

Receive Beamforming Design for Coexisting Wireless Control and Communication Networks

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Abstract—This paper investigates the design of receive beamforming for a networked control system that shares its uplink with conventional communication users. A set of sensors observe independent dynamical processes and transmit state estimates to a multi-antenna receiver, which applies a common beamforming vector before forwarding the processed information to the corresponding controllers. Concurrently, multiple communication users transmit over the same uplink and are decoded through the same receive beamformer. The main objective is to design control and beamforming policies that jointly minimize the overall control cost while satisfying the quality-of-service requirements of the coexisting users. We formulate this problem as a joint optimization problem, and analytically characterize the structures of the optimal control and the one-step look-ahead beamforming policies. We further propose a practical two-stage beamforming optimization algorithm for real-time implementation.

Index Terms—Multi-antennas receivers, beamforming, Kalman filtering, networked control systems, optimal policies, semantic communication.

I. INTRODUCTION

Next-generation wireless networks are evolving to support diverse objectives that extend beyond conventional data transmission. In particular, in networked control systems (NCSs), wireless communication links are integral to closing feedback loops between sensors, controllers, and actuators, where the reliability and latency of transmissions directly affect overall control performance. At the same time, conventional mobile users can still share the same spectral and infrastructural resources, leading to interference and competition for communication capacity. This coexistence of heterogeneous objectives calls for designing physical-layer strategies that reconcile the quality-of-service (QoS) demands of control systems with those of communication users. Recent advances in goal-oriented communication advocate strategies that transmit only the most significant portions of data with respect to downstream tasks [1, 2]. For NCSs, this hinges on the prompt and accurate delivery of valuable sensory information to controllers [3, 4]. This work contributes to this line of research by investigating how goal-oriented service guarantees for control systems can be achieved without compromising data-centric guarantees for conventional users in coexisting wireless control and communication networks.

In recent years, substantial progress has been made to understanding the interplay between control and communication. Foundational studies established the stability limits of Kalman

filtering and linear quadratic Gaussian (LQG) control over channels subject to packet-drop, delay, and fading [5–7]. This has motivated cross-layer designs that co-optimize control and communication parameters such as power, scheduling, and coding variables to minimize control-centric metrics like estimation error and control cost [8, 9]. With the emergence of dense wireless networks, several works have addressed coexistence scenarios, where control system links exist in parallel with conventional user links. These include uplink schedulers for URLLC/eMBB coexistence in 5G systems [10], NOMA-based interference management [11], and LQG-aware resource allocation under reliability guarantees [9]. Researchers have also begun exploring beamforming designs explicitly tailored to control performance. For instance, transmit beamforming and reconfigurable intelligent surface (RIS) have been optimized to favor critical control links over non-critical ones [12–14]. However, these studies typically assume orthogonal scheduling or neglect the interference.

A. Contributions and Outline

In this paper, we develop a theoretical framework for beamforming for networks where control systems coexist with conventional users. We consider an uplink scenario where multiple sensors transmit state estimates of physical processes alongside conventional users to a multi-antenna receiver that uses a common beamformer. This shared receive strategy intrinsically couples control performance with communication performance, as the beamformer must manage interference across both types of traffic. We formulate this problem as a joint optimization problem that minimizes an aggregate linear-quadratic-regulator (LQR) cost for the control systems while satisfying signal-to-interference-and-noise ratio (SINR) constraints of the conventional users. To the best of our knowledge, this is the first work that explicitly optimizes beamforming for both control and communication objectives in a shared multi-user uplink setting. The remainder of the paper is organized as follows. Section II presents the system model and formulates the problem of interest. In Section III, we derive the optimal control and the beamforming policies. Section IV presents numerical results to illustrate the performance of the proposed methods. Finally, Section V concludes the paper.

