Optimal Quadratic Minorization for Weighted Sum-Rate Maximization in Interference Channels

Zhexian Yang
ShanghaiTech University
Shanghai, China
zhexianyang@shanghaitech.edu.cn

Ziping Zhao
ShanghaiTech University
Shanghai, China
zipingzhao@shanghaitech.edu.cn

***Abstract*—Weighted sum-rate (WSR) maximization is a fundamental but generally nonconvex problem in interference-limited wireless systems. A widely used solution is the weighted minimum mean-square error (WMMSE) algorithm, which can be interpreted as a minorization–maximization method based on a quadratic lower bound of the rate function. In this paper, we investigate whether this quadratic minorizer can be further tightened. We first derive an exact rate–MSE representation in terms of an integral of regularized minimum MSEs, without introducing the auxiliary weight variables used in WMMSE. By minorizing this representation, we obtain a new quadratic lower bound and develop an efficient algorithm, termed XMMSE, for WSR maximization in single-input single-output multicell uplinks with joint scheduling and power control under common within-cell priorities. Each iteration admits fully closed-form power updates and has the same order of per-iteration complexity as the joint scheduling WMMSE method. More importantly, we characterize a natural class of first-order-consistent quadratic minorizers and prove that the XMMSE minorizer is pointwise optimal within this class, in the sense that it has the smallest admissible quadratic coefficient. Consequently, it uniformly dominates the quadratic minorizer induced by WMMSE. Numerical results compare XMMSE with WMMSE under a physical multicell channel model.**

***Index Terms*—Weighted sum-rate maximization, quadratic minorization, minorization–maximization, weighted minimum mean-square error, multicell uplink power allocation.**

I. Introduction

Weighted sum-rate (WSR) maximization is a fundamental problem in communication systems for the design of linear transmit beamformers and power allocation strategies. This problem is generally non-convex and NP-hard [1], and iterative optimization algorithms are therefore commonly employed to obtain stationary solutions.

Over the past two decades, a rich body of work has addressed WSR maximization in various wireless network configurations. In [2], an iterative algorithm is proposed for WSR maximization in multiple-input multiple-output (MIMO) broadcast channels based on the uplink–downlink mean square error (MSE) duality, where a geometric program is solved at each iteration. A distributed pricing algorithm for the WSR maximization problem in multiple-input single-output (MISO) interference channels was developed in [3], and it was shown that the algorithm converges monotonically to a stationary point with current interference prices under certain sufficient utility conditions. Similarly, [4] addresses WSR maximization in MIMO interference channels by optimizing transmit covariance matrices, where each link solves a local convex subproblem. A common limitation of these approaches is that they do not admit closed-form solutions at each iteration, which can result in relatively high computational complexity.

The weighted MMSE (WMMSE) criterion was introduced for MIMO channels in [5], where a generalized formulation was proposed to enable the design of specialized linear precoders through the adjustment of diagonal weight matrices. By exploiting the relationship between the MSE and the SINR [6], the WMMSE algorithm for MIMO broadcast channels was subsequently developed in [7]. That work formulated a matrix-weighted sum-MSE minimization problem and established the connection between the optimal weights and the MSE matrix via the Karush–Kuhn–Tucker conditions. This line of research was further extended in [8] to MIMO interfering broadcast channels, where the authors demonstrated the equivalence between WSR maximization and weighted sum-MSE minimization, and interpreted the WMMSE algorithm as an alternating minimization procedure for solving the latter problem. More recently, [9] revisited the WMMSE framework and proposed reduced-complexity variants that scale linearly with the number of base station antennas by exploiting a low-dimensional subspace property. The connections between WMMSE and minorization–maximization (MM) methods were systematically analyzed in [10].

Despite the success of the WMMSE framework, a fundamental question remains: *Is the matrix weight variable in WMMSE really necessary?* The WMMSE algorithm introduces an auxiliary matrix weight variable that is updated at each iteration as the inverse of the current MSE matrix. This weight variable is not present in the original WSR maximization problem, and its introduction adds computational overhead without, as we shall show, being essential for the equivalence between rate maximization and MSE minimization.

