Distributed RF Beamforming for Wireless Power Transfer over Time Varying Channels

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***Abstract*—Distributed beamforming is a promising technique for transferring power to a node wirelessly, as it allows optimal design of waveforms at each transmitter such that they interact constructively at the receiver node. In this paper, we propose a distributed RF beamforming scheme which involves phase detection and prediction for the sources participating in beamforming process. The proposed method is capable of tracking source drifts and statistical fluctuations of the channel. The phase detection process requires one feedback for synchronizing all the sources to the receiver pairs and provides a closed-form solution for the phase offsets between a pair of received beams under the presence of RF power measurement errors. Autoregressive (AR) model is used for phase prediction which avoid feedback in synchronization process all together. Performance of the proposed detection and prediction model is quantified in terms of average received power, efficiency, and number of message exchange between the sources and the receiver.**

***Index Terms*—Autoregressive process, distributed RF beamforming, phase beamforming, wireless energy transfer.**

I. Introduction

Massive rise in Internet-of-Things (IoT) devices is driving up the demand for energy resources. Though, the senor nodes are equipped with batteries to enable long-term operation, their performance is constrained by limited battery capacity. Consequently, sustainable and green powering technologies are gaining importance due to energy crisis and greenhouse effect [1]. In order to cut the carbon emission and cost of battery replacement, energy harvesting via wireless power transfer (WPT) provides an alternative to charging process.

The general concept behind distributed radio frequency (RF) beamforming is to design the carrier waveforms such that they combine constructively at the receiver after passing through wireless channel [2]–[4]. In distributed beamforming, N independent sources each of transmit power P_t can co-operatively transmit maximum power of $N^2 P_t$ to a particular node. Therefore, distributed beamforming proves to be a green technique allowing N-fold gains in received power with the same hardware footprint. Carrier synchronization in terms of phase and frequency is crucial for achieving these gains. The authors in [2]–[5] captured achievable gain by distributed beamforming but did not provide any means of achieving it.

A. Literature Review and Motivation

The work in [6] proposed a distributed ascent algorithm based on random perturbations involving multiple one bit feedbacks for synchronization. In [7], authors presented the performance of distributed WPT with and without frequency and phase synchronization, and demonstrated that distributed charging improves coverage probability. However, none of these works harness the correlation in phase data, thus necessitating periodic feedbacks. In [8], RF distributed beamforming was proposed which used a master-slave architecture for synchronization. However, the presence of a master controller compromises the premise of distributed beamforming.

In [9], the authors proposed feedback independent receiver-end distributed beamforming scheme with orthogonal transmission of signals with one transmission per slot. However, the application is limited to baseband level. The authors in [10] proposed channel training methods involving sequential and parallel synchronization to achieve energy beamforming (EB). Here, the accuracy of beamforming between two sources depends on number of forward transmissions and feedbacks, which has been contrasted by [6]. The work in [11] proposed scatterMIMO technique to achieve spatial multiplexing gain from the scattered signal in MIMO systems. But its dependence on estimating the path length between the two antennas becomes sensitive to the initial source and channel phase variations, which is difficult to model in practice.

Moreover, the aforementioned beamforming algorithms generally assume memoryless channel and requires synchronization in subsequent coherence intervals. However in practical wireless communication scenarios, channel exhibits strong temporal correlation, leading to correlated phase data. This channel property can reduce the number of feedbacks, thereby reducing the performance degradation due to delays and errors in the feedback packets. In [12], two beamforming algorithms namely predictive vector quantization and successive beamforming algorithm were proposed using auto-regressive (AR) dynamic fading model for transmit beamforming scenario in multiple-input single-output systems. Though this paper uses the AR(1) model in compensating the phase aberrations induced by the fading channel, their inability to capture the measurement error poses a pertinent deployability issue.

As noted above, the existing literature did not consider estimation-regression based approach by using the correlation in phase data, which is expected to reduce the number of transmitter-receiver interactions while accounting for the practical measurement inaccuracy/noise.

