

On Velocity-based Association Policies for Multi-tier 5G Wireless Networks

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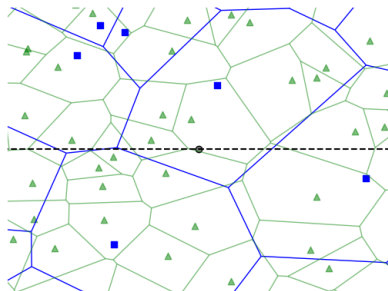
- Beam-based communications for 5G networks: allows to concentrate energy and improve signal power
- Setup: multi-tier network involving different types of base stations (BSs) sharing the same frequency bands
- Key features: beam selection, beam switching and cell handovers may degrade the network performance
- Performance also depends on the velocity of mobile users (MUs): higher velocities lead to more frequent beam selections
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Can we devise velocity-aware association policies for 5G networks ?

Network setup

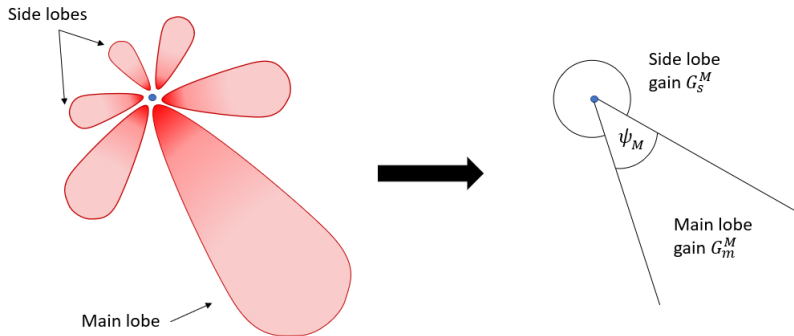
- Two-tier downlink cellular network, with a *macro* tier and a *micro* tier
- Network in open access and MU connect to the closest BS in their association tier
- BSs distributed according to two Poisson point processes (PPPs) Φ_M and Φ_μ of intensities λ_M and λ_μ with $\lambda_\mu > \lambda_M$
- MUs are distributed according to a PPP Φ_u of intensity λ_u
- BSs are always active
- BSs create a Poisson-Voronoi (PV) tessellation of the plane

- MUs move in a straight line along the x-axis
- MU velocity i.i.d with distribution f (in simulations, $f = \mathcal{E}\left(\frac{1}{v_u}\right)$)



Beamforming and beam management

- Each BS in the macro/micro tier has respectively n_M and n_μ beams, with angular width $\psi_M = \frac{2\pi}{n_M}$ (resp. $\psi_\mu = \frac{2\pi}{n_\mu}$)
- Antenna gains: $G_m^M = n_M$ for the main lobe, $G_s^M = \frac{1}{n_M}$ for the side lobe



Beamforming and beam management

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- Antenna gains: $G_m^M = n_M$ for the main lobe, $G_s^M = \frac{1}{n_M}$ for the side lobe
- The antenna gain in the macro tier is:

$$G^M(\theta) = \begin{cases} G_m^M & \text{if } |\theta| \leq \psi_M/2 \\ G_s^M & \text{else} \end{cases}$$

- The antenna gain w.r.t. the typical user located at the origin is:

$$g_{M,x} = \begin{cases} G_m^M & \text{w.p. } p_{M,m} \equiv \frac{\psi_M}{2\pi} = \frac{1}{n_M} \\ G_s^M & \text{w.p. } 1 - p_{M,m} \end{cases}$$

