Approaches to Joint Base Station Selection and Adaptive Slicing in Virtualized Wireless Networks

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Thesis submitted to the Faculty of the
Virginia Polytechnic Institute and State University
in partial fulfillment of the requirements for the degree of

Master of Science
in
Electrical Engineering

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August 1, 2018 (TBD)
Blacksburg, Virginia

Keywords: TBD

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(ABSTRACT)

This work received support in part from the National Science Foundation via work involved with the Wireless @ Virginia Tech research group.

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Chapter 1

Virtual Network Builder Model

This chapter establishes the mathematical foundation for the work completed in this thesis. First, a geographic model is presented, defining an area of interest, the pool of resources maintained by the RPs for use by the VNB, a characterization for service demand communicating the needs for the SPs' VWNs, and the SPs' end users to be satisfied. Second, a two-stage stochastic program utilizing this model is proposed to solve the posed problem of resource selection and adaptive slicing for use in VWN construction within the VNB.

1.1 Network Area Definitions

Consider POV and voice; at least change "we"s to "I"s, though that might further change if "I" is too personal or unprofessional.
Ensure equations are spaced well for full page and devoid of unnecessary horizontal or vertical spacing that may have been left behind from the trimming and formatting from the conference paper; this will require a bit of polish later during a formatting pass after most writing is accomplished.
Improve on overall wording to add consideration for the presence of RPs and SPs in the architecture; BSs come from the RPs to be aggregated into a pool for use by the VNB, and SPs have a service or services to satisfy, and must present that service to the VNB in some coherent manner for the VNB to build an optimal VWN considering other SPs' needs and the available resources.

Go through section notes, and break them down to where and what.

Consider a geographical area of width X meters and length Y meters that contains a set $\mathcal{S} \overset{\text{def}}{=} \{1, 2, \ldots, S\}$ of BSs available to be leased to the VNB by a set of $\mathcal{N} \overset{\text{def}}{=} \{1, 2, \ldots, N\}$ RPs. The rate capacity of BS $s \in \mathcal{S}$ is denoted by r_s, its cost is denoted by c_s, and its coverage radius is denoted by b_s.

Mention the relationship between the RPs and the VNB See Note

An SP seeking a VWN from the VNB is assumed to know the distribution of traffic demand

Mention weighted-sum LN and α-stable distributions as approximations See Note within the region the VWN would cover. It has been shown that a log-normal distribution or a mixture of log-normal distributions can approximate traffic demand in real-world cellular networks [1,2]. It has also been shown that traffic distribution is spatially correlated [2,3]. I model the spatial traffic demand of a single SP using a similar, continuous form of the SSLT (Scalable, Spatially-correlated, and Log-normally distributed Traffic) model as proposed by Lee, Zhou, and Niu [4].

Change "I"?

To generate this spatial distribution over the area of consideration, an initial Gaussian field, $\rho^G = \rho^G(x,\, y)\,,\, x \in [0,\, X]\,,\, y \in [0,\, Y]$, is generated by

$$\rho^G(x,\, y) = \frac{1}{L} \sum_{l=1}^{L} \cos(i_l x + \phi_l)\, \cos(j_l y + \psi_l) \tag{1.1}$$

Consider expanding on these definitions autocorrelation functions maybe add an image of the resulting ρ^G

where $\mathcal{L} \overset{\text{def}}{=} \{1,\, 2,\, \ldots,\, L\}$ is a set of the products of two cosines with angular frequencies $i_l,\, j_l\, \sim \mathcal{U}(0,\, \omega_{\max})\,,\, l \in \mathcal{L}$ and phases $\phi_l,\, \psi_l\, \sim \mathcal{U}(0,\, 2\pi)\,,\, l \in \mathcal{L}$. As L increases, ρ^G approaches a Gaussian random field with a spatial autocorrelation dependent on $\omega_{\max}$ according to the central limit theorem.

The approximate Gaussian distribution ρ^G is then normalized to a standard normal distribution. The final log-normal distribution, $\rho = \rho(x,\, y)\,, x \in [0,\, X], y \in [0,\, Y]$, is determined by assigning location and scale parameters

$$\rho(x,\, y) = \exp\left(\frac{\sigma}{\sqrt{\mathrm{Var}(\rho^G)}}\, \rho^G(x,\, y) + \mu\right) \tag{1.2}$$

Consider an image showing the standardized and log-normal fields, and accompanying pdfs and histograms maybe separate ρ^S and ρ

where $\mathrm{Var}\left(\rho^G\right)$ is the variance of ρ^G.

$\rho(x,\, y)$ can be sampled over the space into individual pixels as per Lee with each pixel's value indicating the number of homogeneous demand points within the pixel [4]. In contrast, I allow $\rho(x,\, y)$ to provide a continuous, spatially-correlated log-normal distribution depicting the demand density over the region for the SP.