In this paper, we answer this question in the negative. Our starting point is the observation that the relationship between the achievable rate and the MSE can be expressed in a form that does not require an explicit weight variable. Specifically, by integrating the regularized MSE over a regularization parameter $\tau \in [0, 1]$, we obtain an *exact* rate–MSE relation that is complementary to the exact variational identity used

in WMMSE [8]. This exact relation allows us to transform the WSR maximization problem into an equivalent sum-regularized-MSE minimization problem without introducing any auxiliary weight variables. We term the resulting algorithm XMMSE.

Building on this formulation, we develop the XMMSE algorithm for joint scheduling and power control in the single-input single-output (SISO) multicell uplink, using the per-cell candidate selection framework of [11]. Within the MM framework [12], the XMMSE surrogate constitutes a tighter quadratic lower bound of the scalar rate than the surrogate induced by WMMSE. Candidate powers admit closed-form updates without requiring a multiplier search. Both XMMSE and WMMSE have per-iteration complexity $\mathcal{O}(J\sum_i |\mathcal{U}_i|)$, where J is the number of cells and $\mathcal{U}_i$ is the user set of cell i.

The main contributions of this paper are as follows:

- **Exact rate–MSE relation.** We derive an exact integral representation of the rate function in terms of the regularized MSE, which avoids the need for the matrix weight variable employed in WMMSE.
- **XMMSE algorithm.** We develop a novel MM-based algorithm for WSR maximization in the SISO multicell uplink with joint scheduling and power control. With common priorities within each cell, the algorithm features closed-form candidate power updates and per-cell user selection.
- **Theoretical optimality.** We prove that the quadratic surrogate function constructed by XMMSE is the *tightest possible* within the first-order-consistent family Q_a defined in (9), which is affine in y and has quadratic term $-a|x-\underline{x}|^2$. Specifically, the XMMSE coefficient is the unique smallest admissible coefficient in this family.
- **Convergence analysis and numerical validation.** We establish monotone convergence of the joint algorithm's objective values and compare its convergence and runtime with WMMSE.

Preliminary results of this work were presented in [13] for the general MIMO case. This paper provides a comprehensive treatment of the SISO setting, including the full theoretical optimality analysis and detailed numerical comparisons.

II. Problem Formulation

We adopt the joint uplink scheduling and power control model of [11]. There are J cells, each containing a single-antenna base station (BS) and a set $\mathcal{U}_i$ of single-antenna users. On the shared resource, BS i schedules one user $s_i \in \mathcal{U}_i$. Let $h_{i,s}$ denote the channel from user s to BS i, p_s its transmit power, and $w_s > 0$ its priority. The received signal is

$$r_i = h_{i,s_i}\sqrt{p_{s_i}}d_{s_i} + \sum_{j\neq i} h_{i,s_j}\sqrt{p_{s_j}}d_{s_j} + n_i,$$

where the Gaussian data symbols d_s are independent with zero mean and unit variance, and $n_i \sim \mathcal{CN}(0,\sigma^2)$. Define

$$F_i = \sum_{j\neq i} |h_{i,s_j}|^2 p_{s_j} + \sigma^2, \qquad \gamma_i = \frac{|h_{i,s_i}|^2 p_{s_i}}{F_i}.$$

Treating interference as noise, the WSR problem is

$$\begin{aligned} \max_{\mathbf{s},\mathbf{p}} \ & \sum_{i=1}^{J} w_{s_i}\log(1+\gamma_i) \\ \text{s.t. } & s_i \in \mathcal{U}_i, \quad 0 \le p_s \le P. \end{aligned} \tag{1}$$

Only scheduled users transmit. Scheduling and power are jointly updated, as in [11].

A. Joint Scheduling and Power Updates

Assume a common priority within each cell, $w_s = w_i$ for $s \in \mathcal{U}_i$. For a frozen surrogate, both methods below reduce to independent per-cell maximizations. For each candidate $s \in \mathcal{U}_i$, define

$$p^\star_{i,s} = \min\left\{\left(\frac{b_{i,s}}{a_{i,s}}\right)^2, P\right\}, \quad s^\star_i = \arg\max_{s\in\mathcal{U}_i} \Phi_{i,s}, \tag{2}$$

where $\Phi_{i,s} = k_{i,s} + 2b_{i,s}\sqrt{p^\star_{i,s}} - a_{i,s}p^\star_{i,s}$. Set $p_{s^\star_i} = p^\star_{i,s^\star_i}$. If $a_{i,s} = 0 < b_{i,s}$, use $p^\star_{i,s} = P$; if both vanish, retain the cell's current power. Ties retain the incumbent user.