Beam reselection and cell handover

- When a MU crosses a beam boundary, beam reselection happens. Time intensity of beam boundary crossings along a line (cf Theorem 2 of [?]):

$$v_{M,b} = \frac{n_M \sqrt{\lambda_M}}{\pi} v$$

- Beam selection happen during synchronization signal block (SSB) with periodicity τ . The effective time intensity of beam reselections is equal to:

$$v_{M,e} = \min\left(\frac{1}{\tau}, v_{M,b}\right)$$

- When a MU crosses a cell boundary, a cell handover happens. If the MU moves at velocity v , the time intensity of cell handovers is equal to:

$$v_{M,c} = \frac{4\sqrt{\lambda_M}}{\pi} v$$

- The overhead per unit of time is defined as:

$$T_O^M = v_{M,c} T_{M,c} + v_{M,e} T_{M,b}$$

Mobility-induced beam misalignment

- Beam misalignment: happens if a MU moves out of its reference beam between two SSBs without reselecting a new beam. Spatial intensity of beam boundary crossing along a straight line:

$$\mu_{s,b} = \frac{n_M \sqrt{\lambda_M}}{\pi}$$

- Beam misalignment for a MU moving at velocity v happens with probability:

$$p_{\text{bm}}^M(v) = 1 - \exp(-v\mu_{M,b}\tau)$$

- The antenna gain at the serving BS of the typical MU located at the origin is:

$$g_{M,0} = \begin{cases} G_m^M & \text{w.p. } 1 - p_{\text{bm}}^M(v) \\ G_s^M & \text{w.p. } p_{\text{bm}}^M(v) \end{cases}$$

- Path-loss function: $\ell(x) \triangleq Kx^{-\alpha}$, with $\alpha > 2$ and $K = \left(\frac{c}{4\pi f_c}\right)^2$
- Transmit powers $P_M \geq P_\mu$ and thermal noise power σ^2
- We assume Rayleigh fading h_x for a BS located at x with power 1
- Interference experienced by the typical MU located at the origin associated with the macro tier:

$$I_M(\Phi_M) = \sum_{x \in \Phi_M} h_x g_{M,x} P_M \ell(\|x\|).$$

- SINR at the typical MU conditioned on the closest BS to the origin $X_{M,0}$ being at distance r :

$$\text{SINR}_M = \frac{h_0 P_M g_{M,0} K r^{-\alpha}}{\sigma^2 + I_M(\Phi_M \setminus \{X_{M,0}\}) + I_\mu(\Phi_\mu)},$$

Coverage probability

Coverage probability at T in a tier: CDF of the SINR in this tier

Theorem (Coverage probability)

The coverage probability with the macro tier association is

$$p_M(v, T) = (1 - p_{bm}^M(v))q_M(G_m^M, T) + p_{bm}^M(v)q_M(G_s^M, T)$$

where $\delta = 2/\alpha$ and:

$$q_M(G, T) = \pi \lambda_M \int_{r \geq 0} e^{-\pi \lambda_M r - \frac{T \sigma^2}{P_M K G} r^{1/\delta}} \exp\left(-\pi r \left(\frac{T}{P_M G}\right)^\delta \left(\lambda_M P_M^\delta \rho_M(G, T) + \lambda_\mu P_\mu^\delta \kappa_\mu\right)\right) dr$$

with:

$$\rho_M(G, T) = p_{M,m}(G_m^M)^\delta \int_{\left(\frac{T G_m^M}{G}\right)^{-\delta}}^{\infty} \frac{du}{1+u^{1/\delta}} + (1 - p_{M,m})(G_s^M)^\delta \int_{\left(\frac{T G_s^M}{G}\right)^{-\delta}}^{\infty} \frac{du}{1+u^{1/\delta}}$$
$$\kappa_\mu = \left(p_{\mu,m}(G_m^\mu)^\delta + (1 - p_{\mu,m})(G_s^\mu)^\delta\right) \int_0^{\infty} \frac{du}{1+u^{1/\delta}}$$

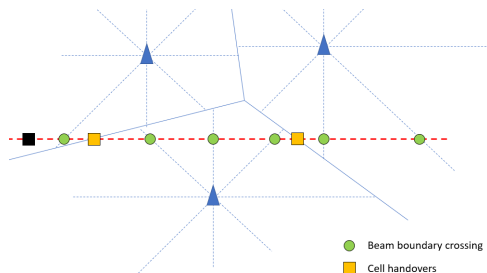
Shannon Rate and Mean Effective Shannon Rate

