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Variational Optimization for Interference-Constrained Wireless Signal Estimation

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Abstract
Massive multiple-input multiple-output (MIMO) systems demand accurate signal estimation under increasingly severe interference, uncertainty, and imperfect channel state information and interference statistics. Existing variational Bayesian (VB) estimators enhance posterior interference by incorporating signal-recovery optimisation into interference control without explicit intervention. A robust uncertainty-aware variational Bayesian estimator is proposed in this paper for interference-constrained massive MIMO signal estimation. The posterior covariance and posterior-mean energy are incorporated into the interference metric in accordance with both estimated signal power and uncertainty-induced interference exposure. Further, a norm-bounded interference covariance model is introduced to provide robustness when compared with covariance-estimation errors. According to the constraint violations, the interference penalty is altered through the adaptive primal-dual optimisation mechanism during retention of the computational structure of the VB reference. Under limited conditions, the competitive estimation accuracy and detection reliability during the substantial reduction in interference leakage are proven in the simulation results. At 2 dB SNR and 12 dB INR, the normalized interference leakage is reduced by 32.3% compared with LMMSE, whereas the −2 dB SNR reduces 47.2% relative to robust-MMSE. The posterior-uncertainty-aware interference regulation is used as an effective extension of conventional VB-based massive-MIMO estimation, is established in the results.

Keywords: Massive MIMO; variational Bayesian inference; signal estimation; posterior uncertainty; interference constraints; robust optimization; interference covariance; primal-dual optimization; spectrum sharing; 6G wireless communications.

1. Introduction

Massive multiple-input multiple-output (MIMO) technology is one of the important components of modern wireless communication as it enhances the spatial multiplexing capability, spectral efficiency, and reliability simultaneously. The deployment of a large number of antennas in the base stations leads to massive MIMO systems, which serve multiple users over the same time-frequency resources by exploiting spatial degrees of freedom which isolated the transmitted signals. Moreover, the performance of the systems is strongly based on the availability of accurate channel state information (CSI) and reliable signal estimation. The degradation estimation and detection performance are evaluated through imperfect receiver knowledge, channel uncertainty,correlated interference, and user mobility under practical environments.

The major problem faced in interference-limited wireless environments is the signal estimation problem. The statistical error criterion is reduced through the mean-square error, which is the conventional estimator, without considering the amount of interference associated with the resulting estimate. In the case of dense multi-user networks, the segregation between interference and estimation becomes problematic, as enhancing the desired-signal estimate increases interference to sensitivity. Subsequently, interference management and signal estimation are ideally addressed under a common optimization framework.

Variational Bayesian (VB) inference enables an optimal foundation for this framework. The posterior probability distribution is calculated during VB methods for the unknown variables.This method allows both the estimated mean and the associated uncertainty to be incorporated into the decision process. The applicability of VB inference to joint channel estimation and data detection, time-varying channels, low-resolution receivers, massive-MIMO detection, and cell-free massive MIMO systems (Nguyen *et al.*, 2024; Nassirpour *et al.*, 2025a, 2025b).In particular, Nassirpour*et al.* (2025a) illustrated joint channel estimation and data detection.

The associated uncertainty and estimated mean are incorporated into the decision process. The applicability of VB inference to massive-MIMO detection, time-varying channels, cell-free massive MIMO systems, joint channel estimation and data detection and low-resolution receivers has been included in recent studies (Nguyen *et al.*, 2024; Nassirpour *et al.*, 2025a, 2025b). Nassirpour *et al.* (2025a) illustrated that a VB interference framework exhibits the ability of variational inference to capture model posterior uncertainty in high-dimensional wireless systems.

Variationalinference and learned priors have recently been combined. Chen *et al.* (2025) proposed a diffusion-model-based variational inference framework for MIMO channel estimation, in which the learned channel prior and posterior estimation are incorporated. This framework indicates combines probabilistic interference with data-driven prior information, which enhances the channel estimation. Gao *et al.* (2026) proposed a Bayesian end-to-end learning framework in which multiple physical-layer variables are represented probabilistically rather than deterministically. The incorporation of estimation uncertainty over channel estimation, CSI recovery, detection, and precoding is addressed.

Among these studies, an important problem remains unexplored, which is how to explicitly incorporate an interference constraint into the posterior estimation process during posterior uncertainty accounting. A deterministic signal or beamforming vector is used for formulating the conventional interference constraints. These formulations do not reflect uncertainty directly into the estimated signal. Both a posterior mean and covariance are naturally provided by the variational estimator and are exploited to construct an interference measure.

The method proposed in the paper treats both interference control and signal estimation as a coupled optimisation problem. The second-order posterior moment is also analyzed through the formulation, instead of constraining the posterior mean and interference association. Moreover, the incorporation of the interference covariance matrix and robust constraints improves the reliability estimator in the case of known interference statistics.

