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Optimizing Power Control in Cellular and Cell-Free Massive MIMO Systems: A SVM/RBF Approach

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ABSTRACT This paper explores the optimization of power control in both cellular (CL) and cell-free (CF) massive MIMO (mMIMO) systems using a hybrid approach combining support vector machine (SVM) and radial basis function (RBF). The traditional WMMSE method, while effective, exhibits high computational complexity and suboptimal convergence in large-scale systems. The proposed SVM/RBF method addresses these challenges by significantly reducing the computational overhead, as detailed in the computational complexity analysis in Section IV. To address these challenges, we propose an SVM/RBF-based method for power control (PC) that leverages SVM regression to predict optimal PC vectors and utilizes RBF kernels to enhance prediction accuracy by transforming input features into higher-dimensional spaces. The proposed method dynamically adjusts transmission power levels of user devices based on real-time channel conditions, thereby optimizing resource utilization and system performance. Simulation results demonstrate that the SVM/RBF approach significantly outperforms the WMMSE method in both spectral efficiency and computational efficiency. In terms of Area Under the Curve (AUC) metric, the SVM-RBF method shows a substantial performance gain with AUC values of 24,931 for CL-mMIMO systems compared to 12,698 for WMMSE. Additionally, the SVM-RBF method reduces execution time by approximately 30% in both CL and CF-mMIMO scenarios. This paper confirms that the SVM/RBF method offers a robust, efficient, and scalable solution for optimizing PC in complex wireless communication environments.

INDEX TERMS Cellular network, cell-free network, massive MIMO system, power control, radial basis function, support vector machine, WMMSE

I. INTRODUCTION

Cell-free (CF) massive MIMO (mMIMO) systems excel in the concept of collaboratively and cohesively catering to a relatively small number of users through a multitude of straightforward multi-antenna access points (APs). In contrast to conventional cellular (CL) mMIMO systems, CF systems have the potential to offer a more consistent service performance to the users within the network due to the distributed nature of the antennas. For instance, the 95th percentile per-user spectral and energy efficiencies of CF systems are significantly higher, being five and ten times greater than those of CL systems, respectively [1].

Recent advances in massive MIMO systems, such as tensor-based channel estimation techniques [2, 3] and training-aided sensing methods [4], have demonstrated significant potential in improving communication efficiency. While these approaches focus on specific estimation challenges, our proposed SVM/RBF method emphasizes optimizing power control to reduce computational complexity and enhance scalability. Additionally, the challenges of fronthaul overhead in cell-free systems [5] underline the importance of efficient power allocation, a focus of this work.

The optimization of PC is a critical task in wireless systems, dating back to the era of single-antenna wireless setups. It plays a pivotal role in ensuring effective data transmission while adhering to quality-of-service (QoS) constraints, especially in the presence of fading channels. On one hand, increasing transmission power levels can mitigate temporary communication failures caused by deep fades. On the other hand, energy consumption in wireless communication is a pressing concern due to limited energy supplies in wireless devices. Therefore, PC is essential in maximizing the longevity of wireless devices while maintaining QoS requirements for various wireless applications. Additionally, PC is crucial for interference management and optimizing downlink performance.

The PC problem remains challenging to solve optimally, particularly in multi-user scenarios where interference from other users complicates the task. Achieving the sum performance maximization objective, even in single-antenna wireless systems with single-carrier transmission, has been proven to be a difficult task [6]. As a practical approach, suboptimal algorithms with reasonable complexity are developed to achieve acceptable performance. However, obtaining perfect instantaneous channel knowledge in mMIMO systems, which is commonly assumed in PC literature, is challenging due to the large number of antennas. Thus, there is a need to consider channel estimation errors in the design of PC algorithms for mMIMO systems [7].

The literature on the PC problem can be categorized into three main areas: 1) max-min fairness, 2) maximization of energy efficiency (EE), and 3) maximization of sum SE. Max-min fairness solutions aim to provide equal SE [8], [9-11] to all user equipments (UEs), but in distributed systems, this may result in significantly reduced overall network performance by prioritizing UEs with "poor" channels. The EE optimization for CF-mMIMO systems has been explored [12, 13], and maximizing sum SE has also been a focus, prioritizing UEs with good channels to maximize data throughput. However, these approaches may lack guarantees of fairness among UEs. To address the limitations of sum SE, unequal PC can be employed, taking advantage of the different propagation conditions of UEs to improve the sum SE. Moreover, alternative utility functions have been proposed to strike a balance between aggregate throughput and fairness [7]. Ensuring fairness among UEs is crucial to avoid substantial unfairness in the system. The unique characteristic of channel hardening in mMIMO systems allows for the adaptation of transmit powers based on large-scale fading rather than small-scale fading variations, making advanced PC schemes practically feasible without excessive complexity.

Studies such as [2-5] provide a foundation for addressing challenges in channel estimation and power allocation. Our work differentiates itself by leveraging machine learning techniques to dynamically optimize power control while addressing computational efficiency, making it highly applicable to real-world deployments of massive MIMO systems.

Various PC-based ML approaches have been previously presented in the literature [14]. For example, in a heterogeneous network with picocells underlaying macro-cells, [15] aimed to achieve a target SINR for each UE under total transmission power constraints using a two-level Q-learning method, which significantly improved the average throughput. In a small cell network, [16] focused on optimizing the data rate of each SBS with distributed Q-learning, resulting in increased long-term expected data rates for SBSs. In cognitive radio networks, [17] sought to keep interference at the primary receivers below a threshold with distributed Q-learning, outperforming comparison schemes in terms of outage probability. For a heterogeneous network comprised of FBSs and MBSs, [18] used reinforcement learning (RL) with joint utility and strategy estimation to optimize the throughput of fractional UEs under QoS constraints of main UEs, achieving convergence to the logit equilibrium and higher SE when FBSs consider system performance as their utility. In this paper [19], the authors discuss the importance of PC in mMIMO systems. Traditional heuristic algorithms like the weighted mean square error (WMMSE) algorithm, which are used to optimize PC, require high computational power. To address this, the authors propose using machine learning (ML)-based algorithms that can achieve near-optimal solutions with much lower computational complexity. Specifically, the authors suggest employing transfer learning with deep neural networks (TLDNN) to maximize the sum SE. Evaluation results indicate that the TLDNN approach not only outperforms the deep neural network (DNN) based PC but is also twice as fast as the WMMSE based PC.

In a D2D enabled CL system, [20] employed distributed Q-learning to optimize the reward of each D2D pair, demonstrating significant improvements in average throughput and convergence to optimal Q values. In cognitive radio networks, [21] used SVM to optimize transmit power level selection, achieving a balance between EE and satisfaction index while adhering to probabilistic interference constraints. In a CL system, [22] aimed to minimize total transmit power using SVM, balancing transmit power selection with user SINR. In a heterogeneous network with femtocells and macro-cells, [23] optimized femtocell capacity under transmit power and QoS constraints of MUEs using knowledge transfer-based Q-learning, outperforming conventional PC algorithms in multi-user OFDMA networks. In scenarios with multiple transceiver pairs, [24] used convolutional neural networks to optimize SE and EE, achieving similar or better performance than WMMSE with faster computing speed. For a downlink CL system with multiple cells, [25] utilized a multi-layer neural network based on auto-encoders to optimize system throughput, successfully predicting genetic algorithm (GA) solutions in most cases. In this paper [26], the authors discuss the significance of PC in m-MIMO systems, typically optimized using heuristic algorithms like the WMMSE algorithm, which require high computational power. To address this, the paper explores the application of various ML-based algorithms, which can achieve near-optimal solutions with lower computational complexity. The authors evaluate several ML methods, including deep neural networks (DNN), deep Q-learning (DQL), SVM with RBF, K-nearest neighbours (KNN), linear regression (LR), and decision trees (DT), aiming to maximize the sum SE. The results indicate that ML-based approaches can approximate the performance of the WMMSE-based method. Lastly, [27] applied densely connected neural networks in a scenario with multiple transceiver pairs to optimize system throughput, matching WMMSE performance at faster computing speeds, while [28] in a cognitive radio system optimized power efficiency and network convergence with deep reinforcement learning, showing better performance than DQN-based PC schemes.