B. Contributions and Significance

This paper proposes a deterministic closed-form phase estimation, followed by a generalized AR(p) based phase re-

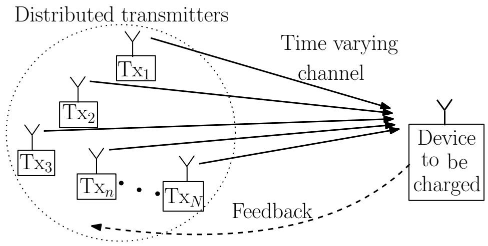


Fig. 1. Generalized system model for distributed beamforming based WPT.

gression, while judiciously accounting for power measurement noise in the process. The key contributions of the work are:

1) A deterministic closed-form expression for initial phase estimation using 3 subsequent power measurements is proposed, while accounting for the measurement error. 2) The estimated phase is fine tuned using the past phase measurements, and an AR based phase prediction is employed. 3) Performance of the AR prediction filter is analyzed in terms of time-averaged received power for N sources. 4) Finally, the efficacy of the complete setup is contrasted against the state-of-the-art for varying block lengths and measurement error statistics. 5) It is shown that AR based phase tracking compensates for the measurement errors and eliminates the repeated transmission over long duration.

The work in this paper is significant in offering energy efficient information communication and power transfer by facilitating constructive interference of multiple sources at the receiver. Our simulation results demonstrate that the beamforming process is considerably agnostic to the channel phase variation and the power measurement noise. This is by the virtue of data correlations extracted by the AR model employed in the proposed setup.

Layout of the paper is as follows: Section II discusses the underlying system model. Section III proposes the distributed beamforming method and protocol, followed by results, and conclusion in Sections IV and V, respectively.

II. System Model

Fig. 1 depicts the distributed beamforming system with N independent transmitters and a receiver. The transmitters are deployed at random locations, each equipped with a single antenna, with the n^{th} transmitter denoted as Tx_n. Each transmitter is viewed as a power beacon which generates an RF signal for wireless power transmission. Receiver is assumed to be a battery equipped sensor node. We consider narrowband Rician fading channel in which propagation is dominated by the LOS link and all the multipath components reach roughly on top of one another. Since objective of this work is to demonstrate phase beamforming, we assume that transmitter generates an unmodulated carrier signal, given by $s_n(t) = \Re\{A_n \exp\left(j(2\pi f_c t + \phi_{sn})\right)\}$, where A_n and ϕ_{sn} respectively denotes the peak amplitude and fixed phase offset of n^{th} sources' transmit signal, and f_c is the carrier frequency. Under the assumption of frequency synchronized transmitters, the resultant signal from the interference of N sources is expressed as $r_n(t) = \Re\{\sum_{n=1}^{N} A_n \alpha_n \exp(j(2\pi f_c t + \phi_{sn} + \beta_n))\}$, where α_n and β_n denote accumulated gains and phase shifts due to multipath components in the wireless channel, respectively. Therefore, the average power received is given as

$$P_R = \frac{1}{T}\int_0^T |r(t)|^2\, dt = \frac{1}{2}\sum_{n=1}^{N} P_n + \frac{1}{2}\sum_{m=1}^{N}\sum_{n=1, n\neq m}^{N} \sqrt{P_m P_n}\cos(\phi_m - \phi_n) \tag{1}$$

where $P_n = (A_n\alpha_n)^2$, $\phi_n = \phi_{sn} + \beta_n$ and $T = \frac{1}{f_c}$. If $\phi_{sn} = -\beta_n$, then P_R is optimal which is expressed as

$$P_{opt} = \frac{1}{2}\sum_{m=1}^{N}\sum_{n=1}^{N}\sqrt{P_m P_n} \tag{2}$$

In practical scenarios, perfect CSI is not available, increasing the possibility of inaccuracy in phase determination. Furthermore, even the availability of perfect CSI at individual transmitter does not guarantee near-optimal power gains owing to the phase offsets between the sources. In the next section, we propose a phase beamforming method which can jointly tackle the source phase offsets and channel statistical fluctuations allowing near optimal beamforming.

III. Proposed Distributed RF Beamforming

In this section we first present a closed-form phase detection algorithm which computes the phase corrections for individual source followed by application of AR model in phase prediction in time varying channels.