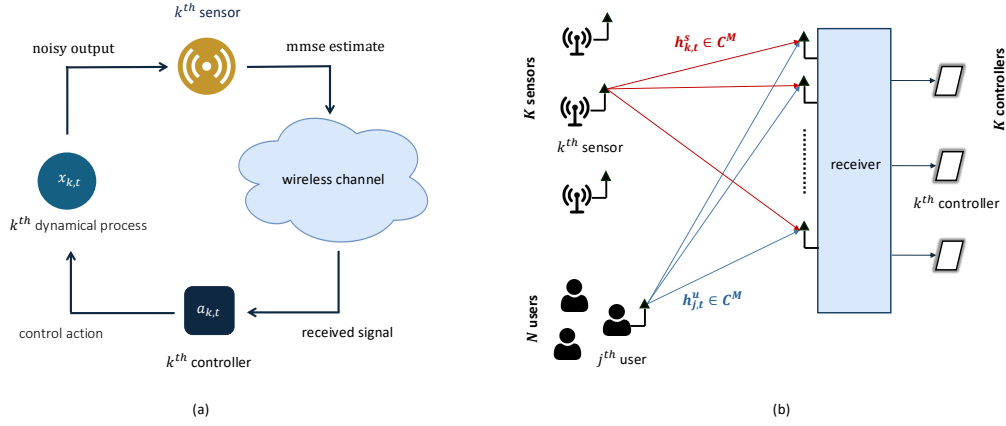


Fig. 1: A networked control system that shares its uplink with conventional communication users: (a) The control loop of the k th dynamical process; (b) The links between K sensors, K controllers, N users, and the receiver.

B. Notation

For the rest of the paper, the sets of real numbers, non-negative integer numbers, and complex numbers are denoted by $\mathbb{R}$, $\mathbb{N}$, and $\mathbb{C}$, respectively. For $x, y \in \mathbb{N}$ and $x \leq y$, the set $\mathbb{N}_{[x,y]}$ denotes $\{z \in \mathbb{N} | x \leq z \leq y\}$. For matrices X and Y , the relations $X \succ 0$ and $Y \succeq 0$ denote that X and Y are positive definite and positive semi-definite, respectively. The expected value and the covariance of a random variable x are denoted by $\mathbb{E}[x]$ and $\text{cov}[x]$, respectively. The superscripts T and H denote transpose a matrix and Hermitian transpose of a complex matrix, respectively.

II. PROBLEM STATEMENT

This section presents the system model and formulates the problem of interest. We first describe the dynamics of the networked control system and the wireless communication links, followed by the mathematical formulation of the optimization problem that captures the trade-off between control performance and user requirements.

A. System Model

We consider a multi-user networked system consisting of K sensors, K controllers and N users. A multi-antenna receiver equipped with M antennas collects the uplink signals transmitted by both the sensors and the users and forwards the processed information to the corresponding controllers. The time t is discrete, and the time horizon T is finite. In this networked system, the k th controller is responsible for regulating the behavior of its corresponding dynamical process, whose evolution is described as

$$x_{k,t+1} = A_k x_{k,t} + B_k a_{k,t} + d_{k,t}, \quad (1)$$

for $k \in \mathbb{N}_{[1,K]}$ and $t \in \mathbb{N}_{[0,T]}$, where $x_{k,t} \in \mathbb{R}^n$ is the state of the k th dynamical process at time t , $a_{k,t} \in \mathbb{R}^m$ is the control action of the k th controller at time t , and $d_{k,t}$ is an i.i.d. Gaussian noise with zero mean and covariance $D_k \succ 0$, $A_k \in \mathbb{R}^{n \times n}$ and $B_k \in \mathbb{R}^{n \times m}$ are the state and input matrices of the k th dynamical process. We assume that $x_{k,0}$ is a Gaussian vector with mean $m_{k,0}$ and covariance $M_{k,0} \succ 0$.

At each time t , the k th sensor measures a noisy output of the corresponding dynamical process, which is modeled as

$$y_{k,t} = C_k x_{k,t} + e_{k,t}, \quad (2)$$

for $k \in \mathbb{N}_{[1,K]}$ and $t \in \mathbb{N}_{[0,T]}$, where $y_{k,t} \in \mathbb{R}^p$ is the output of the k th dynamical process at time t , $e_{k,t}$ is an i.i.d. Gaussian noise with zero mean and covariance $E_k \succ 0$, and $C_k \in \mathbb{R}^{p \times n}$ is the output matrix of the k th dynamical process.

At each time t , the k th sensor transmits its MMSE state estimate $\hat{x}_{k,t}^s$ to the receiver over a fading wireless link. In parallel, the users transmit their data to the same receiver. The receiver applies a single receive beamformer $w_t \in \mathbb{C}^M$ to decode the superposed uplink signals. At the k th controller, the estimate $\hat{x}_{k,t}^s$ is correctly decoded with probability $1 - \varepsilon_k$ and discarded with probability ε_k , where ε_k depends on the instantaneous SINR induced by w_t . Let $h_{k,t}^s \in \mathbb{C}^M$ denote the link between the k th sensor to the receiver at time t , and $h_{j,t}^u \in \mathbb{C}^M$ denote the link between the j th user and the receiver at time t . The receiver employs a single common combining vector w_t for all simultaneously transmitted sensor and user signals. The received signal is