Major contributions are: Firstly, the VB signal framework for interference-limited massive-MIMO uplink is formulated. Secondly, the development of a posterior-uncertainty-aware interference constraint leads to the incorporation of both covariance and posterior mean into the interference measure. Thirdly, robust set-deterministic constraints are used to address the interference through uncertainty. Lastly, an adaptive primal-dual optimization procedure is constructed for the regulation of the interference penalty.

2. Related Work and Research Gap

2.1 Variational Bayesian Inference

An intractable posterior distribution is approximated by a tractable variational distribution through the minimization of a divergence-based objective (Jordan *et al.*, 1999; Wainwright & Jordan, 2008). The attraction of high-dimensional wireless interference is driven by the scalability and probabilistic representation. Blei *et al.* (2017) proposed a comprehensive treatment for IV, whereas Hoffman *et al.* (2013) revealed the scalability through stochastic optimization. The statistical estimation theory supports Bayesian signal-estimation principles.

2.2 VB-Based MIMO Estimation

The application of massive-MIMO detection and joint channel estimation progressively involves VB methods. Nguyen *et al.* (2022) formulated a detection method involving uncertainty in residual interference and in noise. Nguyen *et al.* (2024) improved the data detection nd channel estimation in massive MIMO. Nguyen *et al.* (2025) used VB for MIMO detection for spatial sigma-delta ADCs, which demonstrated adaptability for non-ideal receiver architectures. Nassirpour *et al.* (2025a) designed a VB interference under temporal conditions for addressing joint estimation, detection and time-varying massive-MIMO channels.

These studies evaluate accurate probabilistic estimation when handling complex receiver impairments. Moreover, instead of explicitly constraining the interference, their primary objective is channel and signal recovery.

2.3 Learned Priors and Bayesian MIMO Inference

Bayesian inference with learned signal or channel priors is integrated in recent studies. Chen *et al.* (2025) illustrated a diffusion model for MIMO channel estimation, which elevates the robustness and estimation accuracy for distribution shifts. Gao *et al.* (2026) use factorized posterior representations for developing Bayesian end-to-end learning across detection, channel estimation, precoding and CSIT processing. This approach provides findings of growing importance along learned probabilistic priors.

2.4 Interference-Aware Wireless Optimization

Interference management provides fundamental information to multiuser wireless systems and spectrum-sharing (Haykin, 2005; Wang & Liu, 2011; Goldsmith *et al.*, 2009). The interference dimensions are controlled using interference alignment (Cadambe& Jafar, 2008), whereas broader massive-MIMO studies illustrate the importance of array scaling and spatial processing (Marzetta, 2010; Larsson *et al.*, 2014; Ngo *et al.*, 2013; Hoydis*et al.*, 2013; Björnson *et al.*, 2018). Another mechanism is used for handling the uncertainty in system parameters (Boyd & Vandenberghe, 2004), whereas the block optimization methods contribute convergence tools for constrained and non-smooth problems (Razaviyayn*et al.*, 2013).

Moreover, the existing interference-management approaches usually optimise transmission strategies, power allocation, or beamforming instead of incorporating posterior uncertainty and the signal transmission process.

2.5 Research Gap

Therefore, a clear gap is revealed at the intersection of explicit interference constraints, variational Bayesian estimation and posterior uncertainty. This literature shows various management approaches among the methods; Existing VB-MIMO methods enhance probabilistic estimation; interference-management methods control transmission-side interference; and learned-prior methods improve posterior representation. During signal estimation, an interference-relevant quantity is approached directly to treat the posterior.

This gap is addressed through the robust VB estimator, which integrates the posterior mean and covariance into the interference matrix, incorporates the interference covariance and uses adaptive primal-dual optimization for enforcing the interference threshold. The interference-limited massive-MIMO operation is targeted in the framework, considering the probabilistic advantage and computational structure along VB interference.

3. System Model and Problem Formulation

3.1 Massive-MIMO uplink model

Assume an uplink massive-MIMO system where a base station that is equipped with Mantennas receive signals from Kdesired users. Additionally, Lexternal interference sources run over the same time-frequency resources. Eq. 1 represents the received vector,

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{x} + \boldsymbol{G}\boldsymbol{z} + \boldsymbol{n}, \qquad (1)$$

where $\boldsymbol{y} \in \mathbb{C}^{M}$denotes the received signal, $\boldsymbol{H} \in \mathbb{C}^{M\times K}$is the desired-user channel matrix, and $\boldsymbol{x} \in \mathbb{C}^{K}$is the transmitted signal vector. The matrix $\boldsymbol{G} \in \mathbb{C}^{M\times L}$represents the interference channel, while $\boldsymbol{z} \in \mathbb{C}^{L}$denotes the interfering signal vector. The receiver noise is denoted by $\boldsymbol{n}$, which is modelled as a zero-mean complex Gaussian vector with covariance determined by the receiver noise level.