A. Phase Detection Scheme

The proposed phase detection scheme is a method of synchronization that seeks to identify the phase difference between the transmitters involved in the beamforming process. It is based on sequential transmission wherein the transmitters take turns for phase adaptation while adhering to a predetermined order. Within each sequential transmission, every source adapts its phase to the common phase of the active sources. In this process, receiver computes the phase correction and sends it back to the transmitter; emulating two-source beamforming in each synchronization slot. The subsequent part of this section describes the synchronization of a single transmitter to a set of beamformed transmitters.

Let us assume that $(n-1)$ out of N sources are synchronized, and the algorithm wants to synchronize the n^{th} source. In the first transmission slot of $(n-1)^{th}$ synchronization interval, Tx_n transmits with arbitrary phase and let the corresponding received phase is ϕ_n. The total received power is

$$P_{rn} = P_{n-1}^s + P_n + 2\sqrt{P_{n-1}^s P_n}\cos\theta_n + \epsilon_n \tag{3}$$

where P_n the n^{th} source power, $P_{n-1}^s = \left[\sum_{k=1}^{n-1}\sqrt{P_k}\right]^2$ denotes the collective power received by the $(n-1)$ synchronized sources, $\theta_n = \phi_1 - \phi_n$ denotes the offset and $\epsilon_n \sim \mathcal{N}(0, \sigma_n^2)$ denotes the power measurement error. In the next two transmission slots, Tx_n transmits with preassigned

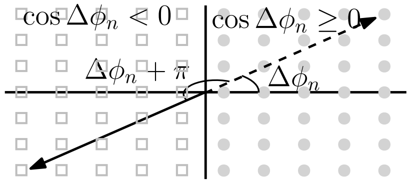


Fig. 2. Illustration of selection of the quadrant in which $\Delta\phi_n$ lies.

phase shifts of $-\psi$ and ψ. Power received by the receiver in both the transmission slots individually is given by

$$P^a_{rn} = P^s_{n-1} + P_n + 2\sqrt{P^s_{n-1}P_k}\cos(\theta_n + \psi) + \epsilon^a_n \quad (4)$$

$$P^b_{rn} = P^s_{n-1} + P_n + 2\sqrt{P^s_{n-1}P_n}\cos(\theta_n - \psi) + \epsilon^b_n \quad (5)$$

where $\epsilon^a_n, \epsilon^b_n \sim \mathcal{N}(0, \sigma^2_n)$ are the measurement errors in the respective slots. The synchronization unit uses P_{rn}, P^a_{rn} and P^b_{rn} to obtain θ_n . Subtracting (5) and (3) from (4), we get

$$P^a_{rn} - P^b_{rn} = -4\sqrt{P^s_{n-1}P_n}\sin\theta_n \sin\psi + \epsilon^a_n - \epsilon^b_n. \quad (6)$$

$$\begin{aligned} P^a_{rn} - P_{rn} = 2\sqrt{P^s_{n-1}P_n}[&\cos\theta_n\,(\cos\psi - 1) \\ &- \sin\theta_n \sin\psi] + \epsilon^a_n - \epsilon_n. \end{aligned} \quad (7)$$

Solving (6) and (7) simultaneously we obtain θ_n as

$$\theta_n = \tan^{-1}\left[\frac{\zeta(P^a_{rn} - P^b_{rn} - \epsilon^a_n + \epsilon^b_n)}{(2P_{rn} - P^b_{rn} - P^a_{rn} - 2\epsilon_n + \epsilon^b_n + \epsilon^a_n)}\right] \quad (8)$$

where $\zeta = (\cos\psi - 1)/\sin\psi$. The value of phase offset θ_n obtained using (8) will lie in the range $[-\pi/2, \pi/2]$. Thus, it is not sufficient to determine the correct offset θ_n. Fig. 2 shows the conditions for the selection of quadrants in which the phase obtained using (8) lies. Adding (4) and (5) we get,

$$\begin{aligned} P^a_{rn} + P^b_{rn} = 2(&P^s_{n-1} + P_n) \\ &+ 4\sqrt{P^s_{n-1}P_n}\cos(\theta_n)\cos\psi + \epsilon^a_n + \epsilon^b_n. \end{aligned} \quad (9)$$