$$r_t = \sum_{k=1}^K w_t^H h_{k,t}^s z_{k,t} + \sum_{j=1}^N w_t^H h_{j,t}^u s_{j,t} + w_t^H n_t, \quad (3)$$

for $t \in \mathbb{N}_{[0,T]}$, where r_t is the received signal at time t , $z_{k,t}$ is the signal transmitted by the k th sensor, $s_{j,t}$ is the signal transmitted by the j th user, and n_t is an i.i.d. Gaussian noise with zero mean and variance $N_0 \succ 0$. The noise power at the receiver after beamforming, $w_t^H n_t$ is given by N_0 , as $\|w^H n_t\|^2 = 1$. Let p_t^s denote the transmit power of the sensor signal $\hat{x}_{k,t}^s$, and p_j^u is the transmit power of the user signal $s_{j,t}$. The SINR of the k th controller $\text{SINR}_{k,t}^c$ and that of the k th user $\text{SINR}_{k,t}^u$ can be obtained accordingly at each time t .

B. Optimization Problem

In this system, the decision variables are the beamforming w and the control actions $u_{k,t}$. We represent a beamforming policy by $W = \{w_t\}_{t=0}^{T-1}$ and a control policy by $A = \{a_{1,t}, \dots, a_{K,t}\}_{t=0}^{T-1}$. Our aim is to design beamforming and

control policies that jointly optimize the following optimization problem:

$$\min_{W,A} \mathbb{E} \left[\sum_{t=0}^T \sum_{k=1}^K x_{k,t}^T \Omega_k^x x_{k,t} + \sum_{t=0}^{T-1} \sum_{k=1}^K a_{k,t}^T \Omega_k^a a_{k,t} \right], \quad (4)$$

$$\text{s.t. } \|w_t\|^2 = 1, \quad t \in \mathbb{N}_{[0,T-1]} \quad (5)$$

$$\text{SINR}_{j,t}^u \geq \gamma_{j,th}^u, \quad j \in \mathbb{N}_{[1:N]}, t \in \mathbb{N}_{[0,T-1]}, \quad (6)$$

where $\Omega_k^x \succ 0$ and $\Omega_k^a \succ 0$ are weighting matrices associated with the k th dynamical process, and $\gamma_{k,th}^u$ is an SINR threshold that must be satisfied for each user.

Remark 1. The cost function in (4) is the standard LQR cost, serving as a benchmark for control performance. This cost function should be minimized jointly by the beamformer and the controllers. The weighting matrices Ω_k^x and Ω_k^a encode priorities across processes and trade-offs between state deviation and control effort within each process.

III. MAIN RESULTS

This section presents the derivations, reductions, and resulting algorithms. We first derive the optimal control law and thereby reduce the joint design to a beamforming problem. We then characterize an optimal beamforming formulation and introduce two tractable solution: a one-step look-ahead policy and a two-stage instantaneous optimization scheme.

A. Optimal Control Policy

At each time t , the k th sensor sends its current MMSE estimate $\hat{x}_{k,t}^s$ to the k th controller. Define the decode-success indicator $\delta_{k,t} \in \{0,1\}$, where $\delta_{k,t} = 1$ if the message is correctly decoded at the k th controller and $\delta_{k,t} = 0$ otherwise. This event depends on the receive beamformer w_t applied at the multi-antenna receiver; equivalently, the packet error probability is $\varepsilon_k(w_t) \triangleq \Pr[\delta_{k,t} = 0 \mid w_t]$. We define the information sets available to sensors and controllers as follows:

$$\mathcal{I}_{k,t}^s = \left\{ y_{k,t'}, a_{k,t''} \mid t' \in \mathbb{N}_{[0,t]}, t'' \in \mathbb{N}_{[0,t-1]} \right\}, \quad (7)$$

$$\mathcal{I}_{k,t}^c = \left\{ \delta_{k,t'}, \hat{x}_{k,t'}^s, a_{k,t''} \mid t' \in \mathbb{N}_{[0,t]}, t'' \in \mathbb{N}_{[0,t-1]} \right\}. \quad (8)$$