Expand on the differences between the model proposed by Lee and as implemented here

Let $\mathcal{M} \overset{\text{def}}{=} \{1,\, 2,\, \ldots,\, M\}$ be the set of the SP's demand points seeking to connect to the VWN; the value of total traffic demand at each point is denoted by d_m. Further, let $u_{ms} \in [0,\, 1]$, $m \in \mathcal{M}$, $s \in \mathcal{S}$, represent the normalized capacity (with respect to r_s) of BS s at point m, i.e., the normalized maximum rate that a user can receive at point m from BS s. $u_{ms} = 0$ when m is outside the coverage area of s and $u_{ms} = 1$ when m is within a small distance of s. The specific position of the points in $\mathcal{M}$, and therefore the values of u_{ms}, is determined via a non-stationary 2D Poisson point process (PPP) with M points using the demand field, ρ, as the spatial intensity function. To generate this non-stationary PPP, I use an acceptance-rejection method. Each point of a stationary PPP with an intensity of $\rho_{\max} = \max_i \rho(x_i,\, y_i)$ is retained with probability $\frac{\rho(x_i, y_i)}{\rho_{\max}}$, where x_i and y_i are the x- and y-coordinates of the i^{th} point of the stationary PPP.

Change "I"?

See note

Change "I"?

I assume that a BS $s \in \mathcal{S}$ can be allocated between multiple demand points, and $\delta_{ms} \in$

Change "I"?

$[0,\, r_s]$, $m \in \mathcal{M}$, $s \in \mathcal{S}$, represents the rate of BS s that is allocated to point m.

Throughout this paper, stochastic variables will be differentiated from deterministic variables with a tilde ($\sim$) placed above the symbol.

1.2 Stochastic Optimization

Replace "we"s to "I"s or find alternate wording/tense/voice. Ensure equations are spaced appropriately for full page column and that there are no unnecessary vertical or horizontal spacing. Expounding on the various components of the stochastic optimization problem might be worthwhile. Might be worthwhile to also mention that the stochastic nature of this specific formulation is limited to handling stochastic demand point locations. As with 1.1, modify wording and phrasing accordingly to accommodate the possibility for multiple RPs and SPs in the model. When referring to "Problem"s (e.g., Problem 1 from section 1.2), refer to the equations that make up that problem; see first reference of Problem 1 in Chapter **??** *for reference.*

We formulate the presented problem as a two-stage stochastic optimization problem. We introduce $z_s, s \in \mathcal{S}$ as a binary decision variable defined as

$$z_s \overset{\text{def}}{=} \begin{cases} 1, & \text{if BS } s \text{ is selected for the created VWN,} \\ 0, & \text{otherwise.} \end{cases}$$

To balance the interest of maximizing demand satisfaction against minimizing cost, we introduce the positive real number α as a weighting coefficient between the two stages.

Problem 1 (Two-Stage Stochastic Optimization Problem)

$$\underset{\{z_s,\, s\in\mathcal{S}\}}{\text{minimize}} \left\{ \sum_{s\in\mathcal{S}} c_s\, z_s + \alpha\mathbb{E}\left[h\left(z,\, u\right)\right] \right\} \tag{1.3}$$

subject to:

$$z_s \in \{0,1\}, \forall s \in \mathcal{S} \tag{1.4}$$

where $h(z,u)$ is the optimal value of the second-stage problem, which is given by:

$$\underset{\{\delta_{ms}, m\in\mathcal{M}, s\in\mathcal{S}\}}{\text{minimize}} \left\{ -\sum_{m\in\mathcal{M}} \sum_{s\in\mathcal{S}} \delta_{ms}\, \tilde{u}_{ms} \right\} \tag{1.5}$$

subject to:

$$z_s = \mathbb{1}_{\left\{\sum_{m\in\mathcal{M}} \delta_{ms} > 0\right\}}, \forall s \in \mathcal{S} \tag{1.6}$$

$$\sum_{s\in\mathcal{S}} \delta_{ms}\, \tilde{u}_{ms} \le d_m, \forall m \in \mathcal{M} \tag{1.7}$$

$$\sum_{m\in\mathcal{M}} \delta_{ms} \le r_s, \forall s \in \mathcal{S}. \tag{1.8}$$

The first stage objective function (1.3) minimizes the total cost of the selected network with respect to that network's ability to satisfy the demand contained within the region. The second stage objective function (1.5) maximizes demand satisfaction by maximizing the total demand allocated to the resources comprising the network, as specified by δ_{ms} as the decision variable of the second stage.

Constraints (1.4), (1.6), and (1.8) implement the defined ranges and values of the decision variables z_s and δ_{ms}, with (1.6) ensuring that demand is allocated only to selected resources. For constraint (1.6), $\mathbb{1}_{\{*\}}$ is defined by

$$\mathbb{1}_{\{*\}} \stackrel{\text{def}}{=} \begin{cases} 1, & \text{if condition } \{*\} \text{ is true,} \\ 0, & \text{otherwise.} \end{cases}$$

Constraint (1.7) ensures a demand point $m \in \mathcal{M}$ is not allocated more resources than it demands.

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