WMMSE: At the current $(\underline{\mathbf{s}}, \underline{\mathbf{p}})$, first update γ_i to the current SINR and then set

$$y_i = \frac{\sqrt{w_{\underline{s}_i}(1+\gamma_i)|h_{i,\underline{s}_i}|^2 \underline{p}_{\underline{s}_i}}}{\sum_j |h_{i,\underline{s}_j}|^2 \underline{p}_{\underline{s}_j} + \sigma^2}. \tag{3}$$

Here $y_i = \sqrt{w_i t_i}u_i$, where u_i is the phase-aligned MMSE receiver and $t_i = 1+\gamma_i$ is the inverse MSE weight. The coefficients are

$$\begin{aligned} a_{\mathrm{W},i,s} &= \sum_j y_j^2 |h_{j,s}|^2, \\ b_{\mathrm{W},i,s} &= y_i\sqrt{w_s(1+\gamma_i)|h_{i,s}|^2}, \\ k_{\mathrm{W},i,s} &= w_s\big(\log(1+\gamma_i) - \gamma_i\big). \end{aligned} \tag{4}$$

Together with (2), these WMMSE updates coincide with the power and utility-minus-price scheduling updates in [11, Eqs. (13)–(18)].

XMMSE: Write $x_i = |h_{i,s_i}|\sqrt{p_{s_i}}$. For the phase-aligned scalar receive filter u_i, the MSE is

$$e_i = 1 - 2u_i x_i + u_i^2(F_i + x_i^2).$$

The exact rate–MSE identity is

$$\int_0^1 \min_{u_i}\big(e_i - \tau u_i^2 x_i^2\big)\,\mathrm{d}\tau = 1 - \log(1 + x_i^2/F_i), \tag{5}$$

with $u_i^{\mathrm{opt}}(\tau) = x_i/[F_i + (1-\tau)x_i^2]$. Freezing these filters at the reference point gives a global rate lower bound. Define

$$\rho_i = \frac{1}{1+\underline{\gamma}_i}, \qquad \beta_i = \frac{\log(1+\underline{\gamma}_i)}{\underline{\gamma}_i}, \qquad \underline{\gamma}_i = \frac{\underline{x}_i^2}{\underline{F}_i}, \tag{6}$$

and the interference price $c_i = w_i\underline{\gamma}_i\rho_i/\underline{F}_i$. The XMMSE coefficients are

$$a_{\mathrm{X},i,s} = \frac{w_i(\beta_i - \rho_i)}{\underline{F}_i}|h_{i,s}|^2 + \sum_{j\neq i} c_j|h_{j,s}|^2, \tag{7a}$$

$$b_{\mathrm{X},i,s} = \frac{w_i\beta_i\underline{x}_i}{\underline{F}_i}|h_{i,s}|, \qquad k_{\mathrm{X},i,s} = 0. \tag{7b}$$

Algorithm 1 Joint Uplink Scheduling and Power Control

Input: Channels $h_{i,s}$, user sets $\mathcal{U}_i$, noise σ^2, budget P, and priorities w_s (common within each cell).

1: Initialize one $s_i \in \mathcal{U}_i$ and $0 < p_{s_i} \le P$ per cell.
2: **while** stopping tolerance is not met and iteration limit is not reached **do**
3: Compute current SINRs γ_i.
4: For WMMSE, update y_i and coefficients via (3)–(4); for XMMSE, use (6)–(7).
5: Compute $p^\star_{i,s}$ and $\Phi_{i,s}$ for every $s \in \mathcal{U}_i$.
6: Simultaneously update all scheduled users and powers via (2).
7: **end while**

Output: Schedule $\mathbf{s}$ and powers $\mathbf{p}$.

