}), \tag{1}$$

where B is the available bandwidth (e.g. 20 MHz), $N_{i,f}$ is the total number of UEs sharing that bandwidth during subframe f, and $SINR_{ui,f}$ is the Signal to Interference and Noise Ratio (the ratio of the received signal strength to the sum of all interfering signal strengths from all other cells in the network including background thermal noise) from source cell i to UE u during subframe f.

Network performance statistics are computed across the "full frame" $\mathcal{F}$ of 40 subframes (i.e. 40 ms of network run time). Network operators typically seek to maximise network throughput with respect to proportional fairness. The industry standard metric for measuring network performance with respect to this utility is defined as:

Michael Fenton, David Lynch, and Michael O'Neill are with the Natural Computing Research and Applications group (NCRA) in UCD, Ireland (e-mail: michaelfenton1@gmail.com, david.lynch.1@ucdconnect.ie, m.oneill@ucd.ie). Stepan Kucera and Holger Claussen are with Bell Labs Nokia in Dublin, Ireland (e-mail: stepan.kucera@nokia-bell-labs.com), holger.claussen@nokia-bell-labs.com).

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[1] Any connected device, e.g. smartphones, tablets, laptops, etc.

$$Performance = \sum_{u \in \mathcal{U}} \log(R_u^{avg}). \quad (2)$$

where R_u^{avg} is the average downlink rate of UE u across the full frame $\mathcal{F}$. Maximisation of this utility results in a "Robin-Hood" effect, where resources are taken from the best performers in the network and given to the worst performers.

2 CHALLENGES

The 3GPP-LTE eICIC paradigm presents a number of optimisation challenges for network operators. We consider three such challenges:

(1) the setting of optimal transmission power and cell selection bias levels for multiple SCs in a network in order to ensure optimal offloading from the MC tier,
(2) the setting of optimal ABS patterns to ensure vulnerable cell-edge UEs see adequate performance, and
(3) the scheduling of data transmissions to multiple attached UEs across the full frame $\mathcal{F}$.

In this paper we consider each of the above challenges in turn, and finally attempt to optimise all three simultaneously. In a field full of such NP-hard optimisation problems, heuristic optimisation techniques such as Evolutionary Computation offer a means to provide bespoke, scalable solutions.

2.1 Approach

Our approach utilizes Grammatical Evolution (GE) [5], a grammar-based form of Genetic Programming [3]. The use of a formal grammar to define the function and terminal set allows us to generate solutions in an arbitrary language, and to bias solutions towards desired outcomes. The terminal set for each of the experiments is comprised of key numerical information about particular aspects of the network specific to the problem at hand. The form of all grammars used in this study supports the evolution of evaluable symbolic expressions. In each case, an algorithm is evolved which aims to configure relevant aspects of the network for optimal performance.

The first three experiments described in Section 2 were performed sequentially, with each successive experiment using the results of the previous experiments to optimally configure specific components of the network. For example, after an optimal power and bias update algorithm was evolved, this was used to configure the network for the evolution of ABS algorithms, and so on. The final fourth experiment was designed to compare this sequential approach to an all-encompassing optimisation approach, where all three control aspects of the network were evolved simultaneously.

3 RESULTS

In all experiments, results are compared against two separate methods:

(1) a simple baseline technique designed to give a minimum acceptable level of performance, and
(2) an industry standard benchmark [4].

The best results were seen from the three sequential experiments. Although the single simultaneous experiment was able to match two out of three of the algorithms from the simultaneous experiments, the fitness function as defined was not able to effectively leverage the benefits of SC scheduling.

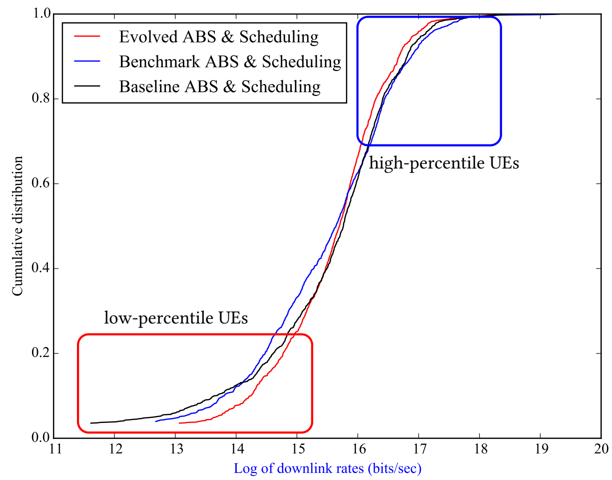

Figure 1: Comparison of performance between evolved, baseline, and benchmark solutions using asynchronous ABS patterns.

The results show that the best evolved algorithms are capable of providing minimum downlink rates three times higher than the naive baseline, and twice that of the industry standard benchmark. Furthermore, 5$^{\text{th}}$ percentile downlink rates are increased by 25% over the benchmark.

These trends are illustrated graphically in Fig. 1, which shows an example Cumulative Distribution Function (CDF) plot of the downlink rates of all UEs in the network using three techniques: baseline, benchmark, and evolved. The graph clearly shows that the evolved methods result in an increase in downlink rates (i.e. the red curve is shifted to the right) for the worst performing UEs in the network (as indicated by the red box), and a corresponding decrease in downlink rates (i.e. the red curve is shifted to the left) of the best performing UEs (indicated by the blue box).

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