Accordingly, we can define the following state estimates and error covariances at the k th sensor and the k th controller at time t as

$$\begin{aligned} \hat{x}_{k,t}^s &= \hat{x}_{k,(t|t)}^s = \mathbb{E} [x_{k,t} \mid \mathcal{I}_{k,t}^s], \\ \hat{x}_{k,t}^c &= \hat{x}_{k,(t|t)}^c = \mathbb{E} [x_{k,t} \mid \mathcal{I}_{k,t}^c], \\ \hat{Q}_{k,t}^s &= \hat{Q}_{k,(t|t)}^s = \text{cov} [x_{k,t} \mid \mathcal{I}_{k,t}^s], \\ \hat{Q}_{k,t}^c &= \hat{Q}_{k,(t|t)}^c = \text{cov} [x_{k,t} \mid \mathcal{I}_{k,t}^c], \end{aligned}$$

and the following prior variables as

$$\begin{aligned} \hat{x}_{k,(t|t-1)}^s &= \mathbb{E} [x_{k,t} \mid \mathcal{I}_{k,t-1}^s], \\ \hat{x}_{k,(t-1|t-1)}^c &= \mathbb{E} [x_{k,t} \mid \mathcal{I}_{k,t-1}^c], \\ \hat{Q}_{k,(t|t-1)}^s &= \text{cov} [x_{k,t} \mid \mathcal{I}_{k,t-1}^s], \\ \hat{Q}_{k,(t-1|t-1)}^c &= \text{cov} [x_{k,t} \mid \mathcal{I}_{k,t-1}^c]. \end{aligned}$$

By the separation principle, estimation and control can be designed independently. Hence, the optimal control input depends only on the estimated state, i.e.,

$$a_{k,t}^* = \Delta_{k,t} \hat{x}_{k,t}^c, \quad (9)$$

with exception $a_{k,T}^* = 0$, where

$$\hat{x}_{k,t}^c = \delta_{k,t} \hat{x}_{k,t}^s + (1 - \delta_{k,t}) A_k \hat{x}_{k,t-1}^c, \quad (10)$$

$$\Delta_{k,t} = -(B_k^T S_{k,t+1} B_k + \Omega_k^a)^{-1} B_k^T S_{k,t+1} A_k, \quad (11)$$

and $S_{k,t}$ is a solution of the Riccati equation

$$\begin{aligned} S_{k,t} &= A_k^T S_{k,t+1} A_k + \Omega_k^x - A_k^T S_{k,t+1} B_k \\ &\quad \times (B_k^T S_{k,t+1} B_k + \Omega_k^a)^{-1} B_k^T S_{k,t+1} A_k, \end{aligned} \quad (12)$$

with initial condition $S_{T,t} = \Omega_k^x$.

B. Reduced Beamforming Problem

Following the derivation in [5], replacing $a_{k,t}^*$ into the cost function in 4, the cost function can be expressed as

$$\begin{aligned} \sum_{k=1}^K \text{tr} (S_{k,0} \hat{Q}_{k,0}^c) &+ \sum_{t=0}^{T-1} \sum_{k=1}^K \text{tr} (S_{k,t+1} D_k) \\ &+ \sum_{t=0}^{T-1} \sum_{k=1}^K \text{tr} (L_{k,t} \mathbb{E} [\hat{Q}_{k,t}^c]), \end{aligned} \quad (13)$$

where the first term is independent for the decision variables., and can be discarded. Note that $\hat{Q}_{k,t}^c$ can be written, depending on whether the controller has correctly decoded the transmitted message at time k or not, as

$$\hat{Q}_{k,t}^c = \begin{cases} A_k \bar{Q}_{k,t-1}^c A_k^T + D_k & \text{if } \delta_{k,t} = 0 \\ \hat{Q}_{k,t}^s & \text{if } \delta_{k,t} = 1, \end{cases}$$

where $\bar{Q}_{k,t}^c = \mathbb{E} [Q_{k,t}^c]$ and

$$L_{k,t} = A_k^T R_{k,t+1} A_k + \Omega_k^x - R_{k,t}, \quad (14)$$

$$\hat{Q}_{k,t}^s = \left((A_{k,t-1} \hat{Q}_{k,t-1}^s A_{k,t-1}^T + D_k)^{-1} + C_{k,t}^T E_k^{-1} C_{k,t} \right)^{-1} \quad (15)$$

Using this equation, we find

$$\begin{aligned} \bar{Q}_{k,t}^c &= f(\bar{Q}_{k,t-1}^c, \varepsilon_k(w_t)) \\ &= \hat{Q}_{k,t}^s (1 - \varepsilon_k(w_t)) + (A_k \bar{Q}_{k,t-1}^c A_k^T + D_k) \varepsilon_k(w_t), \end{aligned}$$