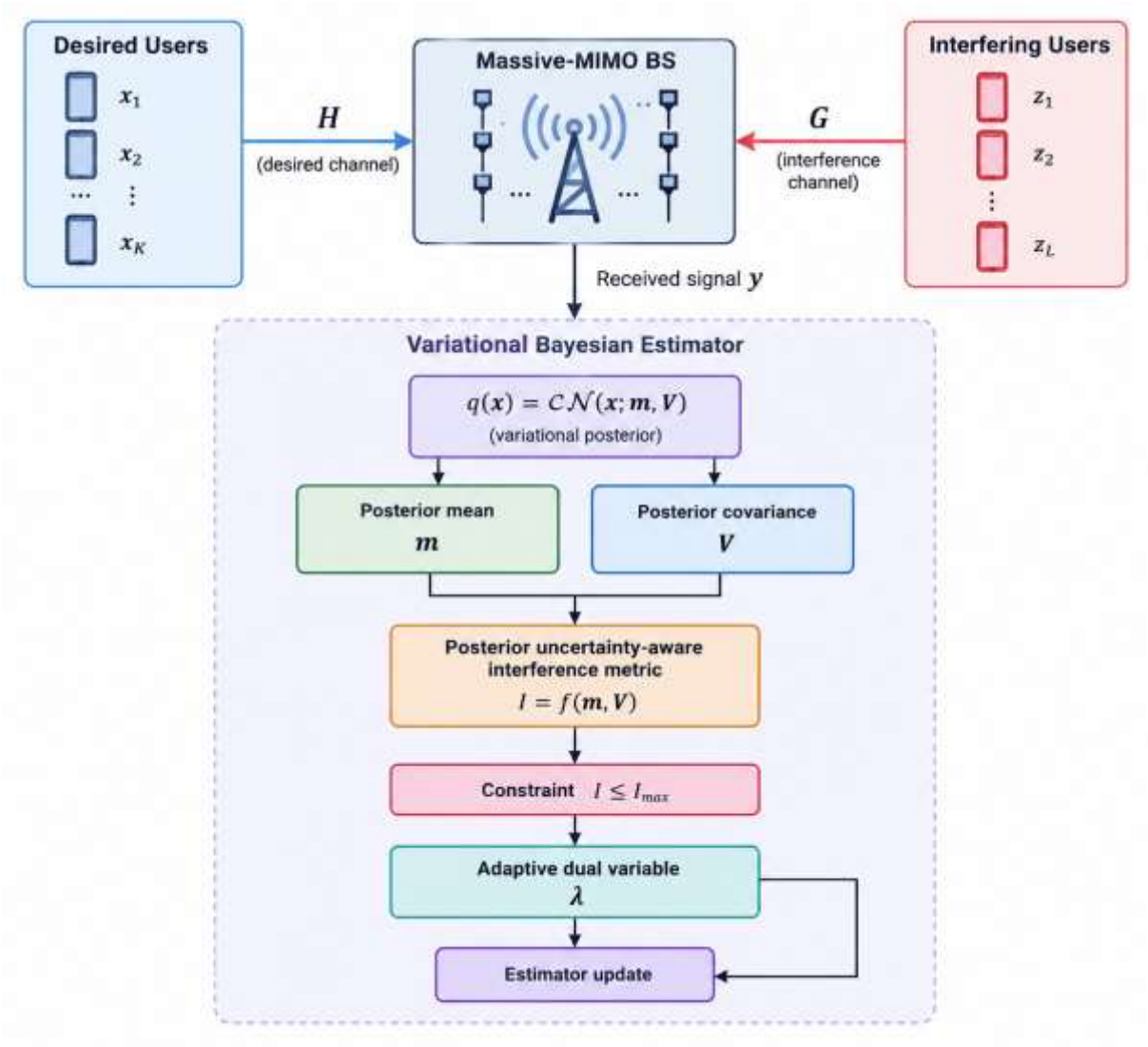


Figure 1. System model of the proposed robust variational Bayesian estimator

Figure 1 represents the uplink massive-MIMO architecture that consists of desired users, a variational Bayesian receiver, a multi-antenna base station, and external interferers, together estimating the posterior certainty and desired signal. The received signal contains both the interference and the desired-user distribution before performing the posterior interference.

Both the external and intra-cell interference are accommodated through the model. The desired channel $\boldsymbol{H}$may be imperfectly known due to pilot contamination, mobility, channel ageing, or estimation errors. Likewise, the interference channel $\boldsymbol{G}$may be accessible through an estimate. This uncertainty motivates the robust formulation, which is later introduced.