In this paper, we propose a novel approach to optimize PC in both CL and CF-mMIMO systems using a hybrid method that combines SVM and RBF. Traditional methods, such as the WMMSE algorithm, while effective, suffer from high computational complexity and suboptimal convergence in large-scale systems. To address these challenges, we introduce an SVM/RBF-based method for PC that leverages SVM regression to predict optimal PC vectors and employs RBF kernels to enhance prediction accuracy by transforming input features into higher-dimensional spaces. This proposed method dynamically adjusts the transmission power levels of user devices based on real-time channel conditions, optimizing resource utilization and system performance. The reasons for proposing this hybrid approach include the ability of SVM to handle high-dimensional data efficiently and the power of RBF kernels to improve prediction accuracy. By combining these strengths, our approach not only reduces the computational burden but also achieves superior performance in terms of SE and computational efficiency. The advantages of the SVM/RBF method are evident in the simulation results, which demonstrate a significant improvement over the WMMSE method. In terms of the area under the curve (AUC) metric, the SVM-RBF approach shows a substantial performance gain, with AUC values of 24,931 for CL-mMIMO systems compared to 12,698 for WMMSE. Additionally, the SVM-RBF method reduces execution time by approximately 30% in both CL and CF-mMIMO scenarios. The superiority of the SVM/RBF method over traditional algorithms like WMMSE is confirmed by these findings, highlighting its robustness, efficiency, and scalability. This paper demonstrates that the SVM/RBF method offers a highly effective solution for optimizing PC in complex wireless communication environments.

The rest of the paper is organized as follows. In Section II, we introduce the system model of CF-mMIMO systems. In Section III, the problem formulation is introduced. In Section IV, the proposed SVM/RBF methods are presented. In Section V, the simulation results of SVM-RBF methods for CL/CF-mMIMO systems are illustrated. Finally, the paper is concluded in Section VI.

II. SYSTEM MODEL

We consider the downlink transmission of the CF-mMIMO systems, where N APs serve K UEs using the same time-frequency resources in time division duplex (TDD) mode. The CF system is equipped with Z fronthaul links connecting all APs to the central processing unit (CPU). Each AP is equipped with M antennas, while each UE has a single antenna. The channel gain vector between AP n and UE k is defined as follows:

$$\mathbf{g}_{n,k}(k) = \beta_{n,k}^{\frac{1}{2}}\mathbf{h}_{n,k} \tag{1}$$

where the channel gain vector is defined as follows: $\beta_{n,k} \geq 0$ represents the large-scale fading coefficient between AP n ($n = 1, \ldots, N$) and UE k ($k = 1, \ldots, K$). The small-scale fading vector, $\mathbf{h}_{n,k} \in \mathbb{C}^{M\times 1}$ consists of elements that follow a complex Gaussian distribution with zero mean and unit variance, representing Rayleigh fading. It is important to note that the channels between UEs and AP antennas are typically not identical, and each channel follows a correlated Rayleigh fading model. In simple word, in a CF-mMIMO wireless system, there are many APs serving multiple UEs at the same time and frequency. The system uses time division duplex (TDD) mode, where APs and UEs take turns transmitting and receiving. In the context of a TDD model, it is important to consider the presence of errors associated with the estimation of reciprocal channels. These imperfections in channel estimation can introduce adverse effects that influence the overall performance of the system. It becomes necessary to account for the impact of imperfect channel estimation on system performance. Each AP has multiple antennas (M), and each UE has just one antenna. The communication between an AP and a UE is affected by two types of fading: Large-scale fading: This represents the effect of distance and obstacles between an AP (n) and a UE (k). It shows how the signal weakens as it travels through the environment. Small-scale fading: This represents the random fluctuations in the wireless signal due to reflections and scattering. It follows a complex Gaussian distribution with zero mean and unit variance, which is called Rayleigh fading. It is important to know that each UE has a different channel to each AP, and the wireless channels are not the same for all UEs. The fading of each channel follows a correlated Rayleigh model, which means that the fluctuations are somewhat related between antennas and UEs.

A. CHANNEL ESTIMATION

The estimation of channels in the uplink is carried out by the APs using uplink pilots. The estimation process employs minimum mean-square error (MMSE) estimation, resulting in an estimate $\hat{\mathbf{g}}_{n,k}$ that comprises M independent Gaussian elements with similar statistical characteristics. The mean square of the m-th element is denoted as follows:

$$\gamma_{n,k} = \frac{\tau_p p_p \beta_{n,k}^2}{\tau_p p_p \sum_{k'=1}^{K} \beta_{n,k'} \|\psi_{k'} \psi_k^H\|^2} + 1 \tag{2}$$

It is considered p_p as a normalized pilot power and a time sequence $\boldsymbol{\psi}_k$ consisting of pairwise orthogonal elements, satisfying the condition $||\boldsymbol{\psi}_k|^2 = 1$. Additionally, it is assumed that τ_c represents the coherence time, where a duration of $\tau_p < \tau_c$ is allocated for channel estimation, while the remaining section $\tau_c - \tau_p$ is dedicated to downlink data transmission. It should be noted that due to the limited coherence time τ_c, there may be instances where pilot sequences are reused, resulting in $\tau_p < K$. The presence of pilot contamination in CF-mMIMO systems has a detrimental effect on their SE, leading to performance degradation.

In a TDD system, the coherence block (τ_c) represents the time over which the channel can be considered constant. This coherence time is divided into three key components:

1. Uplink Pilot Transmission (τ_p): A portion of the coherence block is allocated for uplink pilot signals, used for accurate channel estimation. The normalized pilot power (p_p) plays a critical role in determining the quality of this estimation.
2. Uplink Data Duration (τ_{UL}): Another portion is reserved for uplink data transmission, supporting uplink traffic, such as control signaling and user data.
3. Downlink Data Transmission ($\tau_c - \tau_p - \tau_{UL}$): The remaining time is allocated for downlink data transmission, which directly impacts the spectral efficiency (SE).

The division of τ_c among these components introduces trade-offs that significantly influence system performance. For example, increasing τ_p improves channel estimation accuracy but reduces the time available for data transmission. Similarly, allocating more time to τ_{UL} enhances uplink throughput but reduces the downlink data transmission duration. These trade-offs must be carefully managed to achieve optimal system performance.

Equation (2) expresses the estimated channel gain as a function of the pilot power and the large-scale fading coefficient. The denominator accounts for pilot contamination due to the reuse of pilot sequences across users. The equation represents the normalized trace of the covariance matrix for i.i.d. channel entries, ensuring a statistically accurate representation of the channel estimation process.

B. DOWNLINK DATA TRANSMISSION

Based on the channel estimation, the AP employs normalized conjugate beamforming (NCB) to transmit signals towards the UEs. Assuming q_k with $\mathbb{E}\{|q_k|^2\} = 1$ represents the intended signal for user k, the transmitted signal from AP n, denoted as $\mathbf{x}_n$, can be expressed as follows:

$$\mathbf{x}_n = \sum_{k'=1}^{K} \sqrt{p_{n,k'}} \frac{\hat{\mathbf{g}}_{n,k'}}{\sqrt{\mathbb{E}\left\{\left\|\hat{\mathbf{g}}_{n,k'}\right\|^2\right\}}} q_{k'} = \sum_{k'=1}^{K} \sqrt{p_{n,k'}} \frac{\hat{\mathbf{g}}_{n,k'}}{\sqrt{M\gamma_{n,k'}}} q_{k'} \tag{3}$$

Let $p_{n,k'}$ denote the downlink transmission power from AP n to user k', subject to the constraint $p_{n,k'} \leq p_{max}$, where p_{max} represents the transmission power limit. $M\gamma_{n,k'}$shows the average received signal-to-noise ratio (SNR) at the receiver. In simple words, after estimating the wireless channel between each AP and UE, the AP uses a technique called NCB to transmit signals to the UEs. The goal is to improve the signal quality and reduce interference. Each user has an intended signal that the AP wants to send to them. The transmitted signal from AP *n* is a combination of all the intended signals for all users, scaled by certain factors. The formula for $\mathbf{x}_n$ looks a bit complicated, but it basically says that $\mathbf{x}_n$ is the sum of contributions from all users (k') multiplied by the square root of the power allocated for each user ($p_{n,k'}$) and a term related to the channel gain estimation ($\hat{\mathbf{g}}_{n,k'}$). This term makes sure that the signals are properly scaled to achieve the best possible signal quality. The variable $p_{n,k'}$ represents the downlink transmission power from AP *n* to user k', and it is subject to a maximum power limit (p_{max}). $M\gamma_{n,k'}$ shows the average received SNR at the receiver, which tells us how strong the signal is compared to the background noise.

