Space-Time Coded Over-the-Air Computation With Receive Diversity for 6G Massive IoT Networks

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***Abstract*—This letter proposes a novel space-time line-coded over-the-air computation technique (STLC-AirComp) for massive Internet-of-Things (IoT) sensing networks. The STLC-AirComp technique enables efficient computation of objective functions by exploiting a simple linear channel inversion structure between IoT sensors and an access point (AP) in single-input multiple-output (SIMO) networks. In particular, this technique enhances the performance of function computation, including metrics such as mean squared error (MSE), without the need for global channel state information (CSI) at the access point (AP). Additionally, STLC-AirComp allows function computation to be performed in a one-shot manner, eliminating the need for complex learning or optimization processes. We perform a rigorous analysis to derive the exact MSE performance of STLC-AirComp, providing fundamental insights into computational reliability for massive IoT networks. Within the STLC-AirComp framework, we show that the MSE approaches zero as the SNR increases sufficiently. Finally, Monte Carlo simulations validate our mathematical analysis, demonstrating strong agreement between the analytical and simulation results.**

***Index Terms*—Over-the-air computation, space-time line code, Internet-of-Things, mean squared error, multiple antennas.**

I. Introduction

FUTURE Internet-of-Things (IoT) networks are expected to connect approximately 38.9 billion devices by 2029 [1]. In this context, massive IoT (mIoT) networks have garnered significant attraction across various vertical applications, including autonomous driving, industrial IoT, and factory/building automation [2]. Accordingly, processing the vast amounts of data generated by IoT sensors (stations: STAs) is considered one of the key challenges in future wireless mIoT networks. IoT networks are fundamentally task-oriented, focusing not on individual raw data but on efficiently performing specific tasks such as edge learning and function computation. Thus, task-driven processing is likely to play a crucial role in leveraging sensing data from STAs [3].

Over-the-air computation (AirComp) has recently been recognized as a representative example of task-oriented mIoT network operations [4]. AirComp efficiently computes objective functions by exploiting the *superposition* property of wireless channels. Specifically, each STA transmits its analog-modulated measurement data to the access point (AP) concurrently over a shared frequency resource (e.g., subcarrier or subband). The AP receives the superimposed signal from multiple STAs and directly computes the objective function. In [5], [6], several examples of the AirComp framework are presented, where pre- and post-processing functions are utilized to compute various nonlinear functions (e.g., Euclidean norm, geometric mean) as well as simple affine functions (e.g., arithmetic mean). In addition, to enhance computational performance, an *opportunistic* function computation framework is proposed in [7], [8], in which only a subset of sensors with channel gains exceeding a certain threshold transmit their sensing data to a fusion center. Fading in wireless channels remains a critical challenge for efficient function computation. To address this issue, various transmit and receive beamformer optimization techniques have been studied for AirComp [9], [10], [11]. Studies on spatial multiplexing techniques for the AirComp framework, enabling multi-function computation in multiple-input multiple-output (MIMO) systems, have been presented in [12], [13]. Recently, the AirComp framework has been utilized for fast global model aggregation in federated learning, as presented in [14], [15]. Moreover, studies on AirComp utilizing reconfigurable intelligent surfaces (RIS) to enhance received signal power while expanding wireless coverage areas have been presented in [16].

In many existing studies, transmit and receive beamformers were heuristically designed using complex iterative optimization techniques to address the AirComp framework's non-convexity. This approach allows the receiver to perform channel inversion while considering fading effects, thereby improving the function computation's mean squared error (MSE) performance. However, designing a receive beamformer while considering practical fading channels requires the receiver to know the global channel state information (CSI). Accordingly, communication latency due to channel estimation, execution of iterative algorithms, and the feedback process of transmitting the optimized beamformer vector from the receiver to the transmitters becomes an inevitable requirement. Moreover, in scenarios with many STAs, accurately estimating global CSI at the receiver may be practically infeasible [17]. On the other hand, the space-time line coded

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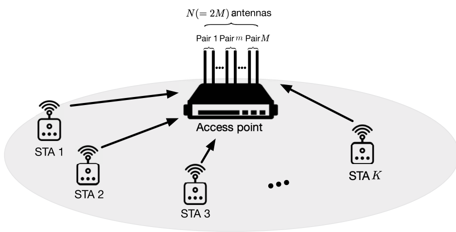

Fig. 1. System model of multi-antenna pair selection-based STLC-AirComp.