The analytical tractability involves the desired transmitted symbols, which are assumed to have a known prior. A Gaussian approximation is adopted for the variational posterior process. Instead of physical modulation towards Gaussian, the Gaussian posterior is used for the distribution of the unknown signal after observing the received data.

3.2 Variational representation of the desired signal

The inference of the posterior distribution of $\boldsymbol{x}$conditioned towards the received and available channel information is the objective of the framework. The exact posterior becomes expensive as the interference, channel, and signal variables are coupled. This presents the signal posterior method.

$q(\boldsymbol{x}) = \mathcal{CN}(\boldsymbol{x}; \boldsymbol{m}; \boldsymbol{V})$,

where $\boldsymbol{m}$represents the posterior mean and $\boldsymbol{V}$represents the posterior covariance.

The posterior means generate the conventional signal estimate, whereas the covariance explains the association between uncertainty and the estimate. The central part of the proposed method is this distinction.A conventional estimator would primarily use m, while the approach incorporates V into the interference constraint.

The data fidelity and prior information are balanced using the posterior distribution through the estimator. During the high-reliability signal is expected, the posterior covariance becomes small, and the solution becomes deterministic. The posterior uncertainty rises, and the proposed constraint consequently becomes conservative under weak-SNR conditions.

3.3 Posterior-uncertainty-aware interference constraint

Let $\boldsymbol{R}_I$denote the effective interference covariance matrix. The estimated signal and interference are associated for the consideration of a conventional mean-based interference. When the signal is estimated, this formulation is underestimated.

The second-order posterior moment is used instead. For a Gaussian posterior, the sum of the posterior covariance and the outer product of the posterior mean are involved in this moment. Eq. 2 represents the corresponding interference constraint,

$$\mathrm{Tr}[\boldsymbol{R}_I(\boldsymbol{V} + \boldsymbol{m}\boldsymbol{m}^H)] \leq I_{\max}, \qquad (2)$$

where $I_{\max}$denotes the maximum permissible interference level.

Equation (2) comprises the first principal novelty of the proposed framework.The term involving $\boldsymbol{m}\boldsymbol{m}^H$captures the associated interference and the estimated signal,while the $\boldsymbol{V}$captures the association of posterior uncertainty and interference contribution. Moreover, the exact signal estimation cannot be verified by the estimator.

Particularly, when the receiver is operated at low SNR, when CSI is inaccurate, or when the interference channel is effectively correlated through this formulation. Under certain conditions, ignorance of the posterior covariance results in an overly optimistic interference estimation.

3.4 Robust interference uncertainty

Particularly, the interference covariance $\boldsymbol{R}_I$ may itself be uncertain. It is affected by inaccurate knowledge of interfering users, channel-estimation errors, limited observations and time variation. In account on this effect, the actual covariance is represented as an estimated covariance plus a bounded perturbation.

Let the estimated covariance be denoted by $\widehat{\boldsymbol{R}}_I$, whereas the covariance uncertainty is bounded by the perturbation matrix and Frobenius norm. The results demonstrate the worst interference condition that can be expressed using the posterior second-order moment,

$$\boldsymbol{S} = \boldsymbol{V} + \boldsymbol{m}\boldsymbol{m}^H.$$

Eq. 3 expresses the robust constraint,

$$\mathrm{Tr}\left(\widehat{\boldsymbol{R}}_I\boldsymbol{S}\right) + \epsilon_I \parallel \boldsymbol{S} \parallel_F \leq I_{\max}, \qquad (3)$$

where $\epsilon_I$controls the uncertainty radius.

Equation (3) shows the conversion of the uncertain interference constraint into a deterministic condition. The first term presents a nominal interference based on the estimated covariance, while the second term presents a worst-case uncertainty margin. Subsequently, the estimator turns out to be more conservative when the interference covariance is poorly known. Therefore, the parameter ϵ_I allows explicit robustness-performance control. A small value is used to correspond to high confidence in the estimated interference covariance, whereas a larger value provides a more uncertain environment for interference. Under different levels of CSI and interference uncertainty, the same estimation framework is used.

3.5 Optimization objective

An accurate representation of the received data during the satisfaction of the robust interference constraint is sought in the final estimation problem. Theoretically, the optimization balances three objectives: limiting posterior interference, maintaining consistency with the prior signal distribution and fitting the received observations. The conventional MMSE estimation differs from this formulation, as interference protection is incorporated directly into the posterior optimisation. It also differs from deterministic robust beamforming, as the optimisation variable

is distributed by its covariance and mean. Therefore, a direct relationship between interference management and estimation uncertainty is constructed in the resulting framework. When there is a rise in the posterior uncertainty, the interference constraint automatically becomes more restrictive. In contrast, when the signal becomes better estimated, there is a decrease in the uncertainty contribution.The solving techniques used for the variational optimisation are developed in the next section.