- The Shannon rate experienced by the typical MU located at the origin in the macro tier is equal to:

$$\begin{aligned}\mathcal{R}_M &= \mathbb{E}[\log(1 + \text{SINR}_M)] \\ &= \int_0^{Q_{max}} \frac{p_M(T)}{T+1} dT\end{aligned}$$

- The *Mean effective Shannon rate* (MESR) by the same MU is equal to:

$$\mathcal{R}_{M,\text{eff}} = \mathcal{R}_M (1 - T_{o,M}(v))^+$$



Velocity-based association policy

Velocity-based association policy in the network: criterion \mathcal{P} *only depending on velocity* such that:

- If $\mathcal{P}(v)$, the MU is associated with the micro tier
- If $\bar{\mathcal{P}}(v) = \neg\mathcal{P}(v)$, it is associated with the macro tier

The *average MESR* under a given association policy \mathcal{P} is given by:

$$\mathcal{R}(\mathcal{P}) = \int_0^\infty (\mathcal{R}_{\mu,\text{eff}}(v)\mathbb{1}_{\mathcal{P}(v)} + \mathcal{R}_{M,\text{eff}}(v)\mathbb{1}_{\bar{\mathcal{P}}(v)}) f(v)dv$$

Admits an ergodic interpretation (Birkhoff's ergodic theorem, [?])

Velocity-based Association Policy

The *threshold* policy with threshold v_T is $\mathcal{P}(v) = \mathbb{1}\{v < v_T\}$.

The average MESR under a threshold policy with threshold v_T is given by:

$$\mathcal{R}(v_T) = \int_0^{v_T} \mathcal{R}_{\mu,\text{eff}}(v) f(v) dv + \int_{v_T}^{\infty} \mathcal{R}_{M,\text{eff}}(v) f(v) dv$$

First step, we assume that there is only one MU per cell:

Theorem (Threshold velocity-based association policy with one user per cell)

There exists a unique threshold policy the average MESR per user. This optimal threshold v_T^ does not depend on the velocity distribution f of MUs, and is the unique solution to:*

$$\mathcal{R}_{\mu,\text{eff}}(v_T^*) = \mathcal{R}_{M,\text{eff}}(v_T^*)$$

Optimal Threshold Policy

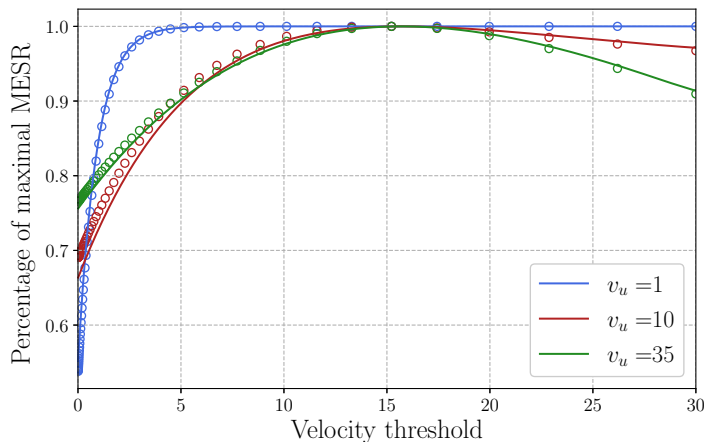


Figure: Normalized MESR in the network as a function of the velocity threshold v_T . The optimal threshold does not depend on the scale parameter v_u

Load-dependent Velocity-based Association Policies

Consider a TDMA setup where radio resources are equally shared among all users sharing the same BS. The average MESR experienced by the typical MU located at the origin under association policy \mathcal{P} is now equal to:

$$\mathcal{R}_{\text{load}}(\mathcal{P}) = \mathbb{E} \left[\frac{\log(1 + \text{SINR}_{0,M})(1 - T_{o,M}(V))^+}{Z_{\mu}^0(\mathcal{P})} \mathbb{1}_{\mathcal{P}(V)} \right] \\ + \mathbb{E} \left[\frac{\log(1 + \text{SINR}_{0,\mu})(1 - T_{o,\mu}(V))^+}{Z_M^0(\bar{\mathcal{P}})} \mathbb{1}_{\bar{\mathcal{P}}(V)} \right]$$

where Z_M^0 and Z_{μ}^0 denote the number of users in the zero-cell of the PV tessellation associated with each tier under association policy \mathcal{P} .