We can then define $G_{k,t}$ that captures the impact of the decoding error probability on the $\bar{Q}_{k,t}^c$ as:

$$G_{k,t} = (A_k \bar{Q}_{k,t-1}^c A_k^T + D_k - \hat{Q}_{k,t}^s)$$

with (15) being the error covariance equation of the Kalman filter. As a result, one can show that the beamforming vector must satisfy the following optimization problem:

$$\min_{w_t} \sum_{t=0}^{T-1} \sum_{k=1}^K \text{tr} (L_{k,t} \bar{Q}_{k,t}^c), \quad (16)$$

$$\text{s.t. } \|w_t\|^2 = 1, \quad (17)$$

$$\text{SINR}_{j,t}^u \geq \gamma_{j,th}^u, \quad j \in \mathbb{N}_{[1,N]}, t \in \mathbb{N}_{[0,T-1]}. \quad (18)$$

C. Optimal Beamforming Policy

With the information available at the receiver being

$$\begin{aligned} \mathcal{I}_t^r &= \left\{ \delta_{l,t'}, w_{t'}, h_{l,t''}^s, h_{j,t''}^u, \mathcal{I}_{l,t}^c \mid t' \in \mathbb{N}_{[0,t-1]}, \right. \\ &\quad \left. t'' \in \mathbb{N}_{[0,t]}, l \in \mathbb{N}_{[1,K]}, j \in \mathbb{N}_{[1,N]} \right\}. \end{aligned} \quad (19)$$

Given this information, the receiver can compute $\bar{Q}_{k,t-1}^c$ at time t by using (15). The value function associated with the reduced optimization problem from the perspective of the receiver is expressed as

$$V_t(\{\bar{Q}_{k,t-1}^c\}_{k=1}^K) = \min_{w_t, \dots, w_T} \sum_{\tau=t}^T \sum_{k=1}^K \text{tr}(L_{k,\tau} \bar{Q}_{k,\tau}^c). \quad (20)$$

The following theorem provides a general procedure for obtaining the optimal receive beamforming.

Theorem 1. *The optimal beamforming policy W^* is given by*

$$w_t^* = \underset{w_t}{\text{argmin}} \left\{ \sum_{k=1}^K \text{tr}(L_{k,t} \bar{Q}_{k,t}^c, \varepsilon_k(w_t)) + V_{t+1}(\{\bar{Q}_{k,t}^c\}) \right\}. \quad (21)$$

Remark 2. *The derived beamforming policy demonstrates that the receiver optimally balances the trade-off between minimizing control cost and maintaining user QoS. The beamformer implicitly prioritizes those with greater influence on the closed-loop control performance, while simultaneously managing interference toward communication users to satisfy their SINR constraints. This results in a beamforming strategy that dynamically adapts to both control-critical and communication-driven demands. Furthermore, the policy relies on solving the value function defined in (20) through backward time recursion, which adds complexity of the beamforming optimization.*

We propose a simple suboptimal method based on one-step lookahead policy, and a two-step instantaneous optimization framework that can be solved respectively using convex tools. Note that the SINR at the k th controller and i th user are written respectively as:

$$\gamma_{k,t}^s = \frac{p_k^s \|w_t^H h_{k,t}^s\|^2}{\sum_{l \neq k} p_l \|w_t^H h_{l,t}^s\|^2 + \sum_{i=1}^N p_i^u |w_t^H h_{i,t}^u|^2 + N_0} \quad (22)$$

$$\gamma_{j,t}^u = \frac{p_j^u \|w_t^H h_{j,t}^u\|^2}{\sum_{i \neq j} p_i^u \|w_t^H h_{i,t}^u\|^2 + \sum_{l=1}^K p_l^s |w_t^H h_{l,t}^s|^2 + N_0}. \quad (23)$$

In the remaining of this section, we assume for convenience that the transmit power of the sensors and users is normalized to 1, that is $p_k^s = p_k^u = 1$. We also consider that the sensors have limited processing power/capacity and do not have access to the instantaneous channel state information (CSI) and hence they transmit at a fixed power (power control is not possible in this case). Let R_k be the bit rate at which the signal is transmitted by the k th sensor and user. The relation between the bit rate, error probability and SINR can be expressed using the finite blocklength capacity framework in [15]. The error probability can be approximated at each time by

$$\varepsilon_k(w_t) \approx Q \left(\frac{\sqrt{r}}{\log_2(e)} \frac{\log_2(1 + \gamma_k) - R_k}{\sqrt{1 - \frac{1}{(1 + \gamma_k)^2}}} \right), \quad (24)$$

where the interference is treated as gaussian noise, r is the number of channel uses used to transmit the finite length codewords $\hat{x}_l^s(t)$ and $Q^{-1}(\cdot)$ is the inverse of $Q(x) =$