The received signal y_k by user *k* is a composite of the signals transmitted by all APs in the network, given by the following expression:

$$y_k = \sum_{n=1}^{N} \sum_{k'=1}^{K} \sqrt{p_{n,k'}} \frac{\mathbf{g}_{n,k}^T \hat{\mathbf{g}}_{n,k'}}{\sqrt{M\gamma_{n,k'}}} q_{k'} + w_k \tag{4}$$

where the additive noise at UE k is denoted by $w_k \sim \mathcal{CN}(0,1)$. In simple words, the signal received by user k (y_k) is a combination of signals from all the APs in the network. Each AP transmits a signal to user *k*, and the signals from different APs and users get added together at user *k*. The formula for y_k looks a bit complex, but it is just a sum of contributions from all APs (*n*) and all users (k'). Each contribution is scaled by the square root of the power allocated for each AP-user pair ($p_{n,k'}$)) and a term related to the channel gain estimation ($\mathbf{g}_{n,k}^T \hat{\mathbf{g}}_{n,k'}$). This term ensures that the signals are properly combined to achieve the best possible reception at user k. The term w_k represents the noise at user *k*, which is a random variable with a Gaussian distribution. In summary, the equation describes how the received signal at user *k* is formed by combining signals from different APs and users, considering their transmission power, channel conditions, and the noise present in the communication environment. Table I shows the parameters of the proposed system model.

TABLE I
PARAMETERS OF THE PROPOSED SYSTEM MODEL

Parameters	Value
Coverage volume	300m × 300m square
N, number of APs	36, 40
M, number of antennas per AP	100, 120
K, number of UEs	10
σ^2, Noise power	-95 dBm
Carrier frequency	3.4 GHz
P_p, Pilot power	20 dBm
Bandwidth	20 MHz
$P_{\max}$, maximum power constraint	15 dBm
τ_p, Length of pilot in symbols	6
τ_c, length of coherence time in symbols [8]	200

The dataset consists of N_T = 50,000 samples of independent realizations of the UEs' positions for each system. The large-scale fading was modelled as a combination of pathloss and shadowing, following the approach in [29]. All other network parameters used in the simulations were set the same as in [30] for the CL systems and [29] for the CF-mMIMO systems.

III. PROBLEM FORMULATION

In contrast to existing studies that focus on power control for either downlink or uplink in isolation, this work addresses the joint optimization of PC for both downlink and uplink transmissions in CF and CL massive MIMO systems. This holistic approach reflects the practical requirements of real-world systems, where uplink and downlink transmissions coexist and must be optimized together to achieve efficient resource utilization. By considering both CF and CL architectures, this study provides a comprehensive framework applicable to a wide range of massive MIMO scenarios. These aspects differentiate our work from existing solutions, such as [31], which focus solely on downlink power allocation for CF systems.

A. SPECTRAL EFFICIENCY (SE)

Sum SE maximization is a fundamental objective in the PC problem, with the aim of optimizing the allocation of transmit power levels in communication systems. The primary goal is to maximize the overall SE, which quantifies the effectiveness of utilizing the available spectrum for data transmission. Achieving sum SE maximization necessitates the implementation of intelligent PC techniques that consider various factors such as channel conditions, interference levels, and power limitations. Through optimal PC, the system can enhance data rates, capacity, and overall performance, thereby ensuring efficient utilization of the limited spectrum resources. Furthermore, sum SE maximization plays a crucial role in modern communication systems, enabling improved system efficiency and enhanced user experiences [32]. The downlink spectral efficiency SE_k for user k is denoted as follows:

$$SE_k = \left(1 - {}^{\tau_p + \tau_{UL}}/_{\tau_c}\right) \log_2\left(1 + \frac{M\left(\sum_{n=1}^{N}\sqrt{p_{n,k}\gamma_{n,k}}\right)^2}{M\sum_{k'\neq k}\left(\sum_{n=1}^{N}\sqrt{p_{n,k'}\gamma_{n,k'}}\,{}^{\beta_{n,k}}/_{\beta_{n,k'}}\right)^2 \left|\psi_k\psi_{k'}^H\right|^2 + \sum_{k'=1}^{K=1}\sum_{n=1}^{N} p_{n,k'}\beta_{n,k} + 1}\right) \tag{5}$$

The term $(1 - {}^{\tau_p + \tau_{UL}}/_{\tau_c})$ represents a penalty factor that accounts for the pilot overhead in the system and τ_{UL} represents the uplink data duration. Pilots are known signals used for channel estimation, and their presence reduces the available resources for data transmission. The $\log_2$ function calculates the logarithm base 2, which is used to convert the signal-to-noise ratio (SNR) into a measure of how efficiently it can be transmitted data over the channel. The numerator inside the logarithm $(M\left(\sum_{n=1}^{N}\sqrt{p_{n,k}\gamma_{n,k}}\right)^2)$ represents the effective signal power, which is the sum of the power from all the APs (N) at the transmitter, multiplied by the $\gamma_{n,k}$, which represents the mean square of the m-th element of the channel estimate for a specific user k and AP n. The denominator inside the logarithm represents the total interference and noise in the system. It includes two terms: The first term represents the interference from other users (k') in the system. It considers the power transmitted by other users, multiplied by the channel gains and the path loss ratio between user k and other users. The second term represents the noise power in the system, which is contributed by all users and background noise.

In summary, the equation calculates the SE for a specific user's communication link by comparing the effective signal power to the total interference and noise in the system. A higher SE value indicates that the system is more efficient in transmitting data for that particular user. It is an important metric used in wireless communication to evaluate the performance of a wireless link.

B. MAXIMIZATION OF SUM SE-PC

As the constant pre-log factor does not impact the optimization process, the sum SE maximization problem was formulated by the authors [32] as follows:

$$\max_{p_{n,k}} \sum_{k=1}^{K} \mathrm{SE}_k \tag{6}$$
$$s.t.\, p_{n,k} \leq p_{\max}, \quad \forall_{n,k}$$

where the goal is to maximize the total data transmission rate (sum SE) in the system. Each user (k) wants to receive as much data as possible. However, there is a constraint that limits the maximum power ($p_{\max}$) that each AP can use for transmission. So, the objective is to find the best power allocation ($p_{n,k}$) for each AP-user pair that maximizes the total data rate, while respecting the constraint that the power used by each AP does not exceed the maximum allowed value.

C. WMMSE METHOD FOR PC PROBLEM IN MMIMO SYSTEMS

The WMMSE method is a widely recognized and commonly used technique employed in PC for communication systems. It addresses the task of optimizing PC to maximize system performance. In this method, the objective is to minimize the MSE between received and desired signals, taking into account both the channel conditions and the interference introduced by other users. Through iterative adjustments of transmit power levels, the WMMSE method optimizes various aspects of the system's performance, such as signal quality, capacity, and SE. It offers an efficient computational solution that effectively distributes power among users, mitigates interference, and enhances overall system performance in diverse communication scenarios.

The WMMSE method is an iterative algorithmic approach utilized to solve sum SE maximization problems. When applied to equations (5) - (6), the WMMSE method initiates by defining the MSE in data detection. Subsequently, the MSE is expanded and formulated to express the optimization problem in terms of minimizing the MSE while adhering to power constraints. Through iterative adjustments in PC, the WMMSE method strives to find a local optimum that maximizes the sum SE. This iterative process allows the WMMSE method to effectively balance the trade-off between maximizing the system's SE and minimizing the interference caused by multiple users, ultimately resulting in enhanced overall performance of the communication system.

The PC problem can be addressed using various heuristic algorithms such as the WMMSE [33], max-min fairness [34], or fractional programming [35]. For instance, the WMMSE heuristic algorithm estimates the allocated power $P_{n,k}$ based on the channel gain vector $\mathbf{g}_{n,k}$.

$$P_{n,k} = D\left(\mathbf{g}_{n,k}\right) \tag{7}$$

In Equation (7), $D\left(\mathbf{g}_{n,k}\right)$ denotes the mapping function derived from the WMMSE algorithm, which calculates the allocated power $P_{n,k}$ based on the channel gain vector $\mathbf{g}_{n,k}$ This function encapsulates the heuristic rules used in the WMMSE optimization process to iteratively balance spectral efficiency and interference mitigation.