AirComp (STLC-AirComp) technique was introduced in [18]. This method was designed to perform function computation and channel inversion using a simple linear structure while improving performance even when the AP does not have global CSI.

In this letter, we propose a novel STLC-AirComp framework as a general extension of [18], which enables the AP to support more than two receive antennas and enhances function computation accuracy through selection diversity. In addition, a simple minimum channel gain estimation procedure is introduced for the STLC-AirComp system, eliminating the need for global CSI at the AP. Furthermore, we provide a rigorous mathematical analysis of the generalized STLC-AirComp performance in terms of MSE and validate the analysis through computer simulations, which demonstrate strong agreement with the theoretical results.

II. Proposed STLC-AirComp Framework

As illustrated in Fig. 1, we consider an IoT network employing the AirComp technique, where each of the K STAs is equipped with a single antenna, and a single AP is equipped with $N = 2M$ antennas, where M is a positive integer. All STAs are assumed to be stationary in this letter.[1] The AP considers M antenna pairs by sequentially grouping the N receive antennas into sets of two. For instance, when $N = 10$, five such pairs are formed. This letter extends the conventional STLC-AirComp [18] to scenarios where the AP has more than two antennas by employing multi-antenna pair selection. The proposed framework consists of three main components: estimating the minimum channel gain, selecting receive antenna pairs, and computing the objective function.

A. Minimum Channel Gain Estimation

In conventional AirComp frameworks, all STAs must align with the STA having the weakest channel gain to satisfy the peak power constraint [6]. In contrast, the proposed STLC-AirComp inherently mitigates the fairness–efficiency trade-off by reducing the probability of deep fading through antenna-pair diversity, thereby enabling all STAs to participate in AirComp without incurring the severe inefficiency observed in conventional single-antenna systems. Moreover, since the MSE performance of the AirComp framework depends on the *minimum* channel gain among all STAs, the AP should estimate the minimum channel gain and select an antenna pair that can enhance the AirComp performance. To choose the

[1]While mobility-induced variations in coherence time may significantly affect channel estimation, this letter focuses on the extended STLC-AirComp framework under static IoT scenarios to establish its fundamental feasibility. The mobility aspect is acknowledged as an important direction for future research.

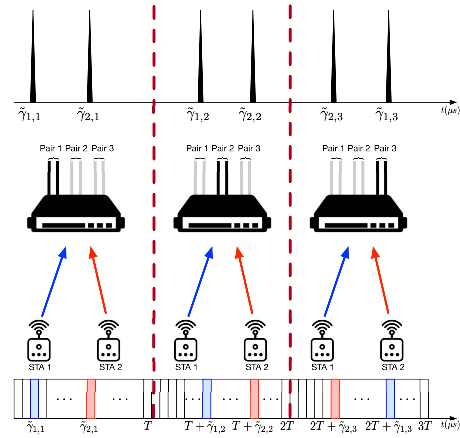

Fig. 2. An example of estimation for the minimum channel gains when $M = 3$ and $K = 2$.

antenna pair to receive STLC symbols at the AP, we design a simple procedure for estimating the minimum channel gain between each STA and all antenna pairs at the AP. It is assumed that each STA knows the CSI between its antenna and all antennas of the AP through a pilot signal broadcast from the AP. The AP allocates T short time slots (or mini slots) for each antenna pair, where T is assumed to be sufficiently large to accurately represent the detailed channel gains γ of each STA. In the context of STLC-AirComp, the channel gain between each STA and an antenna pair can be represented as

$$\gamma_{k,m} = |h_{k,2m-1}|^2 + |h_{k,2m}|^2, \tag{1}$$

where the $m(\in \{1,2,\dots,M\})$-th receive antenna pair is defined sequentially as $(2m-1,\ 2m)$ receive antennas and the $h_{k,j}$ represents the wireless channel between the $k(\in \{1,2,\dots,K\})$-th STA and the $j(\in\{1,2,\dots,2M\})$-th receive antenna of the AP. In this letter, all wireless channels are assumed to be Rayleigh fading channels, following a complex Gaussian distribution with zero mean and unit variance, i.e., $h_{k,j} \sim \mathcal{CN}(0,1)$. Each STA computes the channel gain for each antenna pair using its own local CSI, as defined in (1). The calculated real-valued channel gain is quantized according to a predefined estimation accuracy, and each STA transmits a short pulse of $1\mu s$ in the mini-slot corresponding to its quantized channel gain, similar to a ping. In this letter, accurate synchronization between each STA and the AP is assumed, as recent works on various time-sensitive networks have already demonstrated the practical feasibility of achieving microsecond-level synchronization [19]. The AP records the slot number for each antenna pair receiving the ping. This allows the AP to approximately determine the minimum channel gains between all STAs for all antenna pairs without requiring feedback for channel estimation. It is worth noting that the proposed framework does not require identifying the specific STA with the minimum channel gain. Instead, determining the minimum channel gain value for each antenna pair is crucial.

