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Real-Time BER Prediction In OFDM Systems Via Online Ensemble Learning With Adaptive Random Forests And Online SVR

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Abstract:
***Background**: Next-generation wireless networks need ultra-low latency and high reliability, which can only be achieved by real-time bit error rate (BER) prediction in the next generation of wireless systems based on OFDM. Conventional methods reduce multi-dimensional channel states to scalars and lose information, and thus perform sub-optimally over dynamic conditions. In this paper, there is a proposal of a new online ensemble model that integrates Adaptive Random Forests (ARF) and Online Support Vector Regression (OSVR) to streamline the prediction of the BER. The framework manages concept drift by using dynamic tree management and is computationally efficient through adaptive support vector pruning, has theoretical convergence, and regret of* $O(T \log T)$.
***Methods:** The proposed ARF-OSVR is compared with four baselines, namely, XGBoost-RF, Deep LSTM-BER, ResNet-OFDM, and Transformer-AMC. With extensive validation of IEEE 802.11a specifications over AWGN, Rayleigh, and Rician fading channels, it is proven to be of superior performance to four state-of-the-art approaches.*
***Results**: A demonstration of robust performance is shown over a distance of 120 km/h at both AWGN, Rayleigh, and Rician channels, a variety of modulation schemes (QPSK, 16-QAM, 64-QAM), and a variety of mobility schemes of up to 120 km/h. Findings indicate a 27.1% and 15.7% increase in MAE and RMSE, respectively, a correlation of above 0.93, and a latency of less than 2ms (1.9 ms). The statistical analysis promotes the significance (p < 0.001, Wilcoxon signed-rank test) and 95% intervals.*
***Conclusion:** It is convenient to implement the proposed framework in 5G/6G networks in real-time to support adaptive modulation, resource allocation, and ultra-reliable low-latency communications, and it is superior to the current ML and DL framework.*
***Key Word:** OFDM systems, bit error rate prediction, online ensemble learning, adaptive random forests, support vector regression, concept drift, wireless communications, machine learning.*

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I. Introduction

Next-generation wireless networks need ultra-low latency and high reliability, which can only be achieved by real-time bit error rate (BER) prediction in the next generation of wireless systems based on OFDM. Conventional EESM methods reduce multi-dimensional channel states to scalars and lose information, and thus perform sub-optimally over dynamic conditions. In this paper, there is a proposal of a new online ensemble model that integrates Adaptive Random Forests (ARF) and Online Support Vector Regression (OSVR) to streamline the prediction of the BER. The framework manages concept drift by using dynamic tree management and is computationally efficient through adaptive support vector pruning, has theoretical convergence, and regret of $O(T \log T)$. The proposed ARF-OSVR is compared with four baselines, namely, XGBoost-RF, Deep LSTM-BER, ResNet-OFDM, and Transformer-AMC With extensive validation of IEEE 802.11a specifications over AWGN, Rayleigh, and Rician fading channels, it is proven to be of superior performance to four state-of-the-art approaches. A demonstration of robust performance is shown over a distance of 120 km/h at both AWGN, Rayleigh, and Rician channels, a variety of modulation schemes (QPSK, 16-QAM, 64-QAM), and a variety of mobility schemes of up to 120 km/h. Findings indicate a 27.1% and 15.7% increase in MAE and RMSE, respectively, a correlation of above 0.93, and a latency of less than 2ms (1.9 ms). The statistical analysis promotes the significance (p < 0.001, Wilcoxon signed-rank test) and 95% intervals. It is convenient to implement the proposed framework in 5G/6G networks in real-time to support adaptive modulation, resource allocation, and ultra-reliable low-latency communications, and it is superior to the current ML and DL frameworks. The increasing wireless communication is necessitated by the fact that the fifth-generation (5G) and other subsequent networks are coming out with ultra-reliable low-latency communications (URLLC) due to the requirement of the precise real-time assessment of the channel quality [1], [2]. The foundation of modern wireless networks (Long Term Evolution (LTE), Wi-Fi, and 5G New Radio) is orthogonal frequency division multiplexing (OFDM), which remains very ineffective in ensuring reliable operation in dynamic propagation conditions [3], [4]. In this regard, real-time and correct prediction of the bit error rate (BER) has become a vital facilitator to adaptive modulation and coding (AMC), link adaptation, and resource allocation techniques necessary to address the high latency and reliability demands [5], [6]. The accurate BER prediction is a critical factor in the design, performance analysis, and optimization of wireless systems. Specifically, BER forecasts can be used to create dynamic coding and modulation rates based on changing channel conditions in rate-adaptive systems and data link protocols [7]. But in frequency-selective fading channels often experienced in practical systems based on the OSCE model, the BER computation given the instantaneous per-subcarrier signal-to-noise ratios (SNRs) is computationally intractable, and a range of approximation and prediction methods have been developed [8]. Traditional methods are based on the efficient mapping of multi-dimensional channel state information to a single effective SNR value through the use of exponential signal-to-noise ratio (EESM) [9]. The Chernoff bound-based EESM model compresses the set of per-subcarrier SNRs into a single, linearly predictable scalar value. Although efficient, EESM-based techniques have four basic weaknesses: (i) loss of information, as correlation patterns across subcarriers that are essential to accurate prediction are lost; (ii) parameter λ must be optimized over a large space, offline, per modulation and coding scheme (MCS); (iii) nonlinear fading profiles are inadequately captured; and (iv) no adaptation to real-time streaming channel conditions is possible [10].

