Dynamic Bayesian Optimization for Improving the Performance of Cellular Networks

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Internship Period: 15/04/2024 - 05/09/2024
Internship course code: INF690

September 5, 2024

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Problem Introduction

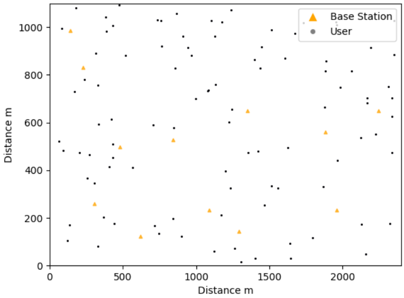

Figure: Example of Dynamic Wireless Cellular Network. BSs position are retrieved from [1].

Key elements

1. Parisian Base Stations (BSs) data. [1]
2. Choose Resource Sharing Mechanism (RSM).
3. Power Allocation strategy:
   - Define parametric obj function to be optimized.
4. Model User Equipments (UEs):
   - Placement distribution.
   - Birth & Death process.
   - Mobility models.
5. Border effect filtering.

RSM choice

Non-Orthogonal Multiple Access (NOMA)

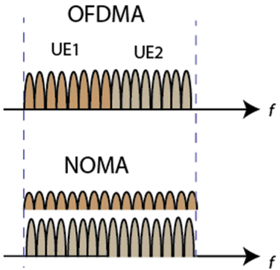

Figure: Spectrum sharing for two users: NOMA vs. OFDMA. Image source: [2].

Key points

- Full spectrum sharing.
- 2 service region partioning per BS.
- $\mathbf{p}_i = \left(p_i^{(\text{in})}, p_i^{(\text{out})}\right)$
- $P_- \leqslant \|\mathbf{p}_i\|_1 \leqslant P_+$ (BS power interval)
- $p^{(\text{in})} \leqslant p^{(\text{out})}$.
- Successive Interference Cancellation (SIC):
  - Inner UEs decode the signal for outer UEs first and cancel their interference.
  - Outer UEs decode only their own signal and treat the inner UEs' signal as noise.
- Literature contribution [2, 3, 4, 5].

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Problem formulation (A)

Propagation model

Recall **NOMA power constraint** for efficient SIC → Define the **parameter space** of the Problem:

$$\underbrace{\left(p_i^{(\text{in})}, p_i^{(\text{out})}\right)}_{\mathbf{p}_i} \rightarrow \underbrace{\left(p_i^{(\text{in})} + p_i^{(\text{out})}, \frac{p_i^{(\text{out})}}{p_i^{(\text{in})} + p_i^{(\text{out})}}\right)}_{\mathbf{x}_i} \tag{1}$$

$$\mathcal{D} = \bigtimes_{w=1}^{n} \mathcal{D}^{(w)} = \left([P_-, P_+] \times \left[\frac{1}{2}, 1\right)\right)^n \tag{2}$$

SINR - inner UE j and outer UE j', BS i:

$$\gamma_{i,j}^{(\text{in})} = \frac{g_{i,j} p_1^{(i)}}{WN + \sum_{i' \in \mathcal{N}_i \setminus \{i\}} g_{i',j}(p_1^{(i')} + p_2^{(i')})} \tag{3}$$

$$\gamma_{i,j'}^{(\text{out})} = \frac{g_{i,j'} p_2^{(i)}}{WN + g_{i,j'} p_1^{(i)} + \sum_{i' \in \mathcal{N}_i \setminus \{i\}} g_{i',j'}(p_1^{(i')} + p_2^{(i')})} \tag{4}$$

N noise power density (dBm/Hz), W signal bandwidth, $g_{i,j}$ radio link gain (computed through standard **log-distance path-loss model**).

Problem formulation (B)

Objective Function

Downlink Shannon capacity for UE j is:

$$c^{(j)} = c(\gamma_{i,j}) = W_j \cdot \log_2(1 + \gamma_{i,j}). \tag{5}$$

Objective

Goal: The natural objective of the model is to maximize the overall downlink capacity, yielding the highest Quality of Service (QoS) for the end-users.
How? $F_\alpha(c_t)$ (Eq. (6))

Include the notion of α-**fairness** for scalar mapping:

$$F_\alpha(c_t) = \begin{cases} \sum_{i=1}^{m} \log c_t^{(j)} & \text{if } \alpha = 1, \\ \sum_{j=1}^{m} \frac{\left(c_t^{(j)}\right)^{1-\alpha}}{1-\alpha} & \text{otherwise}, \end{cases} \tag{6}$$

where $c_t^{(j)}$ denotes $c^{(j)}(\mathbf{x}_t)$.