Then, solving (9) and (3) simultaneously, we obtain

$$P^s_{n-1} + P_n = \frac{P^a_{rn} + P^b_{rn} - \epsilon^a_n - \epsilon^b_n - 2P_{rn}\cos\psi}{2(1 + \cos\psi)}. \quad (10)$$

Now, if $P_{rn} > P^s_{n-1} + P_n$, we infer that $\cos\theta_n$ is positive. Thus, the phase determined using (8) is correct. But if $P_{rn} < P^s_{n-1} + P_n$, implying $\cos\theta_n < 0$, then the value of θ_n obtained using (8) is updated to either $\theta_n + \pi$ or $\theta_n - \pi$. Thus, the ambiguity in exact phase estimation in [11], resulting from the range presented by the inverse tangent function, is resolved.

The phase is then sent back by the receiver to Tx$_n$ for correction. Therefore, the alignment of the n^{th} transmitter's phase with Tx$_1$, requires three synchronization slots and one feedback slot. Thus, each synchronization interval involves 4 message exchanges resulting in a total synchronization duration of 4T$_s$, where T$_s$ denotes length of each transmission slot. The transmitter stores the phases at each synchronization interval, which is used to train filter described in next subsection for predicting the future corrections.

***Remark** 1: The number of synchronization slots needed for two-source beamforming is independent of the number of sources involved in the beamforming process.*

Phase offset obtained in (8) can be written as

$$\theta_n = \theta_{an} + e_{\theta n} \quad (11)$$

where θ_{an} is the actual phase offset obtained by putting $\epsilon_n = \epsilon^a_n = \epsilon^b_n = 0$. Using first-order approximation of the Taylor series expansion of θ_n, we obtain

$$\Delta\theta_n = \frac{\partial\theta_n}{\partial P_{rn}}\Delta P_{rn} + \frac{\partial\theta_n}{\partial P^a_{rn}}\Delta P^a_{rn} + \frac{\partial\theta_n}{\partial P^b_{rn}}\Delta P^b_{rn}. \quad (12)$$

Using (3), (4), (5) and (11), the above equation is written as

$$\begin{aligned} e_{\theta n} &= \frac{\partial\theta_n}{\partial P_{rn}}\epsilon_n + \frac{\partial\theta_n}{\partial P^a_{rn}}\epsilon^a_n + \frac{\partial\theta_n}{\partial P^b_{rn}}\epsilon^b_n \\ &= \zeta/\{(2P_{rn} - P^b_{rn} - P^a_{rn})^2 + (\zeta(P^a_{rn} - P^b_{rn}))^2\} \\ &\times [2(P_{rb} - P_{ra})\epsilon_n + (2P_{rn} - P^b_{rn} - P^a_{rn} - 1)\epsilon^a_n \\ &+ (P^b_{rn} + P^b_{rn} - 2P_{rn} + 1)\epsilon^b_n]. \end{aligned} \quad (13)$$

The accuracy of the computed offset θ_n will depend on the variance of e_{θ_n}. Although, in block fading scenarios the measurement errors are not significant, but future corrections based on erroneous current predictions lead to unacceptable phase estimates over time. Next subsection details the use of error statistics in the estimation of source phases.

B. Autoregressive (AR) Based Phase Prediction

This section demonstrates the use of an AR model in phase predictions for N sources. Let a generalized regression model AR(p) be employed at time $t - 1$, to predict the value at t based on p past values. Then, the estimate of the actual phase corrections in regression form is written as

$$\hat{\theta}_{an}(t) = \sum_{i=1}^{p} b_i \hat{\theta}_{an}(t - i) + e(t) \quad (14)$$

where $\hat{\theta}_{an}(t)$ is the predicted value at time index t and $e(t) \sim \mathcal{N}(0, \sigma^2_e)$ is a white noise. The generalized mathematical equation which relates the AR (p) model parameters to the autocorrelation function of the phase estimates is [13]