$\frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-v^2/2} dv$. according to one-step lookahead policy, By adopting (24) in the above optimization problem, it can be formulated as a constrained optimization problem

$$\min_{w_t} \sum_{k=1}^K \text{tr}(L_{k,t} G_{k,t}) Q \left(\frac{\sqrt{r}}{\log_2(e)} \frac{\log_2(1 + \gamma_{k,t}^s) - R_k}{\sqrt{1 - \frac{1}{(1 + \gamma_{k,t}^s)^2}}} \right),$$

$$\text{s.t. } \|w_t\|^2 = 1,$$

$$\frac{\|w_t^H h_{k,t}^s\|^2}{\sum_{l \neq k} \|w_t^H h_{l,t}^s\|^2 + \sum_{i=1}^N |w_t^H h_{i,t}^u|^2 + N_0} \geq \gamma_{k,t}^s, \forall k,$$

$$\frac{\|w_t^H h_{j,t}^u\|^2}{\sum_{i \neq j} \|w_t^H h_{i,t}^u\|^2 + \sum_{l=1}^K |w_t^H h_{l,t}^s|^2 + N_0} \geq \gamma_{j,t}^u, \forall j.$$

This problem is equivalent to

$$\min_{w_t} \sum_{k=1}^K \text{tr}(L_{k,t} G_{k,t}) Q \left(\frac{\sqrt{r}}{\log_2(e)} \frac{\log_2(1 + \gamma_{k,t}^s) - R_k}{\sqrt{1 - \frac{1}{(1 + \gamma_{k,t}^s)^2}}} \right),$$

$$\text{s.t. } \|w_t\|^2 = 1,$$

$$\|w_t^H h_{k,t}^s\|^2 \geq \gamma_{k,t}^s \left(\sum_{l \neq k} \|w_t^H h_{l,t}^s\|^2 + \sum_{i=1}^N |w_t^H h_{i,t}^u|^2 + N_0 \right),$$

$$\|w_t^H h_{j,t}^u\|^2 \geq \gamma_{j,t}^u \left(\sum_{i \neq j} \|w_t^H h_{i,t}^u\|^2 + \sum_{l=1}^K |w_t^H h_{l,t}^s|^2 + N_0 \right).$$

Note that the last two constraints are nonconvex. A local optimum can be reached by using the Lagrangian technique. Let λ_k the Lagrange multiplier corresponding to the first constraint for each k sensor and μ_i the Lagrangian multiplier corresponding to the second constraint for each user. The Lagrangian problem becomes

$$\min_{w_t} \sum_{k=1}^K \text{tr}(L_{k,t} G_{k,t}) \cdot Q \left(\frac{\sqrt{r}}{\log_2(e)} \cdot \frac{\log_2(1 + \gamma_{k,t}^s) - R_k}{\sqrt{1 - \frac{1}{(1 + \gamma_{k,t}^s)^2}}} \right)$$

$$+ \lambda_k \gamma_{k,t}^s \left(\sum_{l=1, l \neq k}^K \|w_t^H h_{l,t}^s\|^2 + \sum_{j=1}^N |w_t^H h_{j,t}^u|^2 + N_0 - \frac{\|w_t^H h_{k,t}^s\|^2}{\gamma_{k,t}^s} \right) + \sum_{j=1}^N \mu_j \gamma_{j,t}^u \left(\sum_{i=1, i \neq j}^N \|w_t^H h_{i,t}^u\|^2 + \sum_{l=1}^K |w_t^H h_{l,t}^s|^2 + N_0 - \frac{\|w_t^H h_{j,t}^u\|^2}{\gamma_{j,t}^u} \right),$$

$$\text{s.t. } \|w_t\|^2 = 1,$$

We refer to the alternating optimization approach to solve the aforementioned problem, which consists of fixing $\gamma_k \forall k$ and optimizing over w and then fixing w and optimizing γ_k for all k and so on. We denote by $(\mathcal{P}_1)$ the resulting optimization over $\gamma_{k,t}^s$ for all k for given w and $(\mathcal{P}_2)$ the optimization over w given $\gamma_{k,t}^s$. With $(\mathcal{P}_1)$:

$$\min_{\gamma_{k,t}^s} \sum_{k=1}^K \text{tr}(L_{k,t} G_{k,t}) Q \left(\frac{\sqrt{r}}{\log_2(e)} \frac{\log_2(1 + \gamma_{k,t}^s) - R_k}{\sqrt{1 - \frac{1}{(1 + \gamma_{k,t}^s)^2}}} \right)$$

$$+ \lambda_k \gamma_{k,t}^s \left(\sum_{l=1, l \neq k}^K \|w_t^H h_{l,t}^s\|^2 + \sum_{j=1}^N |w_t^H h_{j,t}^u|^2 + N_0 - \frac{\|w_t^H h_{k,t}^s\|^2}{\gamma_{k,t}^s} \right)$$