Assumption:

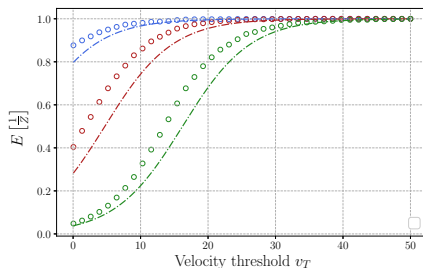
$$\hat{\mathcal{R}}_{\text{load}}(\mathcal{P}) = \mathbb{E} \left[\frac{1}{Z_{\mu}^0(\mathcal{P})} \right] \mathbb{E} [\mathcal{R}_{\mu,\text{eff}}(v) \mathbb{1}_{\mathcal{P}(v)}] + \mathbb{E} \left[\frac{1}{Z_M^0(\bar{\mathcal{P}})} \right] \mathbb{E} [\mathcal{R}_{M,\text{eff}}(v) \mathbb{1}_{\bar{\mathcal{P}}(v)}]$$

Population of the zero-cell

- Mus associated with the macro/micro tier form two PPP of respective intensities $\lambda_u F(v_T)$ and $\lambda_u(1 - F(v_T))$
- Immediate heuristic:

$$\mathbb{E} \left[\frac{1}{Z_0^M} \right] \approx \frac{1}{\mathbb{E}[Z_0^M]} = \frac{1}{1 + 1.28 \frac{\lambda_M}{\lambda_u F(v_T)}}$$

- Predicts poorly the value of the average inverse load in the network



Lemma

Let Φ and Ψ be two PPPs of respective intensities λ and ν . Let V_0 be the 0-cell of the PV tessellation associated with the process Φ and let $Z = 1 + |\Psi \cap V_0|$.

Finally, let $L: x \mapsto x \left(1 - \left(\frac{1}{1 + \frac{2}{7x}}\right)^{7/2}\right)$. The moment of order -1 of Z can be approximated by (see [?]):

$$\mathbb{E} \left[\frac{1}{Z} \right] \approx L \left(\frac{\lambda}{\nu} \right)$$

Under a threshold policy:

$$\mathbb{E} \left[\frac{1}{Z_{\mu}^0(v_T)} \right] = L \left(\frac{\lambda_{\mu}}{\lambda_u F(v_T)} \right) \equiv L_{\mu}(v_T)$$

$$\mathbb{E} \left[\frac{1}{Z_M^0(v_T)} \right] = L \left(\frac{\lambda_M}{\lambda_u (1 - F(v_T))} \right) \equiv L_M(v_T)$$

Population of the zero-cell

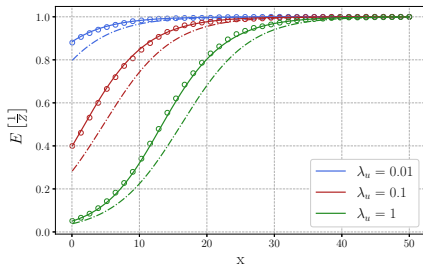
Lemma

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Finally, let $L: x \mapsto x \left(1 - \left(\frac{1}{1 + \frac{2}{7x}}\right)^{7/2}\right)$. The moment of order -1 of Z can be approximated by (see [?]):

$$\mathbb{E} \left[\frac{1}{Z} \right] \approx L \left(\frac{\lambda}{\nu} \right)$$

Provides a much better approximation for the inverse load



- Using the previous lemma, the heuristic for the MESR becomes:

$$\hat{\mathcal{R}}_{\text{load}}(v_T) = L_{\mu}(v_T) \int_0^{v_T} \mathcal{R}_{\mu,\text{eff}}(v) f(v) dv + L_M(v_T) \int_{v_T}^{\infty} \mathcal{R}_{M,\text{eff}}(v) f(v) dv$$