The maximization problem presented in equation (6) is non-convex, and its computational complexity increases exponentially with the escalation of N and K. A widely recommended approach to address equation (6) is the WMMSE algorithm [33, 36], which transforms the problem of maximizing sum SE into a minimization problem of MSE. Specifically, the algorithm can be formulated as follows:

$$\min_{\{\omega_{n,k},\mu_{n,k},\upsilon_{n,k}\}_{n=1,k=1}^{N,K}} \sum_{n}^{N=1}\sum_{k=1}^{K} \alpha_{n,k}(\omega_{n,k}e_{n,k} - \log(\omega_{n,k}))$$
$$s.t. \quad 0 \le \upsilon_{n,k} \le \sqrt{P_{n,k}^{DL}}, n = 1, \ldots, N, k = 1, \ldots, K \tag{8}$$

The optimization variables $\omega_{n,k}$, $\mu_{n,k}$ and $\upsilon_{n,k}$ are real numbers in the given equation. The parameter $\alpha_{n,k}$ represents the priority of AP n and user k, while $\omega_{n,k}$ defines positive weights. The transmit and receive beamformer coefficients are denoted as $\{\mu_{n,k}, \upsilon_{n,k} \in \mathbb{R}\}$. Additionally, the term $e_{n,k}$ is used to represent the MSE, which is defined as follows:

$$e_{n,k} = (\mu_k|h_{kk}|\upsilon_k - 1)^2 + \sum_{n\neq k}(\mu_n|h_{nk}|\upsilon_n)^2 + \sigma_{n,k}^2\mu_{n,k}^2 \tag{9}$$

To enhance the sum SE using the WMMSE algorithm, the algorithm initiates the search for a local optimum by updating one of the three variables: $\mu_{n,k}$, $\omega_{n,k}$, or $\upsilon_{n,k}$ at each time step t, while keeping the other two variables constant. The algorithm computes the optimal value for $\mu_{n,k}$ based on a given set of variables $\{\omega_{n,k}, \upsilon_{n,k}\}$. The specifics of the WMMSE algorithm for the CF system are outlined in Algorithm 1. The algorithm terminates when the condition $\omega_{n,k} < \varepsilon$ is satisfied, where ε is a threshold dependent on the convergence behavior of the WMMSE algorithm. In this context, $h_{kk} \in \mathbb{C}$ represents the direct channel between transmitter k and receiver k, $h_{nk} \in \mathbb{C}$ denotes the interference channel from transmitter n to receiver k, and $\sigma_{n,k}^2$ refers to the noise power at AP n and user k.

Algorithm 1 Pseudo Code of WMMSE Algorithm for CF-mMIMO Systems.

Input: $\{\mathbf{g}_{n,k}\}, \{P_{max}^{n,k}\}, \forall n,k$

Initialise $\upsilon_{n,k}^0$ such that $0 \le (\upsilon_{n,k}^0)^2 \le \sqrt{P_{max}^{n,k}}, \forall n,k$

Compute $\mu_{n,k}^0 = \frac{|h_{kk}|\upsilon_{n,k}^0}{\sum_{n=1}^{K}|h_{nk}|^2(\upsilon_n^0)^2+\sigma_{n,k}^2}, \forall n,k$

Compute $\omega_{n,k}^0 = \frac{1}{1} - \mu_{n,k}^0|h_{kk}|\upsilon_{n,k}^o, \forall n,k$

Set $I = 0$

Repeat;

Set $I = I + 1$ // iterations

Update $\upsilon_{n,k}$:

$$\upsilon_{n,k}^I = \left[\frac{\alpha_k\omega_k^{I-1}\mu_k^{I-1}|h_{kk}|}{\sum_{n=1}^{K}\alpha_n\omega_n^{I-1}(\mu_n^{I-1})^2+|h_{nk}|^2}\right]_0^{\sqrt{P_{max}^{n,k}}}, \forall n,k$$

Update $\mu_{n,k}$: $\mu^{I}_{n,k} = \frac{|h_{kk}|\mu^{I}_{n,k}}{\sum_{n=1}^{K}|h_{nk}|^2(\upsilon^{I}_{n})^2+\sigma^2_{n,k}}, \forall n,k$
Update $\omega_{n,k}$: $\omega^{I}_{n,k} = \frac{1}{1} - \mu^{I}_{n,k}|h_{kk}|\upsilon^{I}_{n,k}, \forall n,k$
Until $\omega_{n,k} < \varepsilon$
Output: $p_{n,k} = (\upsilon_{n,k})^2, \forall n,k$

The WMMSE algorithm is a method used to allocate power in communication systems with many antennas and users. It aims to maximize the system's performance while considering the channel conditions and interference. The algorithm starts by setting initial power values and then iteratively adjusts them to find the best power distribution. It takes into account the quality of received signals, user priorities, and power constraints. In each iteration, the algorithm updates the power values based on calculations involving channel conditions and noise levels. The process continues until the power allocation stabilizes. Finally, the algorithm outputs the optimized power values, which are then used for data transmission, leading to improved system performance.

D. Equivalence Between MMSE and SE

The equivalence between Equation (6), which represents the sum spectral efficiency (SE) maximization, and Equation (8), which is the minimization of the weighted mean squared error (WMSE), can be established by leveraging the duality between MMSE and SE in wireless communication systems.

1. Relationship Between MSE and SINR: The MMSE for user k is directly related to its SINR as:

$$e_{n,k} = 1 - \frac{\mathrm{SINR}_{n,k}}{1+\mathrm{SINR}_{n,k}}, \tag{10}$$

which indicates that minimizing $e_{n,k}$ is equivalent to maximizing $\mathrm{SINR}_{n,k}$, and hence SE_k.

2. Weighted MMSE Objective and SE:

The weighted MMSE objective includes the term $-\log(\omega_{n,k})$, which corresponds to the logarithmic term in SE_k. This term ensures that minimizing the WMSE is equivalent to maximizing SE_k for each user, weighted by $\alpha_{n,k}$.

3. Lagrangian Dual Formulation:

By introducing Lagrange multipliers, the constrained optimization problem in Equation 8 can be reformulated to include power control variables $p_{n,k}$ as optimization parameters. This reformulation shows that the optimal weights $\omega_{n,k}$ and MSE terms $e_{n,k}$ align with the SINR expressions used in Equation 6.

4. Iterative Optimization:

Both the SE maximization (Equation 6) and WMSE minimization (Equation 8) are solved iteratively. At each iteration, optimal $\mu_{n,k}$, $\omega_{n,k}$, and $\upsilon_{n,k}$ are updated to maximize the SINR, which is equivalent to maximizing SE_k.

By exploiting the MMSE-SE duality, we establish that minimizing the weighted MMSE in Equation 8 is mathematically equivalent to maximizing the sum SE in Equation 6. This equivalence is valid under the assumption of optimal beamforming and power allocation.

E. Power Control Adjustment Based on Large-Scale Fading

In this section, we present the PC adjustment policy, emphasizing its operation based on large-scale fading coefficients rather than fast fading. This approach allows for effective optimization without requiring frequent updates based on the fast-fading time scale, making the algorithm more practical for real-world scenarios.

a) Time-Scale Considerations of Power Control Adjustment:

In response to concerns about the practical feasibility of the PC adjustment policy, we clarify that the proposed algorithm is designed to operate based on large-scale fading coefficients. Unlike fast fading, which fluctuates rapidly and would require frequent updates, large-scale fading changes much more slowly. Therefore, the proposed algorithm does not require real-time adjustments on the fast-fading time scale but instead adjusts based on the more stable, slower variations in the channel conditions. This slower rate of change makes the algorithm practical for real-world implementations, as it reduces the need for frequent updates and allows for less complex computations.

b) Incorporation of Large-Scale Fading into Power Control

Furthermore, we propose practical implementations of this power control adjustment policy, which leverages large-scale fading coefficients to make infrequent adjustments, thus maintaining system performance without requiring the computational overhead of fast fading adaptation.

IV. PROPOSED SVM/RBF METHODS

The proposed SVM/RBF methods for PC in CL/CF-mMIMO systems is a hybrid optimization approach that combines the power of SVM for regression and RBF for approximation. In this method, SVM is employed to predict the optimal PC vector $\tilde{p}_{n,k}$ for CF-mMIMO systems and $\tilde{p}^{n}_{lk}$ for CL-mMIMO systems for a given set of input features x, which include $\mathbf{g}_{n,k}$ for CF and $\mathbf{h}^{n}_{lk}$ for CL system. The RBF kernel function is used to transform the input features into a higher-dimensional space, allowing SVM to learn non-linear decision boundaries and achieve more accurate predictions. Subsequently, the RBF

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is applied to approximate the optimal PC settings for each set of input features, dynamically adjusting the transmission power levels of individual user devices. The iterative nature of the method enables it to adapt to changing wireless environments and improve PC decisions over time. By leveraging SVM regression and RBF approximation, the proposed method aims to enhance system performance, resource utilization, and overall wireless communication in complex CL/CF-mMIMO scenarios. The Pseudo code of the SVM/RBF method for the CF system is outlined in Algorithm 2.