The subproblem ($\mathcal{P}_1$) over $\gamma_{k,t}^s$ is nonconvex but since the objective is differentiable and unconstrained, we can solve it using a gradient-based method solvers. Also the subproblem over w ($\mathcal{P}_2$):

$$\min_{w_t} \sum_{k=1}^K \lambda_k \gamma_{k,t}^s \left(\sum_{l=1, l \neq k}^K \|w_t^H h_{l,t}\|^2 + \sum_{j=1}^N |w_t^H h_{j,t}^u|^2 - \frac{\|w_t^H h_{k,t}\|^2}{\gamma_{k,t}^s} \right) + \sum_{j=1}^N \mu_j \gamma_{j,t}^u \left(\sum_{i=1, i \neq j}^N \|w_t^H h_{i,t}^u\|^2 + \sum_{l=1}^K |w_t^H h_{l,t}^s|^2 - \frac{\|w_t^H h_{j,t}^u\|^2}{\gamma_{j,t}^u} \right)$$

$$\text{s.t. } \|w_t\|^2 = 1,$$

This can be solved optimally by minimizing a standard Rayleigh quotient problem. Let $H_{l,t}^s = h_{l,t}^s h_{l,t}^{sH}$, $H_{j,t}^u = h_{j,t}^u h_{j,t}^{uH}$, $W_t = w_t w_t^H$, and

$$\Lambda_{k,t} = \gamma_{k,t}^s \left(\sum_{l=1, l \neq k}^K H_{l,t}^s + \sum_{j=1}^N H_{j,t}^u - H_{k,t}^s \right), \quad (25)$$

$$\Gamma_{i,t} = \gamma_{i,t}^u \left(\sum_{j=1, j \neq i}^N H_{j,t}^u + \sum_{l=1}^K H_{l,t}^s - H_{i,t}^u \right). \quad (26)$$

Define $\Lambda_t = \sum_k \lambda_k \Lambda_{k,t}$ and $\Gamma_t = \sum_i \mu_i \Gamma_{i,t}$. Then, ($\mathcal{P}_3$) is equivalent to

$$\min_{w_t} w_t^H (\Lambda_t + \Gamma_t) w_t, \quad (27)$$

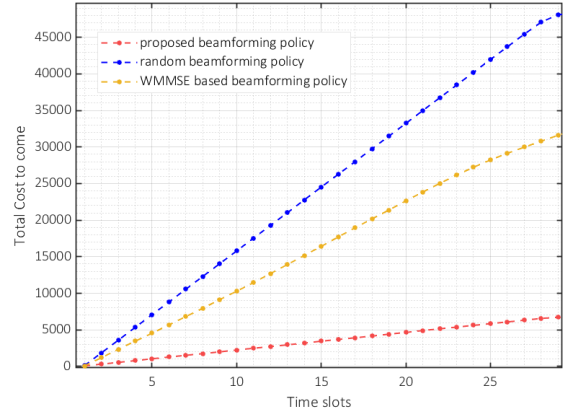
$$\text{s.t. } w_t^H w_t = 1, \quad (28)$$

which has an optimal solution $\lambda_{\min}(\Lambda_t + \Gamma_t)$, i.e., the minimum eigenvalue. Accordingly, the overall receive beamforming solution can be summarized in Algorithm 1.