At zero SINR, use $\beta_i = \rho_i = 1$. Up to the constant $-\sigma^2 \sum_i c_i$, the surrogate is

$$\sum_i \left(2b_{\mathrm{X},i,s_i}\sqrt{p_{s_i}} - a_{\mathrm{X},i,s_i}p_{s_i}\right). \tag{8}$$

Thus XMMSE uses the same candidate-power and scheduling maximization (2) as WMMSE, with different surrogate coefficients. Equal priorities within each cell make the frozen interference prices independent of the selected user.

Both surrogates are globally valid and tight at the current schedule and powers. Their exact maximization therefore produces nondecreasing WSR; boundedness implies convergence of the objective values. This does not guarantee a globally optimal schedule. Each iteration costs $\mathcal{O}(J\sum_i |\mathcal{U}_i|)$ for either method and requires no inner numerical search.

III. Optimality of XMMSE

A. Derivation of XMMSE via Linearization

The XMMSE algorithm can also be derived directly from the MM framework. Consider the scalar rate function $g(x,y) = \log(1+|x|^2/y)$ where $x \in \mathbb{C}$ and $y > 0$. For $\underline{x} \neq 0$ and $\underline{y} > 0$, starting from the identity

$$g(x,y) = \log\left(1+\frac{|x|^2}{y}\right) = \int_0^1 \frac{|x|^2}{y+\tau|x|^2}\,\mathrm{d}\tau,$$

we can minorize the integrand pointwise in τ by linearizing the jointly convex function $|x|^2/z$ in (x,z), then substituting $z = y+\tau|x|^2$. This yields

$$\begin{aligned}
&\log\left(1+\frac{|x|^2}{y}\right)\\
&\ge \int_0^1 \left(\frac{2}{\underline{y}+\tau|\underline{x}|^2}\,\mathrm{Re}\{\underline{x}^* x\} - \frac{|\underline{x}|^2}{(\underline{y}+\tau|\underline{x}|^2)^2}(y+\tau|x|^2)\right)\mathrm{d}\tau\\
&= \frac{2}{|\underline{x}|^2}\log\left(1+\frac{|\underline{x}|^2}{\underline{y}}\right)\mathrm{Re}\{\underline{x}^* x\} - \left(\frac{1}{\underline{y}} - \frac{1}{\underline{y}+|\underline{x}|^2}\right)y\\
&\quad - \left(\log\left(1+\frac{|\underline{x}|^2}{\underline{y}}\right) - 1 + \frac{1}{1+|\underline{x}|^2/\underline{y}}\right)\frac{|x|^2}{|\underline{x}|^2}.
\end{aligned}$$

This expression gives a quadratic lower bound $\underline{g}_{\mathrm{X}}(x,y;\underline{x},\underline{y})$ for $g(x,y)$ at $(\underline{x},\underline{y})$. The XMMSE algorithm can be obtained by applying this quadratic lower bound to each term of WSR.

B. Theoretical Optimality of the XMMSE Algorithm

We now establish that the quadratic surrogate constructed by XMMSE is the *tightest possible* within the first-order-consistent family Q_a defined below, which is affine in y and has quadratic term $-a|x-\underline{x}|^2$.

At a reference point $(\underline{x},\underline{y})$ with $\underline{y} > 0$, define

$$\begin{aligned}
Q_a(x,y;\underline{x},\underline{y}) = &-a|x-\underline{x}|^2\\
&+ 2\,\mathrm{Re}\left\{\left(\frac{\partial g}{\partial x^*}(\underline{x},\underline{y})\right)^*(x-\underline{x})\right\}\\
&+ \frac{\partial g}{\partial y}(\underline{x},\underline{y})\,(y-\underline{y}) + g(\underline{x},\underline{y}),
\end{aligned} \tag{9}$$

where $a \ge 0$ is the quadratic coefficient. The Wirtinger derivative in x and the ordinary derivative in y are

$$\frac{\partial g}{\partial x^*}(\underline{x},\underline{y}) = \frac{\underline{x}}{\underline{y}+|\underline{x}|^2}, \quad \frac{\partial g}{\partial y}(\underline{x},\underline{y}) = -\frac{|\underline{x}|^2}{\underline{y}(\underline{y}+|\underline{x}|^2)}.$$