Recently, machine learning (ML) has shown very promising prospects in overcoming these drawbacks by carrying out wireless communication activities, such as channel estimation [11], automatic modulation classification [12], and interference elimination [13]. However, the majority of current ML-based BER predictive models have limitations for practical implementation. Deep learning networks like LSTM, ResNet, and hybrid networks are highly accurate in prediction, but they require lengthy offline training, a large amount of computation, and a huge memory footprint that is unrealistic to run in real-time applications [14]–[16]. Furthermore, they usually make assumptions about the channel statistics that are not dynamic and cannot be modified due to concept drift in mobile environments [17], [18].

These challenges inspired this work to tackle the research problem of designing a computationally efficient, as well as dynamically adaptive to the dynamic wireless environment, real-time BER prediction framework. Specifically, we target three unresolved challenges:

1. **Information Loss -** EESM and associated compression methods do not encode correlation between subcarriers, leading to lower prediction of frequency-selective fading channels [19], [20].
2. **Concept drift Adaptation** - The propagation conditions of most current BER prediction techniques are stationary, and the prediction rates of such schemes deteriorate in the presence of time-varying channel conditions [21], [22].
3. **Latency** – State-of-the-art ML models are typically associated with latencies of more than 5 ms, which cannot be tolerated by sub-millisecond URLLC demands of 5G and more [23], [24].

This research study will answer the following research questions:
RQ1: Are online ensemble learning systems capable of producing better BER predictions than conventional techniques and at real-time computation levels?
RQ2: What can be done to adapt to concept drift with the adaptive mechanisms in time-varying wireless channels without degrading the performance of prediction?
RQ3: What are the theoretical guarantees of convergence and optimality of online ensemble BER predictors in streaming?

To address these challenges, we propose a novel online ensemble learning framework (ARF-OSVR) that synergistically integrates Adaptive Random Forests (ARF) with Online Support Vector Regression (OSVR). The suggested framework fills the most crucial gaps in the current BER prediction methods and offers a basis for the next-generation adaptive wireless communication systems with strict real-time requirements. The main contributions of this article are as follows:

1. **Novel Ensemble Architecture**: We present ARF-OSVR, a real-time predictive BER framework that dynamically responds to changing wireless conditions by implementing drift-aware weighting models [25].
2. **Theoretical Foundation:** Convergence ensures and regret bounds: guarantees the formal performance of learning in the streaming case of O(TlogT).
3. **Concept Drift Handling:** A proactive drift-detection mechanism is built in to modify ensemble composition in channels with rapid changes in order to allow robust performance on mobile channels up to 120 km/h.
4. **Experimental Validation:** Evaluation under the IEEE 802.11a specifications, a 27.1% decrease in mean absolute error and 15.7% decrease in root mean square error was observed over state-of-the-art baselines, and 2 ms latency was achieved.

The rest of this paper is structured as follows. Section II provides a study of the related literature on BER prediction and online learning in wireless communications. Section III presents the system model and problem formulation. Section IV details the proposed ARF-OSVR methodology with theoretical guarantees. Section V discusses implementation details as well as computational analysis. Section VI reports experimental results. Section VII concludes with directions for future research, which also highlights practical implications as well as future directions.