$$r_{\hat{\theta}}[k] = \begin{cases} r^*_{\hat{\theta}}[-k], & \text{for } k < 0 \\ -\sum_{i=1}^{p} b_i r_{\hat{\theta}}[k - i] + \sigma^2_e, & \text{for } 1 \leq k < q \\ -\sum_{i=1}^{p} b_i r_{\hat{\theta}}[k - i], & \text{for } k > q \end{cases} \quad (15)$$

where, $r_{\hat{\theta}}[k] = \mathbb{E}[\hat{\theta}(t)\hat{\theta}(t - k)]$ denotes the autocorrelation of the phase estimates. This relation gives rise to the Yule Walker equations [14] which allows us to estimate these coefficients in terms of correlation of the past samples. To obtain the filter coefficients we write the above equation in matrix form as

$$\mathbf{b} = -\mathbf{R}^{-1}\mathbf{r} \quad (16)$$

where, $\mathbf{b} = [b_1, b_2, \cdots, b_p]$, $\mathbf{r} = [r_{\hat{\theta}}[1], r_{\hat{\theta}}[2], \cdots, r_{\hat{\theta}}[p]]$ and

$$\mathbf{R} = \begin{bmatrix} r_{\hat{\theta}}[0] & r_{\hat{\theta}}[-1] & \cdots & r_{\hat{\theta}}[1 - p] \\ r_{\hat{\theta}}[1] & r_{\hat{\theta}}[0] & \cdots & r_{\hat{\theta}}[2 - p] \\ \vdots & \vdots & \ddots & \vdots \\ r_{\hat{\theta}}[p - 1] & r_{\hat{\theta}}[p - 2] & \cdots & r_{\hat{\theta}}[0] \end{bmatrix}.$$

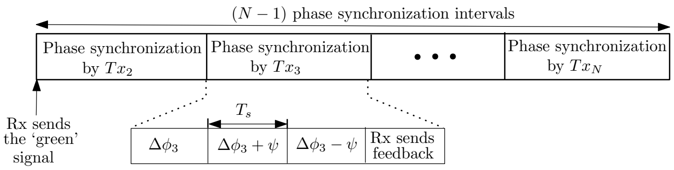


Fig. 3. Synchronization interval for phase detection scheme.

From (16), we observe that AR filter parameters depend upon the correlations of actual phase corrections. But at receiver, observations are θ_n. Therefore, using (11) we modify (14) as

$$\hat{\theta}_{an}(t) = \sum_{i=1}^{p} b_i \hat{\theta}_n(t-i) - \sum_{i=1}^{p} b_i e_{\theta n}(t-i) + e(t) \qquad (17)$$

where $b_0 = 1$. The filter coefficients are obtained using training data generated using phase detection scheme proposed in subsection III-A. Thus, (17) can be visualized as an autoregressive moving average (ARMA) model. Root mean square error (RMSE) is used to determine the optimal model order .

***Remark** 2: With the incorporation of measurement error, AR(p) manifests into ARMA(p, $p+1$) model, which allows compensation of the measurement error in the phase estimates.*

C. Beamforming Protocol

In this subsection, we present the protocol for the proposed phase beamforming algorithm which consists of two stages: 1) phase offset detection using synchronization scheme as shown in Fig. 3, and 2) phase offset prediction using AR model.

1) To initiate the beamforming process, receiver first sends a 'green' signal to all the transmitters.
2) Once the transmitters receive the green signal, all the transmitters except Tx_1 and Tx_2 stop transmitting. Tx_1 and Tx_2 transmit with arbitrary phases s.t. the phases received at the receiver are ϕ_1 and ϕ_2, respectively.
3) The synchronization unit at the receiver aligns the phase of Tx_2 with Tx_1 using the phase detection scheme given in Section III-A. Synchronization unit then feeds back the phase offset θ_2 to the Tx_2, and Tx_2 continues to transmit with the adapted phase ϕ_1 thereafter.
4) In the next synchronization interval Tx_3 aligns via phase detection scheme to match its phase with Tx_1 and Tx_2.
5) (1)-(4) is repeated until all sources are aligned with Tx_1.
6) (1)-(5) is repeated for L_s synchronization intervals, the data of which is used to train the AR model.
7) The synchronization is done using the predicted phase corrections from the AR model until the received power drops below a defined threshold.
8) If the average received power falls below the threshold, the filter is retrained on the past predicted values.
9) If the retraining on the past predicted samples still leads to received power level below the desired threshold, the protocol sequence (1)-(7) is repeated.