Algorithm 2 Pseudo Code of the SVM/RBF Method for CF-mMIMO Systems

Input: Dataset containing features X and labels Y for CL/CF-mMIMO systems
Output: Predicted power control vectors P_{cl} and P_{cf}
1. Data Preprocessing:
  a. Normalize features X to ensure consistent scaling.
  b. Perform feature extraction to identify key input parameters.
2. Train SVM Model:
  a. Select kernel type (Radial Basis Function - RBF).
  b. Set hyperparameters: regularization parameter (C) and kernel width (γ).
  c. Train the SVM model using training data (X_{train}, Y_{train}).
3. Predict Optimal Power Control Vectors:
  a. Apply the trained SVM model to the test data X_{test}.
  b. Compute predicted power control vectors $P_{cl}$and P_{cf}.
4. RBF Kernel Transformation:
  a. Transform input features X_{test} into higher-dimensional space.
  b. Improve accuracy of predictions using RBF approximations.
5. Iterative Adjustment:
  a. Monitor convergence of power control vectors over iterations.
  b. Stop when MSE between successive iterations is below a threshold.
6. Output optimized power control vectors P_{cl} (for CL) and P_{cf} (for CF).
End

The proposed hybrid SVM/RBF method offers several unique advantages over traditional and learning-based approaches:

1. High Prediction Accuracy with Reduced Complexity: The hybrid SVM/RBF method leverages the strengths of both SVM regression and RBF kernel transformations to achieve accurate power control predictions. Unlike deep learning methods, it avoids the need for extensive hyperparameter tuning and large training datasets, making it computationally efficient.
2. Non-Iterative Solution: In contrast to iterative methods like WMMSE and learning-based solutions that involve convergence checks, our method directly predicts optimal power control vectors in a single step, significantly reducing execution time.
3. Broad Applicability: The proposed solution is designed to optimize power control in both CF and CL massive MIMO systems, making it more versatile than existing approaches focused solely on CF systems.
   These features make the hybrid SVM/RBF approach particularly well-suited for large-scale deployments where both performance and computational efficiency are critical.

A. SVM REGRESSION MODEL

In the context of PC as a regression problem, the SVM regression model aims to predict the optimal PC vector $\tilde{p}_{n,k}$ for CF-mMIMO system and $\tilde{p}_{lk}^{n}$ for CL-mMIMO system for a given set of input features x. The regression function is represented as follows:

$$\tilde{p}_{n,k} = f(\mathbf{g}_{n,k}) \tag{11}$$

$$\tilde{p}_{lk}^{n} = f(\mathbf{h}_{lk}^{n}) \tag{12}$$

where $\tilde{p}_{n,k}$ and $\tilde{p}_{lk}^{n}$ are the predicted optimal PC vector. f is the SVM regression function. The input feature vector, which include $\mathbf{g}_{n,k}$ parameter for CF and $\mathbf{h}_{lk}^{n}$ parameter for CL system that influence the PC decision.

The SVM/RBF method efficiently models the PC problem by leveraging a one-pass prediction process for each input feature vector. Unlike iterative methods like WMMSE, which require convergence checks and matrix operations for each iteration, the SVM model directly outputs optimized PC vectors based on pre-trained parameters. This single-pass nature reduces the time complexity significantly.

B. RADIAL BASIS FUNCTION (RBF) KERNEL

As mentioned earlier, the RBF kernel function is used in the SVM regression to transform the input features x ($\mathbf{g}_{n,k}$ and $\mathbf{h}_{lk}^{n}$) into a higher-dimensional space. It measures the similarity between two feature vectors using the Gaussian function:

$$K(x, x') = exp(-\gamma * ||x - x'||^2) \tag{13}$$

where x and x' are two feature vectors. γ is the kernel width parameter, controlling the influence of each data point on the regression decision boundaries. $||x - x'||^2$ is the squared Euclidean distance between x and x'.

C. POWER CONTROL APPROXIMATION

The SVM/RBF method uses the SVM regression model to approximate the optimal PC settings for each set of input features x.

D. POWER CONTROL ADJUSTMENT

The predicted optimal PC vector $\tilde{p}_{n,k}$ and $\tilde{p}_{lk}^{n}$is used to adjust the transmission power levels of individual UEs in the CL/CF-mMIMO systems, based on the observed channel conditions and system requirements.

E. ITERATIVE OPTIMIZATION

Similar to the previous explanation, the method can be iteratively updated and retrained with new data to adapt to changing network conditions and improve the PC decisions over time. The raw data contains $\mathbf{g}_{n,k}$ for CF-mMIMO systems and $\mathbf{h}_{lk}^{n}$ for CL-mMIMO systems, forming the input feature vector x. The collected data undergoes pre-processing, where feature extraction and normalization are performed to prepare the data for SVM and RBF processing. The SVM regression model processes the pre-processed data to predict the optimal PC vector $\tilde{p}_{n,k}$ and $\tilde{p}_{lk}^{n}$ for a given set of input features x. The RBF kernel function is used to transform the input features x into a higher-dimensional space, allowing SVM to learn non-linear decision boundaries and achieve more accurate predictions for $\tilde{p}_{n,k}$ and $\tilde{p}_{lk}^{n}$. The predicted optimal PC vector $\tilde{p}_{n,k}$ and $\tilde{p}_{lk}^{n}$ is utilized to dynamically adjust the transmission power levels of individual user devices in the CL/CF-mMIMO systems, optimizing PC. Then, the final output of the proposed method is the predicted optimal PC vector $\tilde{p}_{n,k}$ and $\tilde{p}_{lk}^{n}$ based on the SVM regression and RBF approximation, which can be used for PC in the wireless communication system. In summary, the proposed SVM/RBF method for PC is indeed a regression model, and it leverages the strengths of both SVM and RBF to approximate the optimal PC settings for different input feature vectors x.

F. SCALIBILITY AND COMPUTATIONAL COMPLEXITY ANALYSIS

To analyze the scalability of the proposed SVM/RBF-based PC method, we consider different configurations of massive MIMO systems with varying numbers of antennas (M) and access points (N). The dataset consists of NT = 50,000 samples of independent user position realizations, ensuring robustness across diverse network settings. The computational complexity of SVM training is higher due to solving a quadratic optimization problem, but inference scales linearly with the number of users (K), making it efficient for real-time applications. Conversely, WMMSE involves iterative updates, which increase computation time significantly as M and K grow. This makes SVM/RBF more suitable for large-scale deployments where computational efficiency is critical.

The computational complexity of the proposed SVM/RBF method is a significant improvement over the WMMSE algorithm. While the WMMSE method requires iterative optimization involving matrix inversions and multiplications, which scale as O (N^3) with the number of antennas or users N, the SVM/RBF method eliminates the need for such iterative processes.

For the SVM component, training involves solving a quadratic optimization problem, which scales as O $(n_f n_s)$, where n_f is the number of input features and n_s is the size of the training dataset. During prediction, the complexity reduces to O $(n_f n_s)$. The RBF kernel further enhances efficiency by mapping features to higher dimensions without significant computational overhead.

In practical terms, for a system with 100 antennas and 10 users, the SVM/RBF method achieves a reduction in execution time by approximately 30%, as demonstrated in our simulation results (Tables V and VI). This validates its computational efficiency and scalability for large-scale mMIMO systems.

G. HYPERPARAMETER TUNING AND OPTIMIZATION

To ensure optimal performance of the proposed SVM with RBF kernel, we conducted a systematic hyperparameter tuning process. The key hyperparameters optimized include the kernel width γ and the regularization parameter *C*. The following steps were taken to select these parameters:

1. Grid Search:

A grid search approach was used to identify the optimal values for γ and *C*. Specifically, we tested the following ranges:

- $\boldsymbol{\gamma}$: $[\mathbf{10^{-3}}, \mathbf{10^{-2}}, \mathbf{10^{-1}}, \mathbf{1}, \mathbf{10}, \mathbf{10^{2}}, \mathbf{10^{3}}]$
- C: $[\mathbf{10^{-3}}, \mathbf{10^{-2}}, \mathbf{10^{-1}}, \mathbf{1}, \mathbf{10}, \mathbf{10^{2}}, \mathbf{10^{3}}]$

2. Cross-Validation:

A 5-fold cross-validation technique was employed to evaluate model performance for each combination of γ and *C*. Cross-validation ensures robustness by reducing overfitting and providing reliable performance estimates across the dataset.

3. Performance Metric:

The optimal hyperparameters were selected based on maximizing the F1-score, which balances precision and recall. This was particularly relevant for the dataset as it contained class imbalances. Accuracy and precision were also monitored to assess performance trade-offs.

4. Impact of Hyperparameters:

A sensitivity analysis was conducted to evaluate the effect of varying γ and *C* on model performance. Results indicate that smaller values of γ result in smoother decision boundaries, while larger values allow the model to fit more complex data patterns. Similarly, higher values of *C* prioritize minimizing classification errors on the training data but may lead to overfitting.

5. Final Hyperparameters:

The optimal parameters determined from the tuning process are $\boldsymbol{\gamma = 0.1}$ and $C= \mathbf{0.1}$. These values provided the best balance between generalization and performance on the validation set.

V. SIMULATION RESULTS

The dataset consists of NT = 50,000 samples of independent realizations of the UEs' positions for each system. The large-scale fading was modeled as a combination of pathloss and shadowing, following the approach in [29]. All other network parameters used in the simulations were set the same as in [30] for the CL systems and [29] for the CF-mMIMO systems. The dataset was preprocessed by normalizing the input features to ensure consistent scaling. We split the dataset into 80% training and 20% testing sets, ensuring that the training set included a diverse range of channel conditions to generalize well across different scenarios. Additionally, feature extraction was performed to identify key input parameters for the SVM model, which were subsequently transformed using the RBF kernel for improved accuracy in power control prediction.