Problem formulation (C)

Scheduling

Optimal Scheduling $s_j^{(k)}$, $j \in \mathcal{A}^{(k)}$, w.r.t the k-th network partition ($k = 1, \cdots, 2n$).

$$s_j^{(k)} = \begin{cases} \mathbb{1}_{j=j*} & \text{if } \alpha = 0, \\ \dfrac{\left(c_t^{(j)}\right)^{(1-\alpha)/\alpha}}{\sum_{i \in \mathcal{A}^{(k)}} \left(c_t^{(i)}\right)^{(1-\alpha)/\alpha}} & \text{otherwise,} \end{cases} \tag{7}$$

Thus, the **objective function** $f_\alpha^{(i)} : \mathcal{D}^{(\mathcal{N}_i)} \to \mathcal{D}$, where $\mathcal{D}^{(\mathcal{N}_i)} = \times_{i' \in \mathcal{N}_i} \mathcal{D}^{(i')}$:

$$f_\alpha\left(\mathbf{x}_t\right) = \sum_{i=1}^{n} \sum_{\mathcal{A}^{(k)} \in \mathcal{A}_i} \sum_{j \in \mathcal{A}^{(k)}} F_\alpha\left(\mathbf{s}^{(k)} \odot \mathbf{c}^{(k)}\left(\mathbf{x}_t^{(\mathcal{N}_i)}\right)\right) \tag{8}$$

Where $\mathcal{N}_i$ denotes the neighbourhood of BS i.

Optimization

How to optimize $f_\alpha\left(\mathbf{x}_t\right)$ (Eq. (8)) ? $\to$ **Power Allocation Strategies**.

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Bayesian Optimization (BO)

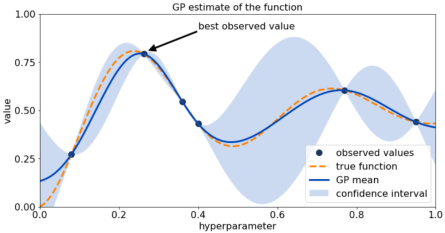

Figure: Example of BO procedure using GP. Image source [6].

How?

Input: objective function f, acquisition function φ, time horizon T

Init dataset $\mathcal{D} = \varnothing$ and surrogate model $\mathcal{G} = \mathcal{GP}(\mu(\mathbf{x}), k((\mathbf{x}), (\mathbf{x}')))$ where $\mu_0(\mathbf{x}) = 0$ w.l.o.s.

for $t \in [1, T]$ **do**

$\mu_t(\mathbf{x}) = \mathbf{k}(\boldsymbol{x}, \mathbf{X})^\top \mathbf{K}^{-1}\mathbf{z}$
$\sigma_t^2(\mathbf{x}) = \sigma_0^2(\mathbf{x}) - \boldsymbol{k}(\boldsymbol{x}, \mathbf{X})^\top \mathbf{K}^{-1}\mathbf{k}(\boldsymbol{x}, \mathbf{X})$

where $\mathbf{k}(\mathbf{x}, \mathbf{X}) = (k(\mathbf{x}, \mathbf{x}_i))_{i \in [1,t]}$, $\mathbf{K} = (k(\mathbf{x}_i, \mathbf{x}_j))_{i,j \in [1,t]}$, $\mathbf{X} = (\boldsymbol{x}_i)_{i=1}^t$, $\mathbf{z} = (z_i)_{i=1}^t$.