An example of minimum channel gain estimation, considering two STAs and an AP with three antenna pairs, is illustrated in Fig. 2. A mini-time slot for each antenna pair represents a value obtained by quantizing the channel gains. It can be observed that larger values of T allow more accurate estimation of the channel gains. However, setting T too large may cause communication latency or lead to variations in wireless channels. Notably, the antenna pair selection process is associated with the minimum channel gain for each antenna pair among all STAs. Therefore, an appropriate value of T may be determined based on the statistical characteristics of the minimum channel gain. For example, since the distribution of the minimum channel gain among K STAs follows the probability density function (PDF) in (11), the probability that the minimum channel gain falls below a threshold can be analytically computed. When $K = 50$, the probability that the minimum channel gain is less than 0.7355 is 99.99%, i.e.,

$$\int_0^{0.7355} f_Y(y)dy = \int_0^{0.7355} yK(1+y)^{K-1}e^{-yK}dy \approx 0.9999.$$

Assuming each STA transmits a short RF pulse of duration 1μs in the corresponding mini-slot, the estimation time for two-decimal precision is $T = 73\mu$s. Similarly, for $K = 100$, the minimum channel gain is 0.4926 with the same probability, yielding $T = 49\mu$s. For mIoT networks accommodating a large number of STAs, i.e., $K \gg M$, this procedure is significantly faster than having the AP estimate the CSI of all STAs sequentially.

On the other hand, conventional AirComp assumes that the receiver possesses global CSI not only for minimum channel gain estimation but also for receive beamformer optimization [6]. However, this assumption requires each STA in an mIoT network to perform individual pilot transmissions. In contrast, the signaling overhead of the proposed framework is based on the statistical property of the minimum channel gain, and thus it can even decrease as the number of STAs in the network increases. For example, for a given number of STAs $K = [10, 20, \ldots, 100]$, when calculating the time at which the cumulative distribution function (CDF) of the minimum channel gain reaches 99.99%, the minimum channel gain estimation time required per antenna pair is obtained as $T = [202, 129, 99, 84, 73, 65, 60, 55, 52, 49]\mu$s. This demonstrates the practicality of the proposed framework for mIoT scenarios.

B. Receive Antenna Pair Selection

Before STAs send signals for function computation, the AP selects the optimal receive antenna pair based on the corresponding minimum channel gain. Conventional STLC-AirComp [18] suffers from rate loss when extended to multiple receive antennas. To address this limitation and ensure better scalability, we adopt a receive antenna pair selection scheme in this letter. As described in Section II-A, the MSE performance of AirComp and the peak power constraint of each STA depend on the minimum channel gains for all STAs. Hence, for the best MSE performance, the index of the selected antenna pair is determined as follows:

$$a = \underset{m}{\operatorname{argmax}}\left(\min_k(\gamma_{k,m})\right), \text{ for all } k, m, \tag{2}$$

where the AP selects the antenna pair whose minimum channel gain value among all STAs is the maximum across all antenna pairs. Then, the AP broadcasts the selected antenna pair index and the corresponding minimum channel gain to all STAs.

C. Objective Function Computation

If the objective function required to be computed by the network is defined as f, then the corresponding pre- andpost-processing functions are also given as ϕ_k and ψ, respectively, according to the characteristics of the objective function [6]. For example, if the arithmetic mean function is considered as the objective function in the network, the function f, the pre-processing ϕ_k, and post-processing ψ are given as follows:

$$f = \frac{1}{K}\sum_{k=1}^{K} x_k, \ \phi_k = x_k, \ \psi = \frac{1}{K}. \tag{3}$$