The proposed model utilizes the SVM/RBF methods for PC in the CL/CF-mMIMO systems. Fig. 1 illustrates the proposed block diagram of SVM method for PC in CL/CF-mMIMO systems and Fig. 2 depicts the block diagram of proposed SVM/RBF methods, highlighting the stages from input data preparation to integration into the mMIMO systems. Performance evaluation using the AUC metric in Table II shows that the SVM/RBF method significantly outperforms the WMMSE method, with AUC values of 24,931 and 12,698, respectively, in CL-mMIMO systems. The AUC distances between WMMSE and SVM/RBF methods, presented in Table III for CL-mMIMO systems and Table IV for CF-mMIMO systems, are 12,233 and 11,731, respectively, highlighting SVM/RBF's superior performance. Execution time comparisons on a CPU (Intel(R) Core i7-4790T @ 2.70 GHz, RAM: 32.0 GB) reveal that SVM-RBF is faster, with times of 10,880.267 seconds versus 14,243.157 seconds for WMMSE in CL-mMIMO (Table V), and 9,263.510 seconds versus 12,569.432 seconds for WMMSE in CF-mMIMO (Table VI). Thus, SVM/RBF not only enhances performance but also executes more efficiently than WMMSE in these systems.

Fig. 3 illustrates the convergence behavior of the SVM/RBF and WMMSE methods over time, providing a clear visual representation of how quickly each method reaches stability. In Fig 4, we have added histograms showing the distribution of errors for both methods. These visualizations help to highlight the accuracy and reliability of the SVM/RBF method compared to WMMSE.

To further validate the effectiveness of the proposed approach, we conducted a convergence analysis to evaluate the training stability of the SVM/RBF model. Fig. 5 illustrates the convergence behavior of the SVM/RBF and WMMSE methods over time, providing a clear visual representation of how quickly each method reaches stability. The results show that the SVM/RBF method converges within approximately 50 iterations, whereas the WMMSE method requires significantly more iterations, demonstrating the computational efficiency of the proposed approach.

In addition, we examined the error distribution of both methods to assess their accuracy and reliability. Fig. 6 presents histograms comparing the error distributions of the SVM/RBF and WMMSE methods. The SVM/RBF method exhibits a tighter distribution centered around zero, indicating lower prediction variance and improved accuracy. In contrast, WMMSE has a wider error distribution, reflecting higher variability in its power control predictions.

TABLE II
AUC FOR EACH PC METHOD IN CL-MMIMO SYSTEMS

PC Method	AUC
WMMSE	1.2698e+04
SVM-RBF	2.4931e+04

TABLE III
AUC DISTANCE BETWEEN WMMSE AND SVM/RBF-BASED PC METHODS IN CL-MMIMO SYSTEMS

PC Method	AUC Distance From WMMSE
SVM-RBF	1.2233e+04

TABLE IV
AUC DISTANCE BETWEEN WMMSE AND SVM/RBF-BASED PC METHODS IN CF-MMIMO SYSTEMS

Methods	AUC Distance From WMMSE
SVM-RBF	1.1731e+04

TABLE V
EXECUSION TIME COMPARISON FOR WMMSE AND SVM/RBF-BASED PC METHODS IN CL-MMIMO SYSTEMS, EXECUSION TIME (CPU: INTEL(R) CORE I7-4790T @ 2.70 GHZ, RAM: 32.0 GB)

PC Method	Execution Time
WMMSE	14,243.157 sec
SVM-RBF	10,880.267 sec

TABLE VI
EXECUSION TIME COMPARISON FOR WMMSE AND SVM/RBF-BASED PC METHODS IN CF-MMIMO SYSTEMS, EXECUSION TIME (CPU: INTEL(R) CORE I7-4790T @ 2.70 GHZ, RAM: 32.0 GB)

PC Method	Execution Time
WMMSE	12,569.432 sec
SVM-RBF	9,263.510 sec

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VI. COMPARISON WITH EXISTING METHODS

Compared to the work of Zaher et al. [31], which addresses learning-based downlink power allocation in CF systems, our study distinguishes itself in the following ways:

- Scope: Zaher et al. focus exclusively on downlink power allocation in CF massive MIMO systems, whereas our work extends the scope to include both uplink and downlink power control in both CF and CL systems.
- Methodology: While Zaher et al. use supervised deep learning methods, our hybrid SVM/RBF approach achieves comparable accuracy with significantly reduced computational complexity. Additionally, our method eliminates the need for iterative convergence during execution, unlike Zaher et al.'s approach, which relies on model training and iterative optimization.
- Performance Analysis: Our study provides a detailed trade-off analysis of coherence time allocation and demonstrates the practical impact of uplink data duration on system performance, aspects that are not explored in Zaher et al.'s work.

These distinctions highlight the broader applicability and computational efficiency of our proposed method, providing a unique contribution to power control strategies in massive MIMO systems.

Table VI compares the AUC and execution time of different PC methods, showing that the SVM/RBF method outperforms WMMSE, DRL, CNN, and Gradient Descent-based approaches in terms of AUC, demonstrating superior performance in both CL-mMIMO and CF-mMIMO systems. Additionally, the SVM/RBF method executes faster than WMMSE and the other reported methods, highlighting its computational efficiency and suitability for practical, real-time applications.

TABLE VI
THE RESULTS OF THE PERFORMANCE EVALUATION OF THE SVM/RBF-BASED PC METHOD IN CL-MMIMO AND CF-MMIMO SYSTEMS ARE PRESENTED IN THE FOLLOWING TABLES

Methods	AUC (CL-mMIMO)	AUC (CF-mMIMO)	Execution Time (CL-mMIMO)	Execution Time (CF-mMIMO)
SVM-RBF	24.931	-	10,880.267 sec	9,263.510 sec
WMMSE	12,698	-	14,243.157 sec	12,569.432 sec
DRL	24,256	23,855	15,658.112 sec	14,503.659 sec
CNN	23,525	23,346	13,001.256 sec	12,827.754 sec
Gradient Descent	22,869	22,532	12,508.691 sec	12,248.998 sec

VII. DISCUSSION

Despite the advantages of the proposed SVM/RBF-based pc method, certain limitations must be acknowledged. One key challenge is the method's sensitivity to input feature noise. Since the SVM model relies on extracted features for decision-making, any inaccuracies or fluctuations in the dataset can affect prediction reliability. In practical wireless environments, channel conditions vary dynamically, and noise in the input features, such as measurement errors or environmental interference, may reduce the effectiveness of the learned model. While preprocessing techniques like normalization and feature extraction help mitigate some of these issues, future enhancements could explore more robust noise-resilient ML techniques [37, 38].

Another limitation is the method's dependency on accurate channel state information (CSI). The proposed approach assumes reasonably precise CSI during both training and real-time application, but in practice, CSI estimation errors are inevitable. Such inaccuracies could lead to suboptimal power control decisions, affecting system performance. Additionally, although the SVM/RBF method significantly reduces computational complexity compared to iterative techniques like WMMSE, the offline training phase requires careful hyperparameter tuning, which can increase the initial setup time. Future research could explore adaptive learning mechanisms that adjust to varying CSI quality and investigate transfer learning techniques to reduce the need for extensive retraining in different network scenarios [39].

VIII. CONCLUSION

In conclusion, this paper introduces a novel approach for optimizing PC in CL/CF-mMIMO systems, utilizing a hybrid SVM/RBF methodology. By combining the predictive power of SVM regression with the flexibility of RBF kernels, our proposed method achieves superior performance in terms of SE and computational efficiency compared to traditional WMMSE methods. Through extensive simulations, we have demonstrated that the SVM/RBF approach not only enhances system performance but also reduces execution time significantly, making it a promising solution for real-world deployment in large-scale wireless networks. Our findings underscore the importance of leveraging advanced ML techniques for addressing the evolving challenges of PC in next-generation communication systems. Overall, this paper contributes to the advancement of wireless communication technology by offering a robust, efficient, and scalable solution for optimizing PC in complex mMIMO environments.

While our method focuses on optimizing power control, future research could explore the integration of tensor-based techniques, such as those discussed in [2, 3], to enhance channel estimation and further improve system performance. By combining the strengths of machine learning-driven optimization with advanced estimation methods, we can address more complex scenarios and extend the applicability of the proposed approach to emerging communication technologies such as terahertz sensing [4]. Additionally, challenges related to fronthaul

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overhead in cell-free systems, as highlighted in [5], could be mitigated through the incorporation of such advanced techniques, further enhancing computational and communication efficiency.