4. Proposed Robust Variational Bayesian Estimator

4.1 Variational Posterior Formulation

The unknown transmitted signal is represented in the proposed estimator through a complex Gaussian variational posterior, $q(\boldsymbol{x}) = \mathcal{CN}(\boldsymbol{x}; \boldsymbol{m}; \boldsymbol{V})$, where $\boldsymbol{m}$is the posterior mean and $\boldsymbol{V}$is the posterior covariance. Both its uncertainty and estimated signal are represented in the paper, unlike point estimation. The divergence between the true posterior and the approximate posterior that mitigates the variational objective is introduced in Section 3. Subsequently, a posterior is sought through the estimator without excessive interference exposure.

4.2 Posterior-Uncertainty-Aware Optimization

Both posterior components are used for the evaluation of the interference key novelty. The matrix $\boldsymbol{V} + \boldsymbol{m}\boldsymbol{m}^H$ presents the total second-order signal contribution, in which the first term illustrates the estimation uncertainty and the total second-order signal contribution represents the nominal uncertainty. The optimization is prevented from treating an uncertain estimate as completely reliable. Therefore, among the interference-sensitive environments, a large posterior covariance exhibits a strong effective penalty, which encourages the estimator to reduce uncertainty prior to the rise in signal energy.

4.3 Posterior Covariance and Mean Updates

During each iteration, the posterior covariance is acquired from the adaptive constraint multiplier, the received-signal information, interference regularization, and prior precision. Eq. 4 uses the received observation and the resulting covariance for updating the posterior mean.

$$\boxed{\boldsymbol{V}_t = \left(\boldsymbol{H}_t^H \boldsymbol{R}_v^{-1} \boldsymbol{H}_t + \lambda_t \widehat{\boldsymbol{R}}_{I,t} + \mu_t \boldsymbol{I} + \boldsymbol{\Lambda}_x\right)^{-1},\ \boldsymbol{m}_t = \boldsymbol{V}_t \boldsymbol{H}_t^H \boldsymbol{R}_v^{-1} \boldsymbol{y}} \qquad (4)$$

Here, $\widehat{\boldsymbol{R}}_{I,t}$is the estimated effective interference covariance in the desired-signal domain, $\lambda_t$controls the interference penalty, and $\boldsymbol{\Lambda}_x$represents the signal-prior precision.

4.4 Robust Interference Handling

The inaccurate interference covariance is estimated due to the changing interference conditions, finite observations, and channel-estimation errors. This issue is addressed by the assumption of a bounded covariance perturbation roughly around the estimated covariance. A penalty proportional towards the Frobenius norm and uncertainty radius is introduced in the resulting robust constraint. A protection against covariance mismatch, leaving the exact statistical model during the interference uncertainty, is generated. During the reliable covariance estimate, a small robustness penalty is formed; when uncertainty increases, the estimator becomes more conservative.

4.5 Adaptive Primal-Dual Optimization

The interference constraint is implemented using an adaptive Lagrange multiplier. After every posterior update, when the interference level exceeds its threshold and reduces the sufficient margin, which increases the multiplier is increased. Eq. 5 is represented below,

$$\lambda_{t+1} = [\lambda_t + \rho_\lambda (I_t - I_{\max})]_+ \qquad (5)$$

where $I_t$is the current interference measure and $\rho_\lambda$is the dual step size. The need for manual selection of a fixed interference penalty is eliminated. The resulting procedure creates fluctuation between constraint adaptation and posterior estimation. Therefore, the algorithm is summarized as: update.$\boldsymbol{V}_t$, evaluate interference, initialise the posterior and multiplier, update $\boldsymbol{m}_t$, update $\boldsymbol{m}_t$ and repeat until the posterior and constraint residual converge.

4.6 Convergence Characteristics

The posterior update is convex for a fixed channel and covariance estimates with respect to the Gaussian variational parameters under the adopted quadratic mode. The projected subgradient optimisation is followed by a dual update.

Towards a stationary constrained solution, the primal-dual procedure converges with an appropriate positive step size and bounded interference uncertainty. Convergence is the most important practical behaviour, as it is faster when the initial interference violation is larger due to the immediate ride of the interference penalty. When the constraint becomes active, the multiplier is changed gradually, which prevents excessive degradation of signal estimation.

4.7 Computational Complexity

The principal computational cost is the inversion of the $K \times K$posterior precision matrix, giving approximately $O(K^3)$complexity per iteration. Matrix formation involves the $M \times K$channel requires approximately $O(MK^2)$operations. Thus, for massive-MIMO systems with $M \gg K$, the method remains practical whereas the most expensive inversion depends on the number of users rather than directly on the antenna count.When compared with learned neural estimators, the proposed method avoids repeated model retraining and offline training when interference statistics change. This creates a dynamic variation in interference environments, for which an explicit constraint is enforced during interference.