The combined framework for phase detection and prediction is outlined in Algorithm 1. Steps 1-5 entail *phase estimation*, step 6 involves *data collection* and AR *model training*, step 7 does *phase prediction*, with *model retraining* in steps 8 and 9. Note that, the output of the proposed beamforming scheme does not vary with the sequence of transmission. Therefore, any sequencing protocol such as token-ring can be used.

Algorithm 1: Phase beamforming algorithm

Data: Initialize $\psi = \frac{\pi}{2}$, $T_c = 1$, $p = 1$, $M = 1000$, $\eta = 3\%$.
for $n = 1 : MT_c$ **do**
  while $n < Ls$ **do**
    for *k=1:N* **do**
      $\text{Tx}_k \to \{\theta_{k,n},\, \theta_{k,n}+\psi$, and $\theta_{k,n}-\psi\}$
      Rx stores P_{rk}, P^a_{rk}, and P^b_{rk} and calculates $\theta_{k,n} \in [0, 2\pi]$ from (8) using wrapping
      if $Pr < P_n + P^s_{n-1}$ and $\Delta\phi_{k,n} \leq \pi$ **then** $\theta_{k,n} = \theta_{k,n} + \pi$;
      elseif $Pr < P_n + P^s_{n-1}$ **then** $\theta_{k,n} = \theta_{k,n} - \pi$;
      end
    end
  end
  if $n \geq L_s$ **then**
    $AR(\Delta\phi_n, p)$ is implemented in parallel $\forall\ k$.
    Step 1: Train $AR(\Delta\phi, p)$; Step 2: Predict $\Delta\phi$.
    if $P_t(1:n) < 0.01\eta P_{th}$ **then** Move to Step 1 **end**
  end
  if Continuous retraining required **then** $n = 1$ **end**
end
end

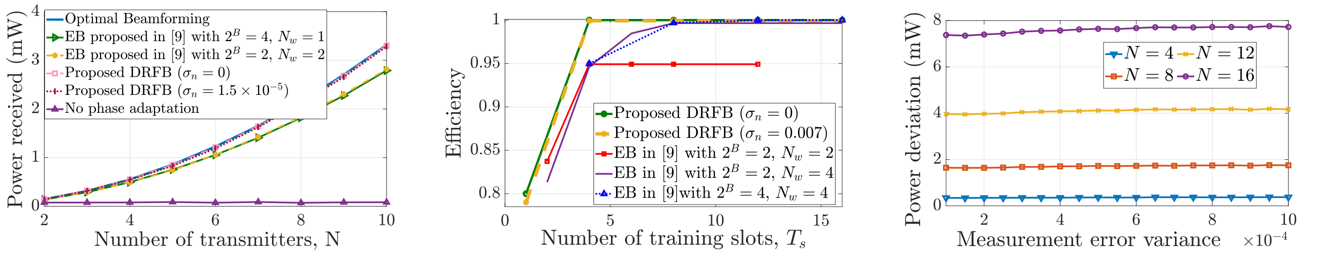
IV. Results and Discussions

In this section, we verify the results of the proposed phase detection scheme and analyze the performance of AR model based phase predictions using MATLAB simulations, and contrast its performance with the most competitive approach in literature. In the context of distributed beamforming, we model $\phi_{sn} \sim U(0, 2\pi)$. Since, optical communication entails a single LOS path between the source and receiver, we model it as path loss only, with attenuation $\alpha_n = K(d_n/d_o)^{-\gamma}$, where d_o is the reference distance for the antenna far field, d_n is the distance between the n^{th} transmitter and receiver, and K is the unitless constant which depends on the antenna characteristics and path-loss exponent. We consider $d_o = 1$m, $K = -20$ dBm, path loss exponent $\gamma = 2$, and distance $d_n \sim U(5, 15)$. Further, we model the statistical RF channel as Rician distributed with the phase distribution as given in [15]. In this work, we analyze the performance of the proposed beamforming method for the time correlated block fading channel of different block lengths. Length of the block is determined by the channel coherence time. Each channel block is assumed to be static, i.e., negligible phase variations.