In the future, we will explore the application of different ML algorithms for PC, such as multi-layer perceptron neural networks (MLPNN) with imperialist competitive algorithm (ICA) [40] or MLPNN with particle swarm optimization (PSO) algorithms [41].

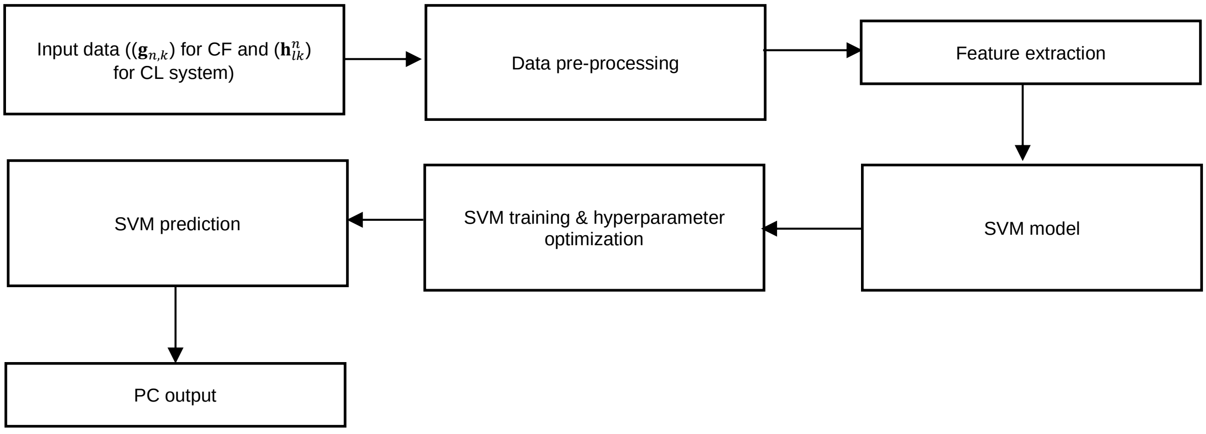

Figure 1. Proposed block diagram of SVM method for PC in CL/CF-mMIMO systems.

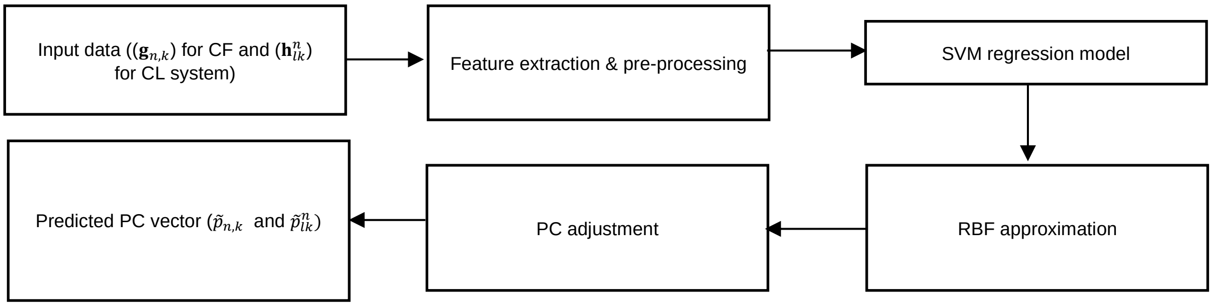

Figure 2. Proposed block diagram of SVM/RBF methods for PC in CL/CF-mMIMO systems.

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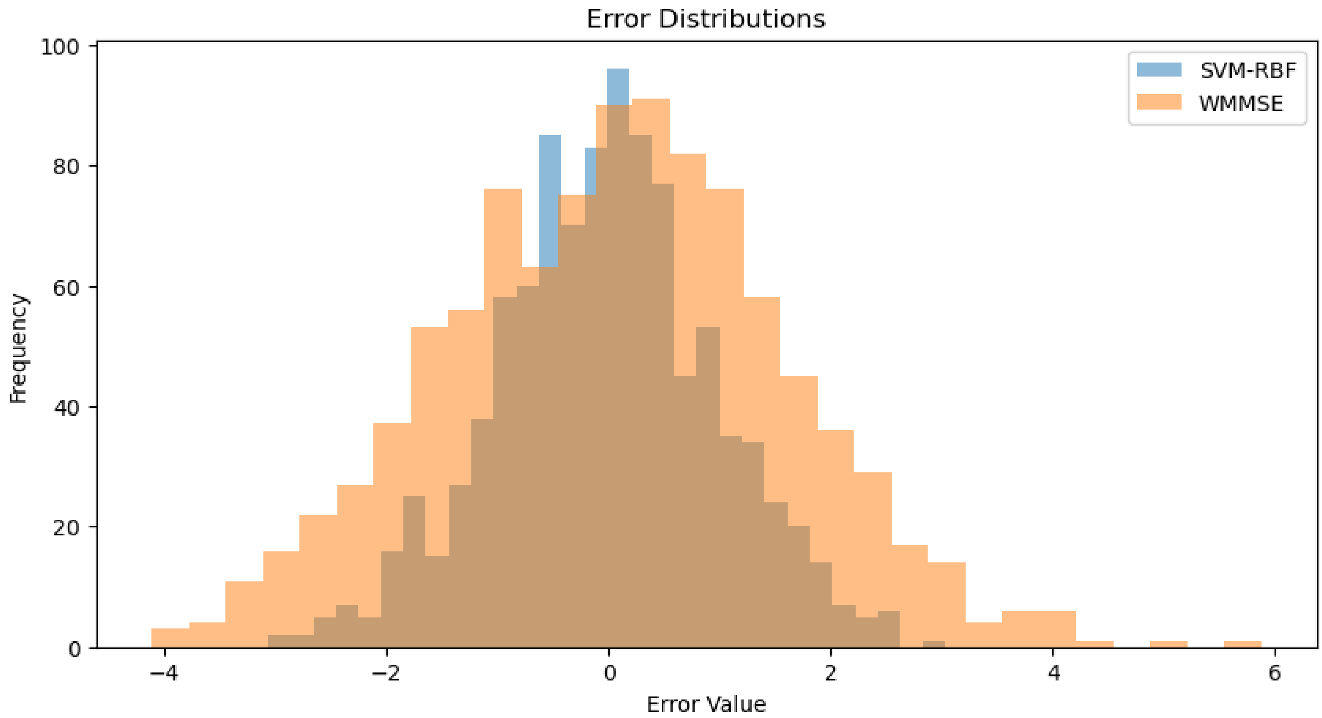