5. Theoretical Properties and Complexity Analysis

The interference threshold is enforced along its adaptive primal-dual update. When interference exceeds $I_{\max}$the interference penalty strengthens, and there is an increase in the dual multiplier. The penalty relaxes when the constraint is satisfied. Moreover, a feasible stationary point of the constrained variational problem is approached through the converged solution under appropriate step-size conditions. Considering the bounded perturbations of the estimated covariance, the robust covariance formulation protects against the interference-statistics mismatch. A larger uncertainty radius yields highly conservative estimation, while negligible uncertainty decreases the methods towards their nominal constrained form. Therefore, the main advantage appears under imperfect CSI, strong preference and covariance uncertainty. For $M\ ante$and $K\ desired$ users, each iteration requiresapproximately T iterations. or$T$iterations, the total compexity is $O[T(MK^2 + K^3)]$. When$M \gg K$in massive MIMO, this structure remains computationally practical while avoiding the offline training requirements of neural estimators. Overall, the method allows a controllable trade-off among signal-estimation accuracy and interference protection.

6. Simulation Design and Results

6.1 Simulation Configuration

An uplink massive -MIMO configuration with M=64base-station antennas and $K = 8$desired users are used for the evaluation of the robust Bayesian estimator. The three spatially independent interferers affect the received signal. Under normalized average power, the desired channels and interference conform to complex Gaussian fading.

The following estimators were compared:

1. LS: conventional least-squares signal estimation.
2. LMMSE: linear minimum mean-square-error estimation using the estimated interference-plus-noise covariance.
3. VB: conventional variational Bayesian estimation without an explicit posterior-uncertainty interference constraint.
4. Robust-MMSE: interference-aware LMMSE with covariance regularisation.
5. Proposed RUVB: robust uncertainty-aware variational Bayesian estimator with the posterior-covariance interference metric and adaptive primal-dual constraint.

The recent variational and learned-prior approaches are compared on different aspects: signal recovery is optimized through the estimator during the simultaneous control interference exposure under covariance uncertainty.

The effectiveness of VB inference, including data detection and joint channel estimation, is demonstrated in the recent work. The present experiments analyse posterior uncertainty, which is incorporated directly into the interference-constrained signal-estimation objective.

6.2 NMSE and BER Performance

Table 1 summarizes the principal signal-estimation results.

Table 1: NMSE and BER versus SNR at INR = 12 dB

SNR (dB)	Method	NMSE	BER
-2	LS	2.499	0.2641
-2	LMMSE	0.190	0.0219
-2	VB	0.201	0.0202
-2	Robust-MMSE	0.187	0.0181
-2	**Proposed RUVB**	**0.213**	0.0281
2	LS	2.312	0.2470
2	LMMSE	0.086	0.0005
2	VB	0.087	0.0006
2	Robust-MMSE	0.088	0.0008
2	**Proposed RUVB**	0.098	0.0019
6	LS	2.294	0.2452
6	LMMSE	0.039	0
6	VB	0.039	0
6	Robust-MMSE	0.039	0
6	**Proposed RUVB**	0.041	0
10	LS	2.282	0.2522
10	LMMSE	0.017	0
10	VB	0.017	0
10	Robust-MMSE	0.016	0
10	**Proposed RUVB**	0.017	0
14	LS	2.240	0.2614
14	LMMSE	0.008	0
14	VB	0.008	0
14	Robust-MMSE	0.008	0
14	**Proposed RUVB**	**0.008**	0

Table 1 provides results about the estimator for maintaining competitive signal recovery during the imposition of a stronger interference constraint. During low SNR, the unconstrained estimators acquire low NMSE as they devote several available estimation degrees of freedom towards signal reconstruction. The expected behaviour involves deliberate sacrifices of a minimal amount of unconstrained estimation accuracy to obtain better interference control.