A. Performance of Phase Detection Scheme

We now study the performance of the proposed phase detection scheme operating within a single block, in synchronizing a set of transmitters involved in the beamforming process.

1) Variation of power with N: Fig. 4(a) shows the variation of received power with number of sources, N. We observe that N-fold beamforming gains are achieved using the proposed phase detection scheme. However, under the presence of the measurement errors this gain reduces as shown in Fig. 4



(a) (b) (c)

Fig. 4. (a) Variation of power with number of transmitters. (b) Efficiency comparison of the proposed phase synchronization scheme with scheme in [10] for two-source beamforming. (c) Power deviation with measurement error. DRFB: Distributed RF beamforming.

for $\sigma_n = 1.5 \times 10^{-5}$. We contrast our proposed scheme with sequential training scheme for energy beamforming (EB) proposed in [10], which requires $2^B N_w$ synchronization slots for two source beamforming, where 2^B denotes the count of sequence of phases applied to source signal for power transmission, and N_w denotes the required number of feedbacks. For fair comparison, we consider the cases $B = 1$, $N_w = 2$, and $B = 2$ and $N_w = 1$, as they require 4 synchronization slots. Performance comparison of the two schemes show that the proposed scheme gives 17.26% higher power compared to that of sequential EB.

2) Efficiency of proposed scheme: Fig. 4(b) shows the efficiency of proposed synchronization scheme with number of training slots required in 2-source beamforming. It is observed that the efficiency tending to 1 is achieved from the proposed synchronization method in just 4 slots. We also contrast our performance with the EB method. From Fig. 4(b), we observe that ($B = 1$, $N_w = 4$) and ($B = 2$, $N_w = 4$) require a minimum of 8 synchronization slots to reach efficiency close to 1, with 4, 1, and 4 feedbacks, respectively. Though, ($B = 2$, $N_w = 1$) requires 1 feedback, but single source synchronization requires adaptation through a sequence of 4 different phases. Also, ($B = 1$, $N_w = 2$) requires 4 synchronization intervals, and achieves a maximum efficiency of 0.95. From these observations, we conclude that the proposed beamforming scheme outperforms the sequential EB method.

3) Effect of Measurement Error: Fig. 4(c) shows the deviation of the received power from the optimal derived in (2) with measurement error variance. We observe that the deviation increases with N. For σ_n up to 10^{-3}, variation is not prominent for small N. However, for $N = 16$ this deviation becomes significant, degrading the received power. Thus, we conclude that as N increases, error in θ_n accumulates.

B. Performance with AR based Phase Predictions

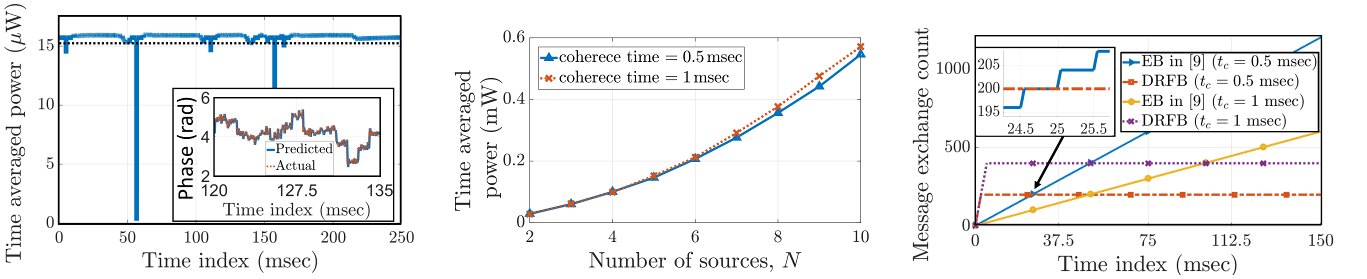
Under realistic time varying channel scenarios, a one time data collection at the start of the beamforming process is sufficient. Once the data is collected, the prediction of the phase for the next instance is done using the AR model. The AR model is first trained using the lag samples of previous 5 fading blocks obtained using the proposed detection scheme. The order of the AR model $p \in \{1, \cdots, 5\}$ is obtained by maximizing the fit of the coefficients to the training data such that the RMSE remains lower than 6.4×10^{-3}. The model is retrained whenever the received power drops to 0.97 times of the maximum power. The performance of the system is analyzed for the channel coherence time of 1 msec and 0.5 msec. σ_n is taken to be 1.5×10^{-5}.