Figure 3. **Convergence plots of SVM/RBF and WMMSE methods.**

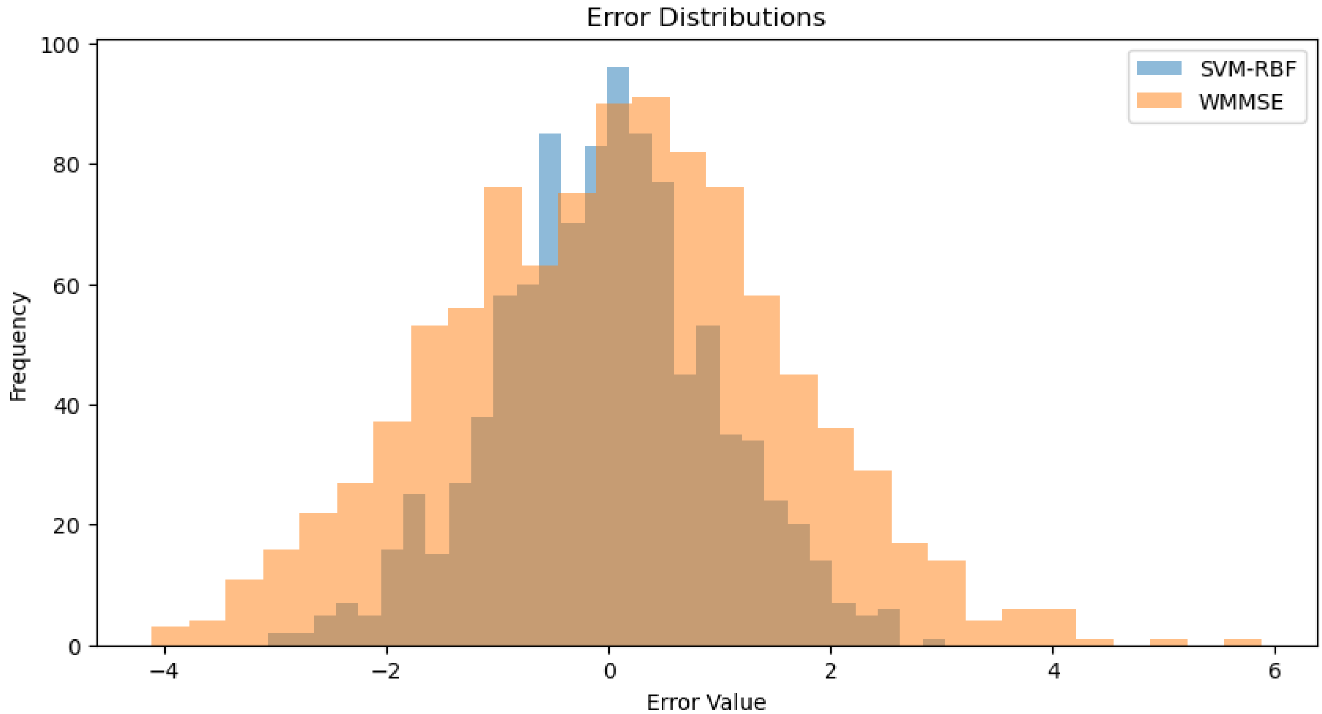

Figure 4. **Error distribution of SVM/RBF and WMMSE methods.**

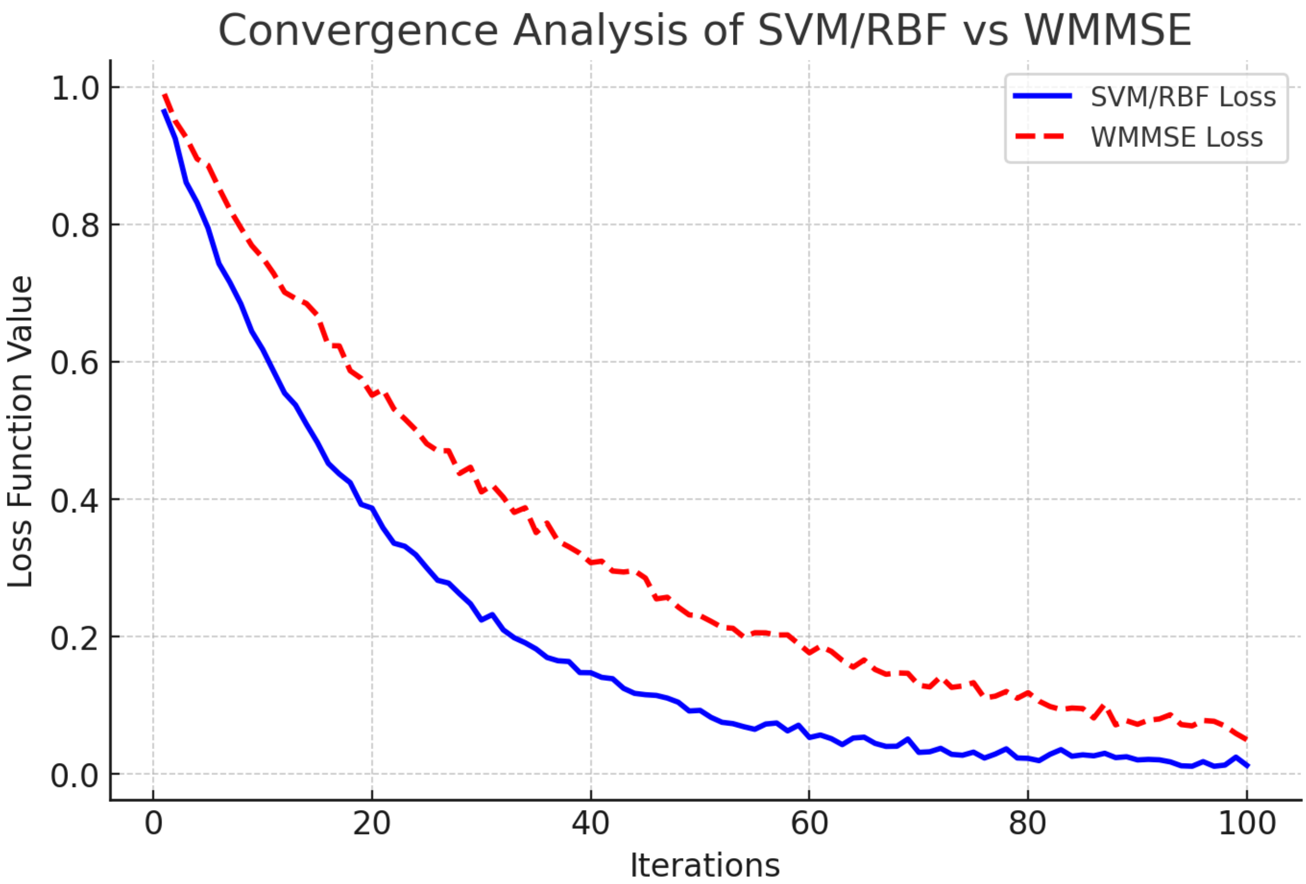

Figure 5. Convergence analysis of the SVM/RBF and WMMSE methods. The SVM/RBF method converges faster, requiring fewer iterations to reach stability compared to WMMSE

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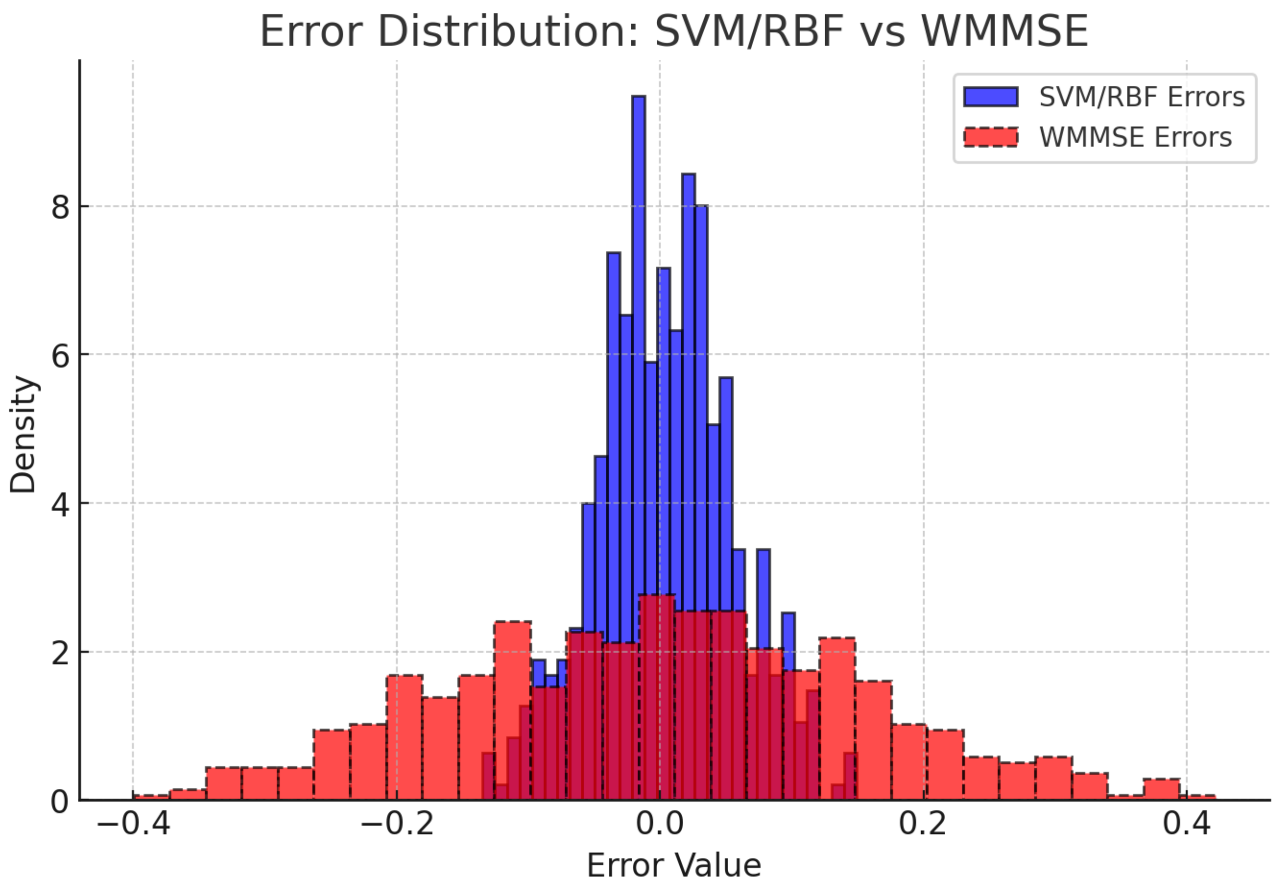

Figure 6. Error distribution of SVM/RBF and WMMSE methods. The SVM/RBF method exhibits lower variance and more accurate power control predictions compared to WMMSE.

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