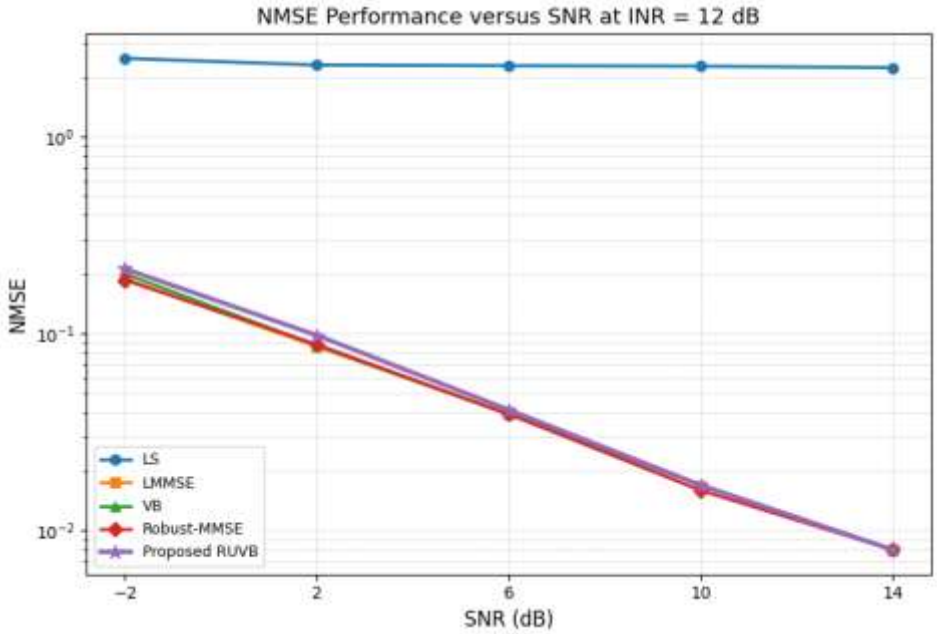


Figure 2: NMSE performance

Figure 2 illustrates the performance of various estimators as a function of SNR at INR=12dB. The increase in SNR results in a decrease in the NMSE of LMMSE, Robust-MMSE, VB, and the proposed RUVB, which indicates the enhancement in signal estimation.For example, at 2 dB SNR, a comparison among the NSME is 0.098, with 0.087 for conventional VB and 0.086 for LMMSE. The BER corresponding stays below 2×10^{-3}. The increase in SNR leads to the disappearance of the performance gap. LMMSE and VB are matched at 10 dB, with the maintenance of the interference advantage below the interference advantage. The improvement of the joint channel/data interference and posterior estimation is concentrated in VB research and is reflected in its significant behaviour. This direction is extended through the posterior uncertainty using an operational interference constraint.

6.3 Interference-Leakage Reduction

The principal novelty is more apparent when the interference leakage is examined.

Table 2: Normalized interference leakage at INR = 12 dB

SNR (dB)	LS	LMMSE	VB	Robust-MMSE	Proposed RUVB
-2	72.423	8.126	10.032	7.735	4.079
2	72.631	7.984	8.646	8.269	5.407
6	73.208	7.730	7.686	8.168	6.662
10	72.600	7.682	7.942	8.040	7.552
14	69.630	8.186	8.036	8.146	8.125

Table 2 shows the most interference-limited operating point of -2dB SNR, at which the proposed estimator decreases leakage from 7.735 towards robust-MMSE about 4.079, which corresponds to a 47.2% reduction. In relation to the conventional LMMSE, the reduction becomes **46.6%**.