1) Average Power Received over Time: Fig. 5(a) shows the phase tracking performance of the AR(p) model and the time averaged power at the receiver node for a channel with coherence time of 1 msec in two source beamforming. The phase correction trajectory has the correlation of $\rho = 0.995$. For the time averaged power as shown in Fig. 5(a), the power threshold lies at 30.45 μW and the model is retrained 9 times for the given phase trajectory with RMSE $= 4.84 \times 10^{-4}$.

2) Effect of Coherence Length: Here, we analyze the performance of the proposed distributed beamforming method in time correlated block fading channel with varying coherence lengths. Fig. 5(b) shows time averaged power transferred collectively by N sources for two different block lengths. We observe that the performance is slightly better for the channel with coherence time of 1 msec compared to the channel with the coherence time of 0.5 msec. This is due to the fact that a channel with a high coherence interval will exhibit increased temporal correlation in channel phase variations. As a result, the AR filter's phase predictions will be more accurate.

3) Number of Message Exchanges over Time: The overhead analysis of the proposed AR-based beamforming is shown in Fig. 5(c). Since the coherence time of the channel is on the order of $\approx 10^{-3}$ sec, we contrast the performance of the proposed beamforming approach based on the number of messages exchanged over a span of 150 msec with [10]. Here, we assume that phase detection is done at every 0.05 msec. As each phase detection requires 4 message exchanges, a total of 40 and 80 message exchanges are required for the block lengths of 0.5 msec and 1 msec, respectively. Since the filter is trained over 5 previous blocks, a total of 200 and 400 message exchanges are required to collect the data for training. Once the filter is trained, no further message exchanges are required.

We also compare the overhead performance of the proposed beamforming method with the EB scheme, which requires transmission at the start of every block. For fair comparison we compare our method with their case requiring least number of exchanges, i.e. 4. From Fig. 5(c) we observe that in



(a) (b) (c)

Fig. 5. (*a*) Time-averaged performance of 2 source beamforming. (*b*) Time-averaged power for different coherence length. (*c*) Number of message exchange over time (t_c represents coherence length of channel).

EB scheme, there is a step rise in the number of message exchanges at the start of every block with the step size of 4. However, for the beamforming method proposed in this paper, it can be inferred that message exchanges are large at the start of the beamforming process, which becomes constant once the model is trained. Over long runtime, the proposed AR based beamforming scheme always outperforms the EB beamforming method in number of exchanges required.

Remark *3: The proposed beamforming framework assumes constant channel statistics during phase detection, and is robust to time-correlated fading. However, synchronization duration being* $\approx 10^{-5}$ *sec, ergodicity is practically achievable owing to the channel coherence time* ≈ 1 *msec [16].*

The algorithm is implemented on an Intel(R) Core(TM) i9-10900 CPU @ 2.80 GHz clock frequency for various channel dynamics and an average training time of 3.25 ms is noted.

V. Concluding Remarks

In this paper, we proposed an RF power measurement-based phase detection scheme at the receiver, followed by a simultaneous AR based phase prediction model for N sources. The phase detection method initially requires one feedback per source, which is relaxed once the regression model is trained, thereby making the bulk of the phase beamforming process feedback-independent. The proposed phase detection and prediction technique can account for static source offsets as well as channel fading. The proposed scheme was contrasted with the most competitive distributed beamforming scheme from the literature over various coherence block lengths, suggesting different channel time varying order. Furthermore, RF power measurement errors in practical systems were accounted in the proposed phase beamforming setup, and it was shown to perform reasonably well. This result also corroborates the benefit of the considered AR based adaptive phase predictions, thereby making the RF beamforming fairly agnostic to the time varying channels. In our future studies we intend to introduce dynamic retraining of the AR model to achieve prolonged RF beamforming under wireless fading.

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