Compute $x_t = \arg\max_{x \in \mathcal{M}} \varphi(x; \mathcal{G})$ *, being $\mathcal{M}$ the domain

Observe $z_t = f(x_t)$ and add (x_t, z_t) to $\mathcal{D}$

end for

* e.g. GP-UCB [7]:
$\varphi_t(\mathbf{x}) = \mu_t(\mathbf{x}) + \beta_t^{1/2}\sigma_t(\mathbf{x})$

Key Components

- **Objective function**: $f : \mathcal{S} \times \mathcal{T} \to \mathbb{R}$, s.t. $\mathcal{S} \subseteq \mathbb{R}^d$, $\mathcal{T} \subseteq \mathbb{R}$.
- **Surrogate Model**: $\mathcal{G} \sim \mathcal{GP}(\mu(\mathbf{x}, t), k((\mathbf{x}, t), (\mathbf{x}', t')))$
  - **Init**: Mean $\mu(\mathbf{x}, t) = 0$, Covariance $k((\mathbf{x}, t), (\mathbf{x}', t'))$
  - Let $k : \mathcal{S} \times \mathcal{T} \times \mathcal{S} \times \mathcal{T} \to \mathbb{R}_+$
- **Kernel Decomposition**:

$$k((\mathbf{x}, t), (\mathbf{x}', t')) = \lambda k_S(\|\mathbf{x} - \mathbf{x}'\|, l_S) k_T(|t - t'|, l_T)$$

  - **Spatial Kernel**: $k_S(\cdot, l_S)$, s.t. $k_S : \mathbb{R}_+ \to [0, 1], l_S > 0$
  - **Temporal Kernel**: $k_T(\cdot, l_T)$, s.t. $k_T : \mathbb{R}_+ \to [0, 1], l_T > 0$
  - **Lengthscale parameters**: λ, l_S, l_T; $\lambda > 0$

W-DBO

Spatio-Temporal BO (2/2)

Key Components

- **W-DBO characteristic**:
  - **MLE Estimation**: Infer (λ, l_S, l_T)
  - **Wasserstein Distance**:

$$W_2\left(\mathcal{GP}_{\mathcal{D}}, \mathcal{GP}_{\tilde{\mathcal{D}}}\right) = \left(\oint_{\mathcal{S}} \int_{t_0}^{\infty} W_2^2\left(\mathcal{N}_{\mathcal{D}}(\mathbf{x}, t), \mathcal{N}_{\tilde{\mathcal{D}}}(\mathbf{x}, t)\right) \, d\mathbf{x} \, dt\right)^{\frac{1}{2}}$$

Measures deviation between two GPs, differing by one removed observation. $\mathcal{D}$ is the original dataset, and $\tilde{\mathcal{D}}$ is the dataset with one observation removed.

Power Allocation Strategies

Random Power Pick

At each optimization round t the vector $\mathbf{x}_{\text{rndm}}^{(t)} \sim \mathcal{U}(\mathcal{D})$.

Constant Power Pick

$\mathbf{x}_{\text{const}} \sim \mathcal{U}(\mathcal{D})$ is sampled just once, during the first round.

W-DBO [8]

- W-DBO instances define different power level suggestions for a common neighborhood: $\mathbf{x}_{\text{wdbo},i}^{(t)} \in \mathcal{D}^{(i)}$, $\forall i \in \mathcal{N}$.
- Median is computed to determine BS power levels: $\mathbf{p}_i = \text{MEDIAN}_{i' \in \mathcal{N}_i}(\mathbf{p}_{i'})$, $\forall i \in \mathcal{N}$.
- Power levels $\mathbf{p}_i$ are retrieved via the bijection in Eq. (1).

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UEs Generation

Placement

- Arbitrary number of UEs can be initialized.
- UEs distributed uniformly over the grid or placed using:
  - Poisson point process [9]
  - Log-Gaussian Cox process [10]
  - Radial-basis distribution (details in Technical Report Appendix A.1.1)

Birth & Death Process

- M/M/1 queue [11, 12]

UEs Mobility

Mobility - Trajectory Based Motion

- **O/D Traffic-flow data available**:
- Custom Probabilistic Mobility Model (details in Technical Report Appendix A.2.1)
- **Cluster-based Motion**:
  - hybrid-GMM (details in Technical Report Appendix A.2.2)
- **User-based Motion**:
  - Biased Random Walk
  - Random Waypoint (RPW) [13]
  - Lévy flight [14]
  - Truncated Lévy flight [15, 16, 17]
  - Brownian motion

Our testbed

For our tesbed we used **hybrid-GMM**, **Biased Random Walk**, **RPW**.
How these models work?