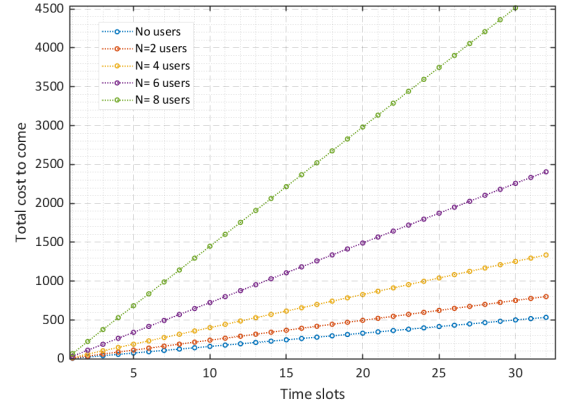
Algorithm 1: Beamforming Alternating Optimization

```

1 repeat
2   for  $t = 0$  to  $T - 1$  do
3     Step 1: Alternating Optimization;
4     repeat
5       (a) Solve  $\mathcal{P}_1$  for a given  $w$  to obtain  $\{\gamma_{k,t}^s\}$ 
           using gradient-based solvers;
6       (b) Solve for  $w$  given  $\{\gamma_{k,t}^s\}$  minimizing the
           Rayleigh quotient in (27);
7     until inner convergence or max inner iterations;
8   end
9   Step 2: Update the Lagrange Multipliers;
10  Update:
       $\lambda_k^{j+1,t} = \left( \lambda_k^{j,t} + \epsilon^j \left( \gamma_{k,t}^s \left( \sum_{l=1, l \neq k}^K \|w^H h_{l,t}\|^2 + \sum_{m=1}^N |w^H h_{m,t}^u|^2 - \|w^H h_{k,t}\|^2 \right) \right) \right)^+$ ,
       $\mu_i^{j+1,t} = \left( \mu_i^{j,t} + \epsilon^j \left( \gamma_{i,t}^u \left( \sum_{m=1, m \neq i}^N \|w^H h_{m,t}^u\|^2 + \sum_{l=1}^K |w^H h_{l,t}^s|^2 - \|w^H h_{i,t}^u\|^2 \right) \right) \right)^+$ ,
11    where  $\epsilon^j$  is the step size at iteration  $j$ ;
12    Increment  $j = j + 1$ ;
13 until convergence or max iterations met;
```



(a) Comparison of Beamforming policies



(b) Proposed policy under varying number of users.

Fig. 2: Total cost-to-come for (a) different beamforming policies and (b) proposed policy's scalability with user interference

IV. NUMERICAL RESULTS

We consider a networked control system composed of $K = 12$ sensor-controller pairs, coexisting with $N = 5$ uplink communication users. The receiver is equipped with a uniform linear array (ULA) of $M = 16$ antennas. The sensors are placed in the first quadrant at distances uniformly drawn from 5 to 20 meters, while the users are placed between 25 and 60 meters. We assume a Rician fading model for all wireless links. Each dynamic process is scalar, i.e., $x_k \in \mathbb{R}$, with state coefficients $A_k \in \{0.5, 3\}$. All other control parameters $B_k, C_k, M_{k,0}, D_k, E_k, L_k, N_k$ in addition to the weighting coefficients Ω_k^x, Ω_k^a are set to 1. The time horizon $T = 30$ time slots. We compare the performance of the proposed joint NCS-communication optimization policy against a random beamforming strategy and weighted minimum mean square error (WMMSE)-based beamformer designed to maximize the sum-rate [16] obtained by solving the following problem:

$$\min_{\|w\|^2=1, \{u_j\}, \{q_j\}} \sum_{j=1}^{K+N} q_j \cdot \text{MSE}_j - \log_2(q_j),$$

where MSE_j is the mean squared error for the j^{th} symbol, the weight $q_j = 1/\text{MSE}_j$ and $u_j \in \mathbb{C}$ is the equalizer

for each transmitted symbol j which is solved with a three block alternating optimization. To evaluate the effect of user-side interference on control performance, we also simulate a reduced setup with $K = 2$ to highlight the system's sensitivity in the shared uplink. The total cost to come is defined in 13 and plotted in Fig. 2 for different settings. In Fig.2.(a), under a fixed number of uplink users, The proposed joint control-communication beamforming achieves the best overall performance, outperforming both the sum-rate-maximizing WMMSE beamformer and the random beamformer. While the WMMSE design focuses on maximizing the throughput, it overlooks the control system's requirements, leading to higher control cost. In contrast, our approach explicitly balances communication reliability and control performance, resulting in significantly lower total cost. The random beamformer, performs the worst. In Fig.2.(b), As the number of users increases, the control system experiences a gradual degradation in performance due to elevated interference on the shared beamforming vector as the total cost rises notably with user count which shows the fundamental trade-off between scalability in user support and control system performance. These results highlight the advantage of goal-oriented beamforming in networked control systems operating under shared spectrum conditions

V. CONCLUSION

In this paper, we proposed a receive beamforming strategy for joint wireless control and communication networks. The beamformer is optimized to minimize control cost while satisfying SINR constraints for the users. Using a one-step lookahead policy and alternating optimization, our method significantly outperforms baseline policies, ensuring both control stability and user QoS. These results highlight the potential of spatial filtering at the receiver to support reliable control-communication coexistence in shared wireless networks.

ACKNOWLEDGMENT

This work is partially funded by the Agence Nationale de la Recherche (ANR) through the France 2030 project ANR-PEPR Networks of the Future under grant agreement NF-PERSEUS 22-PEFT-004.

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