Denote $a_{\mathrm{X}} = \frac{1}{|\underline{x}|^2}\left(\log(1+|\underline{x}|^2/\underline{y}) - 1 + \frac{1}{1+|\underline{x}|^2/\underline{y}}\right)$, and the XMMSE quadratic lower bound $\underline{g}_{\mathrm{X}}$ can be reformulated as

$$\underline{g}_{\mathrm{X}}\left(x,y;\underline{x},\underline{y}\right) = Q_{a_{\mathrm{X}}}\left(x,y;\underline{x},\underline{y}\right).$$

For $\underline{x} = 0$, set $a_{\mathrm{X}} = 0$ by continuity, so $Q_{a_{\mathrm{X}}} = 0$. Define the set of admissible coefficients

$$\mathcal{A}_{\underline{x},\underline{y}} = \left\{a \ge 0 : Q_a(x,y;\underline{x},\underline{y}) \le g(x,y),\ \forall\, x \in \mathbb{C},\ y > 0\right\}.$$

Theorem 1 (Lower bound on the quadratic coefficient)**.** *For $\underline{x} \neq 0$ and any $a \in \mathcal{A}_{\underline{x},\underline{y}}$, we have*

$$a \ge \frac{1}{|\underline{x}|^2}\left(\log(1+\underline{\gamma}) - \frac{\underline{\gamma}}{1+\underline{\gamma}}\right) = a_{\mathrm{X}}, \tag{10}$$

where $\underline{\gamma} = |\underline{x}|^2/\underline{y}$. At $\underline{x} = 0$, the smallest admissible coefficient is $a_{\mathrm{X}} = 0$.

Proof. Consider the sequence $(x_n, y_n) = (\underline{x}/n,\ \underline{y}/n)$ for $n = 1,2,\ldots$. As $n \to \infty$, we have

$$\lim_{n\to\infty} g(x_n,y_n) = \lim_{n\to\infty}\log\left(1+\frac{|\underline{x}|^2}{n\underline{y}}\right) = 0.$$

Now evaluate Q_a at (x_n,y_n). Substituting $x_n - \underline{x} = \underline{x}(1/n-1)$ and $y_n - \underline{y} = \underline{y}(1/n-1)$,

$$\begin{aligned}
Q_a(x_n,y_n;\underline{x},\underline{y}) &= -a|\underline{x}|^2(1-1/n)^2\\
&\quad + \frac{2|\underline{x}|^2}{\underline{y}+|\underline{x}|^2}(1/n-1) - \frac{|\underline{x}|^2}{\underline{y}+|\underline{x}|^2}(1/n-1) + \log(1+\underline{\gamma})\\
&= -a|\underline{x}|^2(1-1/n)^2 + \frac{|\underline{x}|^2}{\underline{y}+|\underline{x}|^2}(1/n-1) + \log(1+\underline{\gamma}).
\end{aligned}$$

Taking $n \to \infty$,

$$\begin{aligned}
\lim_{n\to\infty} Q_a(x_n,y_n;\underline{x},\underline{y}) &= -a|\underline{x}|^2 - \frac{|\underline{x}|^2}{\underline{y}+|\underline{x}|^2} + \log(1+\underline{\gamma})\\
&= -a|\underline{x}|^2 - \frac{\underline{\gamma}}{1+\underline{\gamma}} + \log(1+\underline{\gamma}).
\end{aligned}$$

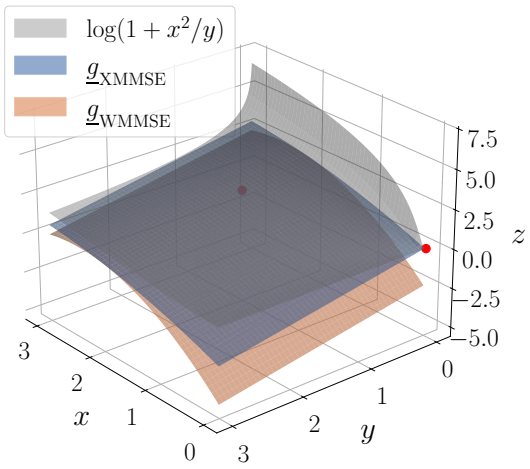


Fig. 1. A 3D visualization of the true rate function $g(x, y) = \log(1+x^2/y)$ and its XMMSE and WMMSE quadratic lower bounds at $(\underline{x}, \underline{y}) = (2, 1)$. The XMMSE surrogate provides a visibly tighter approximation than WMMSE.