Mobility models description

RPW

RPW Model is used in simulations to model the movement of nodes. It involves:

- Moving towards a randomly selected waypoint (Uniformly sampled).
- Pausing at waypoints (Pause time uniformly sampled).
- Selecting new waypoints after pausing (Uniformly sampled).

Biased Random Walk

Biased Random Walk limits erratic movement typical of Random Walks, by introducing a biased direction.

hybrid-GMM

hybrid-GMM combines Gauss-Markov Mobility model and RPW. Modelize transiction:

- Temporal-Spatial correlated movement (GMM contribution)
- Pausing time during motion
- Destinations uniformly sampled *

* In our implementation to define way-points, we considered the BS areal density (computed through DBSCAN algorithm [18]).

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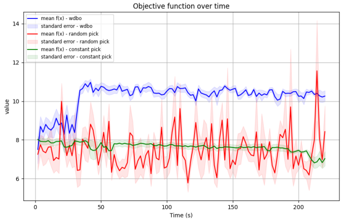
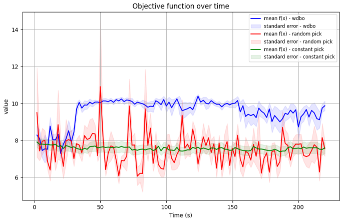
Experimental Results

Obj. Comparison (1/2)

Figure: W-DBO (blue), Random pick (red) and Constant pick (green). α-fairness equal to 1.



(a) Biased Random Walk

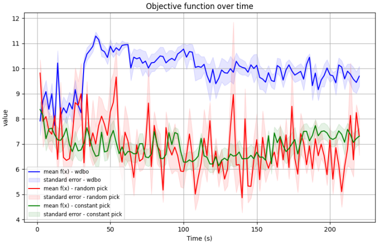


(b) Random Waypoint

Method	**App. W-DBO Time**	**App. Pick Time (Random,Constant)**
Biased Random Walk	85-90 mins	35-40 mins
Random-waypoint	85-90 mins	35-40 mins
Hybrid-GMM	85-90 mins	35-40 mins

Table: Computational Time Comparison - MacBook Pro with a 2.9 GHz Dual-Core Intel Core i5 processor and 16 GB of 2133 MHz LPDDR3 memory. - 2 concurrent threads.

Experimental Results
Obj. Comparison (2/2)

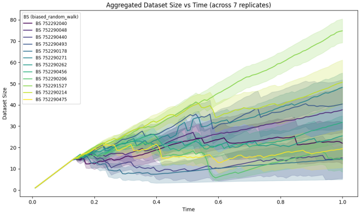


(a) Hybrid-GMM

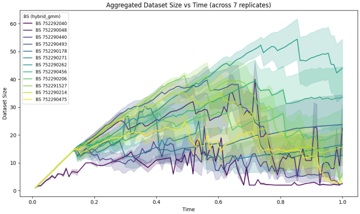
- The Hybrid-GMM model exhibits more dynamic objective function behavior than Biased Random Walk and RPW.
- This is due to moving cluster dynamics, impacting UE density.
- Objective function behavior depends on W-DBO's hyper-parameters, i.e., dataset size, thus temporal lengthscale.
- Spikes in the Random Pick curve result from a higher allocation density of UEs to out-of-border BSs.

Hyper-parameters

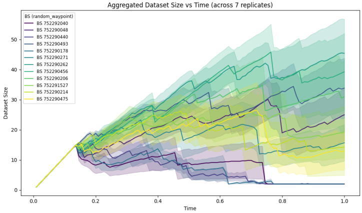
Comparison on disaggregated view - Dataset Size



(a) Biased random walk.



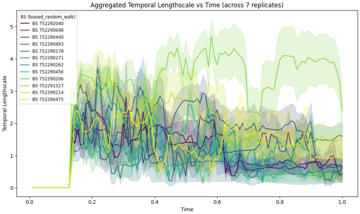
(b) Hybrid-GMM.



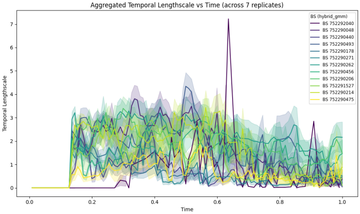
(c) Random waypoint.