- We then define the *load-threshold* heuristic v_{LT} for the optimal MESR in the network as follows:

$$v_{LT} \triangleq \arg \max \hat{\mathcal{R}}_{\text{load}}(v_T)$$

- **Claim** : v_{LT} is uniquely defined and corresponds to a maximum of the MESR in the network.
- In the load-dependent case, v_{LT} depends on the velocity distribution f

Load-threshold heuristic

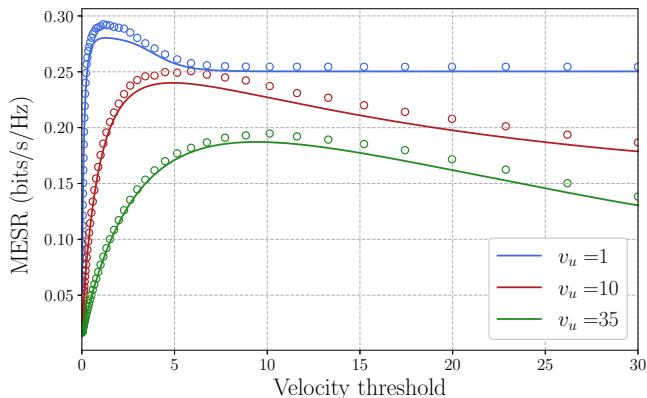


Figure: Comparison of the load-threshold heuristic (plain line) and simulations (circles) for a fixed user density $\lambda_u = 1$

Discussion - Comparison with a Classical Association Policy

Classical Association Policy: Maximum Average Received Power (MARP). Each MU connects to the tier offering the best power

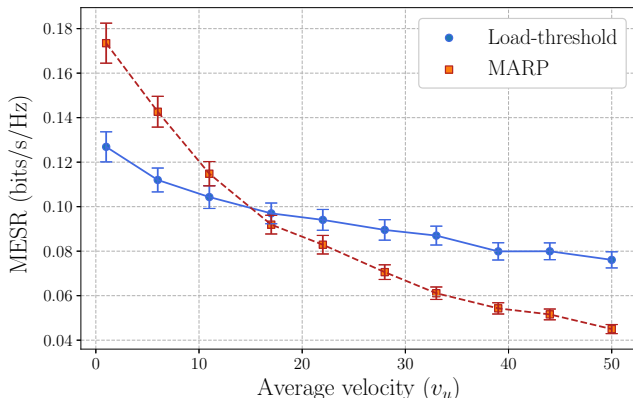


Figure: Comparison between the MARP policy (red) and the load-threshold policy under v_{LT} (blue) with 95% confidence intervals for a fixed user density $\lambda_u = 1$

Discussion - Effect of the Density of MUs in the network

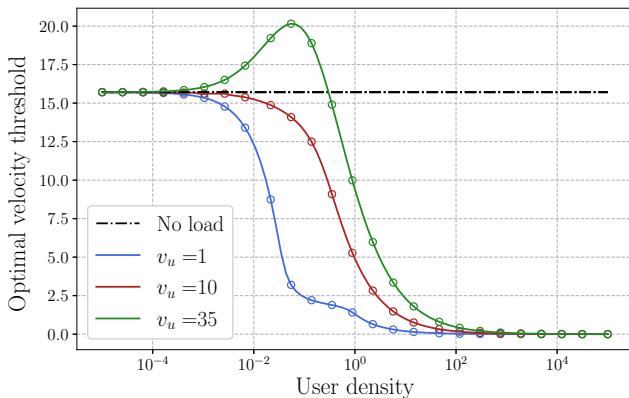


Figure: Optimal velocity threshold obtained for the load-threshold heuristic v_{LT} (in plain line) for three velocity distributions against the density of users. In black, dashed, the equivalent network without load

Extension - Maximum biased received power

MARP: connect the the macro tier if $RP_M > RP_\mu$. Threshold policy: connect to the macro tier if $v > v_T$

Idea: add a bias factor K depending on the velocity

Introduce **K-policies**: define $K: \mathbb{R}_+ \rightarrow \mathbb{R}_+$ such that:

If $RP_M > K(v)RP_\mu$, we connect to the macro tier

If $RP_M < K(v)RP_\mu$

$$\begin{array}{ll} \text{MARP} & \text{Load-threshold policy} \\ K(v) = 1 & K(v) = \begin{cases} 0 & \text{if } v > v_T \\ \infty & \text{else.} \end{cases} \end{array}$$

Extension - Maximum biased received power

Define the conditional CDF for the SINR $\mathbb{P}[\text{SINR}_{0,M} > T \mid |X_{0,\mu}| = s, |X_{0,M}| = r]$

Compute the MESR in the network according to:

$$\mathcal{R}(K) = \int_{v=0}^{\infty} \left((1 - T_{o,M}(v))^+ \int_{r=0}^{\infty} \int_{s=0}^{\infty} \left(\frac{P_{\mu}K(v)}{P_M} \right)^{1/\alpha} r \mathbb{E}[\log(1 + \text{SINR}_{0,M})] e^{-\pi(\lambda_M r^2 + \lambda_{\mu} s^2)} 2\pi\lambda_{\mu} 2\pi\lambda_M ds dr \right. \\ \left. + (1 - T_{o,\mu}(v))^+ \int_{r=0}^{\infty} \int_{s=0}^{\infty} \left(\frac{P_{\mu}K(v)}{P_M} \right)^{1/\alpha} r \mathbb{E}[\log(1 + \text{SINR}_{0,\mu})] e^{-\pi(\lambda_M r^2 + \lambda_{\mu} s^2)} 2\pi\lambda_{\mu} 2\pi\lambda_M ds dr \right) f(v) dv.$$

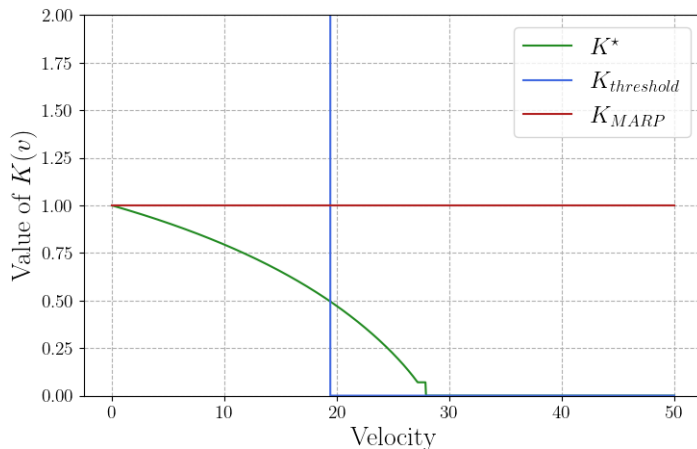
Use Euler-Lagrange's criterion to find a function K^* that maximizes the MESR:

$$\frac{\partial}{\partial K} L(v, K) = 0$$

where $\mathcal{R}(K) = \int_{v=0}^{\infty} L(v, K) f(v) dv$

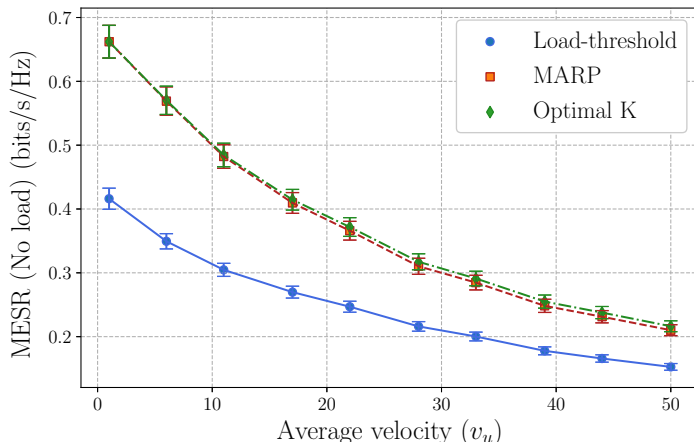
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Obtain an equation tying $K^*(v)$ and v to solve numerically



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References I