Each STA quantizes and maps the measurement data to the range $(0 \sim P_0]$. Then, the channel information between each STA and the selected two antennas is used to form the STLC signals for computing the objective function as follows

$$s_{k,1} = \sqrt{\eta}\frac{h^*_{k,2a-1}\phi_k(x_{k,1}) + h^*_{k,2a}\phi_k(x_{k,2})^*}{\gamma_{k,a}}, \tag{4}$$

$$s_{k,2} = \sqrt{\eta}\frac{h^*_{k,2a}\phi_k(x_{k,1})^* - h^*_{k,2a-1}\phi_k(x_{k,2})}{\gamma_{k,a}}, \tag{5}$$

where $x_{k,t}$ and $s_{k,t}$ represent the measurement data and the STLC signal transmitted by the k-th sensor (STA) transmits at the $t \in \{1,2\}$-th time slot, respectively. The term η denotes a power control factor that limits the transmit power of each sensor below the maximum power P_o, which is derived as follows

$$\eta = \frac{P_o}{2}\min_k \gamma_{k,a}. \tag{6}$$

Here, it is assumed that each STA knows η from the AP through the procedures explained in Sections II-A and II-B. We design the system to select the receive antenna pair with the largest minimum channel gain. It should be noted that the transmit power of each STA is limited by the minimum channel gain among all STAs to prevent even a single STA from exceeding the peak power P_o. If a few STAs experience poor wireless channel conditions due to deep fading, most other STAs cannot fully utilize their available transmit power, resulting in reduced power efficiency and degraded signal detection accuracy at the AP.

Each STA simultaneously transmits STLC signals to the AP using the same radio resources, such as subcarriers, over two time slots within the channel coherence time. The received signal at each selected antenna of the AP can be expressed as

$$\begin{bmatrix} r_{2a-1,1} & r_{2a-1,2} \\ r_{2a,1} & r_{2a,2} \end{bmatrix} = \sum_{k=1}^{K}\mathbf{h}_k\mathbf{s}_k + \begin{bmatrix} w_{2a-1,1} & w_{2a-1,2} \\ w_{2a,1} & w_{2a,2} \end{bmatrix}, \tag{7}$$

where $r_{a,t}$and $w_{a,t}$ denote the received signal at the selected antenna and the additive noise generated during signal reception in the t-th time slot, respectively. In this letter, it is assumed that all additive noise follows the $\mathcal{CN}(0, \sigma_n^2)$ distribution. In addition, $\mathbf{h}_k = \begin{bmatrix} h_{k,2a-1} & h_{k,2a} \end{bmatrix}^T$ denotes the channel vector from each STA to the selected antenna pair of the AP, and $\mathbf{s}_k = \begin{bmatrix} s_{k,1} & s_{k,2} \end{bmatrix}$ denotes the STLC signal vector of each STA. From the four received signals in (7), the AP performs STLC decoding, which consists only of simple linear combinations, as follows:

$$y_1 = \frac{1}{\sqrt{\eta}}(r_{2a-1,1} + r^*_{2a,2}) = \sum_{k=1}^{K}\phi_k(x_{k,1}) + \frac{w_{2a-1,1} + w^*_{2a,2}}{\sqrt{\eta}}, \tag{8}$$

$$y_2 = \frac{1}{\sqrt{\eta}}(r^*_{2a,1} - r_{2a-1,2}) = \sum_{k=1}^{K}\phi_k(x_{k,2}) + \frac{w^*_{2a,1} - w_{2a-1,2}}{\sqrt{\eta}}. \tag{9}$$

Finally, the AP tries to compute the function value in the t-th time slot by exploiting a post-processing function defined according to the objective function, i.e., $\hat{f}_t = \psi(y_t)$.

III. Performance Analysis

In this section, we mathematically analyze the MSE performance of the generalized STLC-AirComp technique. For ease of explanation, we assume that the objective function of the network is the arithmetic mean. The functional equation, pre-processing, and post-processing for the arithmetic mean are represented in (3).