Hyper-parameters

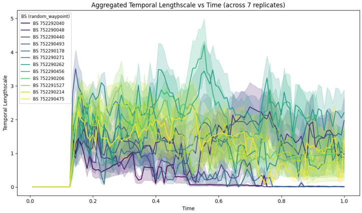
Comparison on disaggregated view - Temporal Lengthscale



(a) Biased random walk.



(b) Hybrid-GMM.



(c) Random waypoint.

Hyper-parameters Discussion

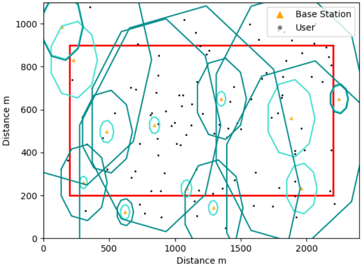
Key points

- Dataset size is driven by the temporal lengthscale curve. If it falls below the threshold (optimization frequency total simulation time $\simeq 1$), uncorrelated observations are considered uncorrelated, hence removed.
- The hybrid-GMM model shows oscillatory trends in dataset size, while RPW and Biased Random Walk models exhibit smoother trends.

Visual tool

Breathing cells visualization

(a) Interactive GIF-visualization. W-DBO power allocation strategy and Biased Random Walk mobility model.



(b) Interactive GIF-visualization. Const-pick power allocation strategy and RPW mobility model.

Figure: Full set of available visualization per motion model and power allocation strategy at NOMA Simulator - Visualizations.

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Conclusion (1/2)

Current Limitations

- Small-scale simulations with simple motion dynamics did not fully justify the use of W-DBO.
- Simulation duration limited to 220 seconds due to computational constraints.

Future Extensions

- Expand simulations to larger-scale settings with over 30 BSs and more complex cluster-based motion dynamics.
- Integrate real urban mobility traces [19] for more realistic simulations.
- Extend simulation duration to over 30 minutes for better analysis of real-world scenarios.
- Implement a control procedure to exclude simulations with high UE density at outer-border BSs.
- Study a W-DBO variant with power adjustments constrained within a confidence interval.

Conclusion (2/2)

Outcomes

- Developed a simulator to test W-DBO algorithm for power allocation in a dynamic wireless cellular networks.
- Benchmarked W-DBO against Random Pick and Constant Pick strategies.
- Demonstrated that W-DBO consistently outperforms these simpler strategies.

Q&A

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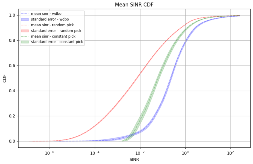
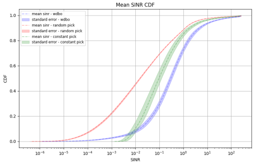
Experimental Results

SINR CDFs comparison

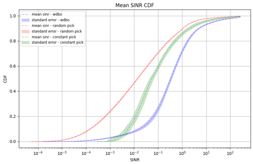
Figure: W-DBO (blue), Random pick (red), and Constant pick (green). α-fairness equal to 1.



(a) Biased Random Walk



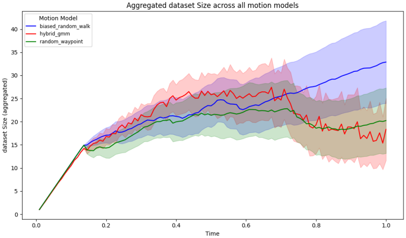
(b) Random Waypoint



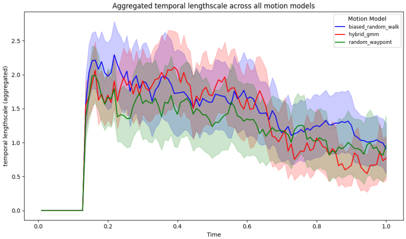
(c) Hybrid-GMM

Hyper-parameters

Comparison on aggregated view - 7 replicates and 12 BSs



(a) Aggregated dataset size metric. Biased Random Walk (blue), hybrid-GMM (red) and RPW (green).



(b) Aggregated temporal lengthscale metric. Biased Random Walk (blue), hybrid-GMM (red) and RPW (green).