Since $Q_a \le g$ for all (x, y), taking the limit yields

$$a \ge \frac{1}{|\underline{x}|^2}\left(\log(1+\underline{\gamma}) - \frac{\underline{\gamma}}{1+\underline{\gamma}}\right),$$

which is exactly (10). □

A direct corollary of Theorem 1 is that the XMMSE surrogate is pointwise tighter than the WMMSE surrogate:

Corollary 2. *For any $x \in \mathbb{C}$ and $y > 0$, the XMMSE quadratic lower bound satisfies*

$$Q_{a_{\text{X}}}(x, y; \underline{x}, \underline{y}) \ge Q_{a_{\text{W}}}(x, y; \underline{x}, \underline{y}),$$

where $a_{\text{W}} = 1/\underline{y} - 1/(\underline{y} + |\underline{x}|^2)$ is the quadratic coefficient induced by the WMMSE surrogate.

This corollary follows immediately from $a_{\text{X}} \le a_{\text{W}}$ (since $\log(1+\underline{\gamma}) \le \underline{\gamma}$ for $\underline{\gamma} \ge 0$) and the fact that both surrogates share the same linear and constant terms.

C. Comparison with WMMSE

To illustrate that the quadratic surrogate in XMMSE provides a tighter lower bound than that induced by WMMSE, we consider a simple two-variable example that captures the essential structure of the WSR objective function. For real x and $\underline{x}$, the quadratic surrogate functions corresponding to XMMSE and WMMSE are given by

$$\begin{aligned} g_{\text{X}}(x, y; \underline{x}, \underline{y}) &= \frac{2\underline{x}}{\underline{y} + \underline{x}^2}(x - \underline{x}) - a_{\text{W}}(y - \underline{y}) \\ &\quad - a_{\text{X}}(x - \underline{x})^2 + g(\underline{x}, \underline{y}), \\ g_{\text{W}}(x, y; \underline{x}, \underline{y}) &= \frac{2\underline{x}}{\underline{y} + \underline{x}^2}(x - \underline{x}) - a_{\text{W}}(y - \underline{y}) \\ &\quad - a_{\text{W}}(x - \underline{x})^2 + g(\underline{x}, \underline{y}). \end{aligned}$$

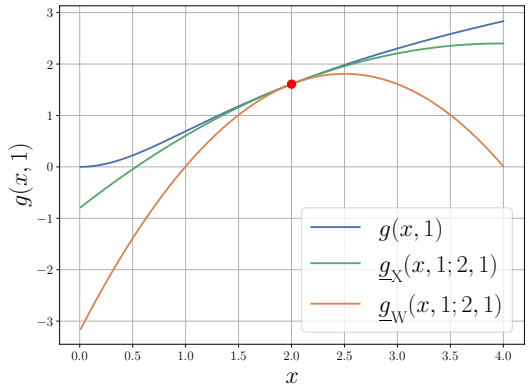


Fig. 2. Slice at $y = 1$ of the lower bounds in Fig. 1, corresponding to $g(x, 1) = \log(1 + x^2)$. The XMMSE surrogate is uniformly at least as tight as the WMMSE surrogate.

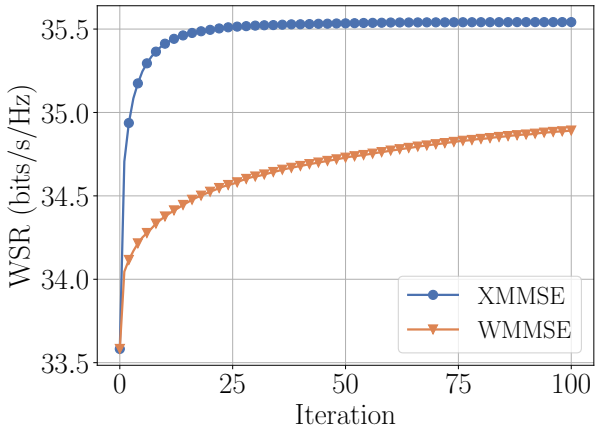


Fig. 3. Mean WSR versus iteration for joint scheduling and power control at a maximum transmit PSD of -47 dBm/Hz.