The MSE between f_t and $\hat{f}_t$ for arithmetic mean function computation is derived as follows

$$\begin{aligned}\mathrm{MSE} &= \mathbb{E}\left[\left|f_t - \hat{f}_t\right|^2\right] = \mathbb{E}\left[\frac{2\sigma_n^2}{K^2 P_0 \min_k \gamma_{k,a}}\right] \\ &= \mathbb{E}\left[\frac{2\sigma_n^2}{K^2 P_0 \min_k \left(\left|h_{k,2a-1}\right|^2 + \left|h_{k,2a}\right|^2\right)}\right], \end{aligned} \tag{10}$$

where the distribution of the channel gain between each STA and the receive antenna pair at the AP in (1) is well-known to follow the Chi-square distribution. Let $X := \gamma_{k,m}$. The PDF of X is given by $f_X(x) = xe^{-x}$. Due to the antenna pair selection in (2), we exploit $f_X(x)$ to calculate the min-max probability distribution. Since it is assumed that wireless channels between all STAs are identically and independently distributed. for a single antenna pair, the PDF of the minimum channel gain among STAs $Y = \min_k (X_1, X_2, \ldots, X_K)$ can be calculated as follows

$$f_Y(y) = yK(1+y)^{K-1}e^{-yK}. \tag{11}$$

Considering the M pairs of receive antennas, once the antenna pair is selected through (2), we can derive the distribution of the maximum value of Y. Since receive antenna pairs are defined in order, channel gains for each antenna pair are independent of each other. Therefore, we define the $Z = \max_m (Y_1, Y_2, \ldots, Y_M)$ and the PDF of the maximum value of minimum channel gains Z can be derived as follows

$$f_Z(z) = zMK(1+z)^{K-1}e^{-zK}\left(1 - e^{zK}(1+z)^K\right)^{M-1}. \tag{12}$$

Let transmit signal to noise ratio (SNR) be defined as $\mathrm{SNR} := P_o/\sigma_n^2$, and by exploiting (12) for the derivation of (10), the MSE of the generalized STLC-AirComp in (10) can be rewritten as

$$\begin{aligned}\mathrm{MSE} &= \frac{2}{K^2\mathrm{SNR}}\mathbb{E}\left[\frac{1}{z}\right] = \frac{2}{K^2\mathrm{SNR}}\int_0^\infty \frac{1}{z} f_Z(z)dz \\ &= \frac{2MK}{K^2\mathrm{SNR}}\int_0^\infty (1+z)^{K-1}e^{-zK}\left(1-e^{-zK}(1+z)^K\right)^{M-1}dz. \end{aligned} \tag{13}$$

By exploiting the binomial expansion and linear property of integration, (13) can express as follow

$$\begin{aligned}\mathrm{MSE} = &\frac{2MK}{K^2\mathrm{SNR}}\sum_{m=0}^{M-1}\binom{M-1}{m}(-1)^{M-m-1} \\ &\times \int_0^\infty e^{-zK(M-m)}(1+z)^{K(M-m)-1}dz. \end{aligned} \tag{14}$$

In (14), the integration is derived as

$$\begin{aligned}&\int_0^\infty e^{-zK(M-m)}(1+z)^{K(M-m)-1}dz \\ &= \frac{e^{(M-m)K}}{\{(M-m)K\}^{(M-m)K}}\Gamma((M-m)K, (M-m)K), \end{aligned} \tag{15}$$

where $\Gamma(s,x) = \int_x^\infty t^{s-1}e^{-t}dt$ means upper incomplete gamma function. Therefore, we can derive an exact MSE performance analysis of the generalized STLC-AirComp technique by substituting (15) into (14) as follows

$$\begin{aligned}\mathrm{MSE} = &\frac{2M}{K\mathrm{SNR}}\sum_{m=0}^{M-1}\binom{M-1}{m}(-1)^{M-m-1} \\ &\times \frac{e^{(M-m)K}}{\{(M-m)K\}^{(M-m)K}}\Gamma((M-m)K, (M-m)K). \end{aligned} \tag{16}$$

In (16), if the number of antenna pairs M is one, i.e., $N = 2$, the MSE analysis is the same with the conventional STLC-AirComp as follows

$$\mathrm{MSE} = \frac{2e^K}{K^{K+1}\mathrm{SNR}}\Gamma(K,K). \tag{17}$$

By exploiting asymptotic behavior of incomplete gamma function that $\Gamma(s,x) \approx x^{s-1}e^{-x}$ as the number of STAs increases [20], the MSE of STLC-AirComp can be approximated as

$$\mathrm{MSE} \approx 2\left(K^2\mathrm{SNR}\right)^{-1}. \tag{18}$$

This implies that when considering mIoT networks, the STLC-AirComp technique can make the MSE of the arithmetic mean function computation converge to zero without optimizing the receive beamformer design to minimize errors. In addition, even if the arithmetic mean function is not considered, the MSE for the superimposed AirComp signal $\sum_{k=1}^K x_k$ converges to $2/\mathrm{SNR}$. In other words, given a sufficiently high SNR, this suggests that both affine and non-affine objective functions can be efficiently computed with very low MSE using the STLC-AirComp framework, which employs a simple linear channel inversion structure without requiring global CSI at the receiver.