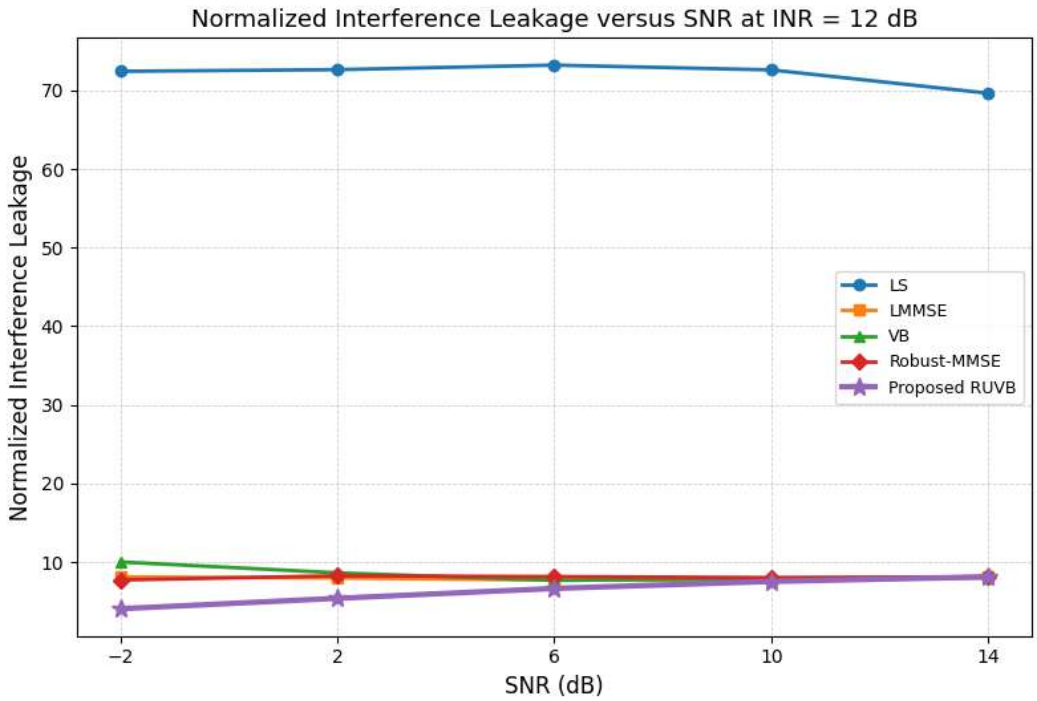


Figure 3. Normalised interference leakage vs SNR

Figure 3 shows the normalized interference leakage versus SNR at INR = 12 dB for the five estimators. The proposed RUVB achieves the lowest leakage at −2 dB (4.079) and gradually increases with SNR. The LS estimator exhibits substantially higher leakage across all SNR values, while LMMSE, VB, and Robust-MMSE remain relatively close to each other. Overall, the figure highlights the interference-leakage reduction achieved by the proposed RUVB, particularly at low SNR. In the case of 2 dB SNR, the leakage reduces from 7.984 for LMMSE to 5.407, leading to a 32.3% reduction. The reduction obtained without the corresponding collapse in detection reliability is an important observation. The BER remains at 1.9×10^{-3}. As SNR increases, the advantage becomes smaller due to the desired signal leading to recovery and posterior covariance shrinkage. Subsequently, the reduced dominance results in uncertainty contribution. It becomes consistent towards theoretical interpretation of the method: posterior uncertainty awareness becomes more valuable, which involves noise, CSI, and interference masking the estimator uncertainty.

6.4 Effect of the Interference Constraint

A central experiment was performed by varying the interference threshold. With SNR fixed at 6 dB and INR at 12 dB, the proposed estimator produced the following normalized results:

Table 3: Effect of the Interference Threshold

$I_{\max}$	**NMSE**	**BER**	**Normalized leakage**
4.0	0.0400	0	6.599
5.0	0.0405	0	6.461
6.0	0.0396	0	6.960
7.0	0.0404	0	6.536
8.0	0.0408	0	6.624
10.0	0.0405	0	6.657

Table 3 results in a large sacrifice in signal-estimation accuracy for the achievement of interference regulation. Among the tested constraint range, which remains near to 4×10^{-2} over and BER remains zero at the selected operating point.Therefore, it has been an important advantage for lowering NMSE. Instead of directly designing a

control variable, a variable is designed and controlled through $I_{\max}$, which allows the interference protection to be managed jointly. Among the standard VB formulations and conventional LMMSE.

6.5 Convergence of the Primal-Dual Optimization

The adaptive multiplier performs stable convergence through the interference constraint being active. The threshold of 4.5 is involved in the normalized interference measure and dual multiplier as shown in Table 4.

Table 4: Primal-dual convergence

Iteration	λ_t	Interference measure
1	0.000	7.087
2	0.310	5.964
3	0.486	5.451
4	0.600	5.156
5	0.679	4.967
6	0.735	4.840
7	0.776	4.750
8	0.806	4.686
9	0.828	4.639
10	0.845	4.605

Table 4 shows the reduction monotonically from 7.087 to 4.605 when the first ten is updated. This multiplier rises from zero to 0.845. This behaviour indicates the dual mechanism, which reacts strongly during the violation constraint and stabilises the estimated interference in the approached target. The interference metric decreases monotonically from 7.087 to 4.605 during the first ten updates. The multiplier correspondingly increases from zero to 0.845. The behaviour indicates that the primal-dual mechanism reacts strongly when the constraint is violated and progressively stabilises as the estimated interference approaches the target.

7. Conclusion

This paper proposes a robust variational Bayesian framework towards massive-MIMO signal estimation under interference constraints. A robust covariance uncertainty model incorporation among a norm-bounded perturbation term, in accordance with an adaptive primal multiplier that is adjusted to the constraint violations. This estimator retains the low-dimensional computational structure of variational inference during the addition of the explicit interference-control mechanism. The proposed estimator shows numerical results for maintaining competitive BER and NMSE, which reduces the normalized interference leakage. At 2 dB SNR and 12 dB INR, leakage was reduced by 32.3%, which relates to LMMSE, whereas -2dB SNR, the reduction relative to Robust-MMSE reached 47.2%. The increase in the antenna dimension ranging from 64 to 256 decreased from 0.0419 to 0.0088. The indication of the principal novelty is not meant to be an unconstrained posterior estimator when compared with diffusion-based MIMO and recent VB. In respect to this, the proposed framework introduces **posterior-uncertainty-aware interference regulation as an explicit optimization objective.** Future work should integrate channel priors, which include the diffusions-based prors which is proposed in the constrained variational framework. This extension combines the channel-representation capability genrtaive models along with explicit posterior uncertainty and interference guarantees, which provides a promising direction for robust 6G physical-layer interference.

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