Fig. 1 visualizes the three surfaces. The XMMSE surrogate hugs the true function more closely than the WMMSE surrogate, consistent with the theoretical optimality established in Section III.

To better appreciate the difference, Fig. 2 shows the slice at $y = 1$ of the same functions. At this slice, $g(x, 1) = \log(1 + x^2)$, and the XMMSE lower bound visibly dominates the WMMSE lower bound, confirming the tighter approximation.

IV. Numerical Simulations

We compare XMMSE and WMMSE in a four-cell wrapped triangular layout with eight users per cell and 800 m BS spacing. Following [11], the channel power gains include pathloss $128.1 + 37.6\log_{10}(d)$ dB, with d in km, and log-normal shadowing of standard deviation 8 dB, without small-scale fading. Uniformly proposed users associate with their strongest BS, conditioned on eight users per cell. Noise PSD is -171 dBm/Hz over 10 MHz. All priorities are one, under which (3)–(4) implement WMMSE. Both methods start with the strongest serving-link user in each cell at full power and subsequently update scheduling and power jointly.

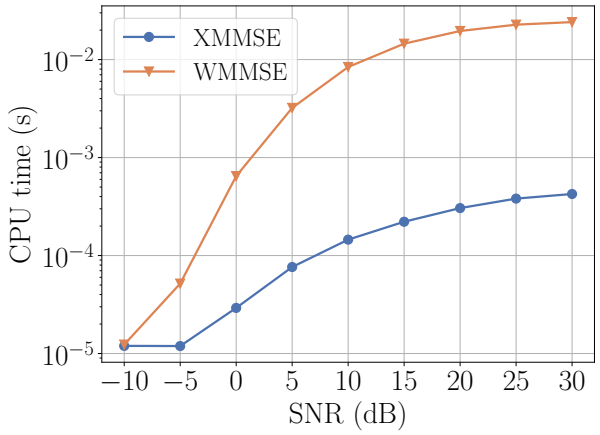


Fig. 4. Mean CPU time versus SNR, including joint scheduling, power updates, objective evaluations, and stopping checks. Runs reaching the iteration limit are included.

Define the SNR for a reference link as $P_{\mathrm{PSD}} - N_{\mathrm{PSD}} - L(0.4)$ in dB, where $L(d) = 128.1 + 37.6 \log_{10}(d)$ and the PSDs are in dBm/Hz. We vary the power budget to sweep this SNR from -10 to 30 dB in 5 dB steps and average over 10000 paired channel realizations. The stopping test requires an unchanged schedule and an absolute WSR increment below 10^{-6} nats, confirmed by one further joint update, with a 10000-iteration limit. Fig. 3 uses the reference transmit PSD of -47 dBm/Hz from [11] and 100 iterations. Both solvers use Numba; CPU time measures elapsed solver time excluding JIT warmup. XMMSE improves the mean WSR more rapidly than WMMSE. Fig. 4 shows lower mean CPU time for XMMSE in this experiment. Some WMMSE runs reach the iteration limit at higher SNRs, so these timings include capped runs and do not represent uniformly converged solutions.

V. Conclusion

In this paper, we have developed XMMSE, an MM-based algorithm for weighted sum-rate maximization in SISO multicell uplinks with joint scheduling and power control under common within-cell priorities. The proposed method has been derived from an exact rate–MSE representation that eliminates the auxiliary weight variables used in WMMSE. Each iteration admits fully closed-form power updates and has a per-iteration complexity of $\mathcal{O}(J \sum_i |\mathcal{U}_i|)$, matching that of WMMSE in order. More importantly, we have characterized a natural class of first-order-consistent quadratic minorizers for the scalar rate function and proved that the XMMSE minorizer is pointwise optimal within this class, in the sense that it attains the smallest admissible quadratic coefficient. Consequently, it uniformly dominates the quadratic minorizer induced by WMMSE. Numerical results compare the convergence and runtime of XMMSE and WMMSE for joint scheduling and power control under the same physical channel model.

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