IV. Simulation Results

In this section, we present the MSE performance of the proposed STLC-AirComp technique, compared to the conventional channel inversion structure with single antenna selection, and verify the mathematically analyzed MSE performance of the STLC-AirComp. We conduct Monte-Carlo simulations using MATLAB software and set the transmit SNR to a fixed value of 10dB.

Fig. 3 shows the MSE performance of STLC-AirComp versus the number of STAs, compared to the conventional AirComp transceiver design based on a single-channel inversion structure through single-antenna selection (AS-AirComp for short) when the number of receive antennas is two and four, i.e., $M = 1$ and $M = 2$. To fairly evaluate the performance of the proposed STLC-AirComp, we compared it with AS-AirComp as a benchmark scheme, which considers function computation rate and CSI availability while assuming that only

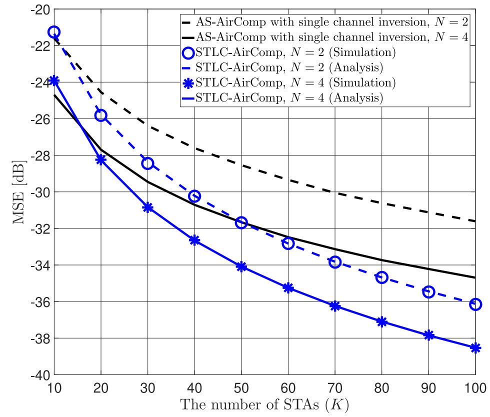

Fig. 3. MSE performance of the proposed STLC-AirComp versus the number of STAs K for different values of N.

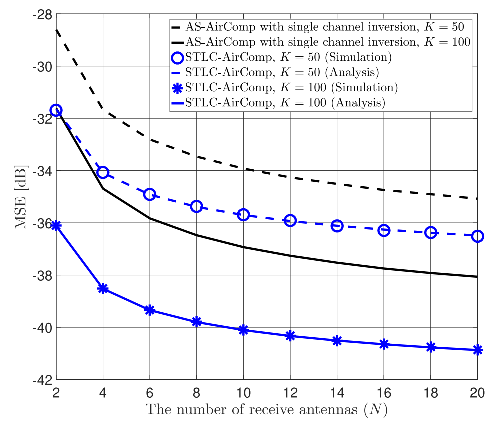

Fig. 4. MSE performance of the proposed STLC-AirComp versus the number of receive antennas N for different numbers of STAs K.

the transmitters have access to local CSI. As mentioned in Section III, when considering the arithmetic mean function as the objective function, it can be observed that the MSE performance of STLC-AirComp rapidly decreases as the number of STAs increases. Furthermore, the mathematically analyzed MSE performance closely matches the simulation results for all numbers of STAs.

Fig. 4 shows the MSE performance versus the number of receive antennas when the number of STAs is 50 and 100, i.e., $K = 50$ and $K = 100$. Both STLC-AirComp and AS-AirComp improve MSE performance as the number of receive antennas increases due to selection gain. As the number of antenna pairs increases, it can be observed that the MSE performance of STLC-AirComp becomes saturated. In (16), the number of receive antenna pairs M has both a negative effect, which increases MSE through linear multiplication, and a positive effect, which reduces MSE through the summation term. Therefore, at a small number of M, the positive effect leads to a steep improvement in MSE performance. However, as M increases, the MSE performance quickly saturates due to the negative effect of M.

V. Conclusion

In this letter, we have proposed a novel STLC-AirComp framework for mIoT sensor networks as a general extension of the previously proposed STLC-AirComp framework designed for two receive antennas. We have mathematically analyzed the function computation performance of the proposed technique in terms of MSE and derived the theoretical limits. In addition, we have designed a minimum channel gain estimation procedure and an optimal antenna pair selection criterion to enhance function computation and improve the power efficiency of each STA without requiring both global CSI at the AP and complicated beamformer optimization. Through computer simulations, we have demonstrated that our theoretical analysis closely matches the Monte-Carlo experimental results. As future work, we will investigate STLC-AirComp by integrating technical advancements such as RIS and opportunistic transmission, along with practical factors including antenna correlation.

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