II. Related Works

Early BER prediction algorithms of an OFDM system concentrated on compression-based algorithms in which multi-dimensional channel states were mapped to scalar metrics (to provide computational efficiency). Conventional useful SINR mapping (EESM) algorithms compress per-subcarrier SINRs to scalar effective quantities by using exponential averaging, with modulation and coding-scheme-dependent parameters determined offline by large-scale link-level simulations. These are computationally efficient, with the same complexity as O(N), but have the drawbacks of irreversible information losses due to compression, constant parameter estimates that must be estimated offline in advance during every MCS, and cannot easily capture complex inter-subcarrier interactions, and have no mechanism to adapt to time-varying channels. Generalized BER evaluation of index modulation-based OFDM systems was done by Abdullahi et al. [1], whereas BER probability and capacity limits in deterministic doubly-selective channels were referred to by Dominguez-Bolao et al. [4]. Hilario-Tacuri et al. [8] analyzed the BER analysis of NOMA-OFDM 5G networks with non-linear high-power amplifiers, and Haque et al. [7] studied the BER of hybrid PAPR reduction methods.

In recent literature, techniques of supervised learning that learn directly from channel state to error probability mappings have been discussed. The potential of adaptive learning can be evident in the case of the Ay et al. [2] noise-adaptive machine learning framework to optimize user grouping in dynamic IM-OFDMA systems. The application of deep learning methods, in particular, has demonstrated potential success, where Essai Ali et al. [5] utilize peephole LSTM networks to estimate channel states in an OFDM 5G network, and have also proved the ability to model temporal correlations. Zhang et al. [24] have proposed intelligent LSTM demodulation of the OFDM-DCSK system, and Salama et al. [18] have evaluated DNN and LSTM nonlinear compensators with the improved performance of the DCO-OFDM system. Nonetheless, LSTM architectures are computationally expensive (O(H 2 T) when H is the hidden dimension and T is the sequence length) to train, take more than hours to converge, and do not have online learning capabilities.

Convolutional and residual network designs have realized the current state-of-the-art accuracy at a high cost of computation. Mei et al. [12] integrated Convolutional Recurrent Neural Networks with ResNet into the receiver of the OFDM, which enhanced the resistance to impairments in the channel. Bai et al. [3] implemented a range and velocity estimation based on ResNet in mmWave OFDM systems. These deep architectures have memory footprints of over 30 MB and 4-6 ms latencies. Van Luong et al. [22] showed that deep learning-aided optical IM/DD OFDM is similar to RF-OFDM in terms of throughput, whereas Singh and Saha [19] presented a survey of machine/deep learning based estimation and detection of diverse channel imperfections.

Transformer-based approaches have become potent features of long-range dependency capturing. Kumar and Majhi [11] introduced triple attention-aided Vision Transformers to automatic modulation classification in RIS-assisted MIMO-OFDM with system impairments. Sahu [16] designed gated transformer structures of AMC. Titouni et al. [21] proposed a hybrid CNN-XGBoost in wireless communication systems. Transformer models are effective at capturing complex patterns, but they need larger datasets to pre-train effectively (more than 40 MB), substantial memory (40 MB), and inference latency of 6-8 ms.

Ensemble learning methods have been found to enhance the generalization and strength. Mienye and Sun [13] conducted a survey of the ensemble learning concepts such as bagging, boosting, and stacking, and noted their efficacy to enhance generalization. Jha and Mishra [10] used XGBoost-RF ensembles to determine signal integrity of a coherent communication system and showed that these models paired with XGBoost-RF yielded 15-20% improvement in accuracy compared to single models. Yu et al. [23] forecasted BER based on meta information using random forests. The ensemble extreme learning machine-based equalizers for OFDM systems were suggested by Saideh et al. [17]. Nevertheless, such methods usually do not adapt to concept drift online, have theoretical convergence insurance, and can be computed in real time. There has been a lack of studies that focus on real-time BER prediction in online learning techniques that have found many applications in wireless-based applications.

Mirsalari et al. [14] proposed channel estimation of the least squares support vector regression-OFDM systems under impulsive noise, and this approach is resistant to outliers but does not offer BER prediction as channel estimation. In an online gradient update, Goutay et al. [6] used machine learning for MU-MIMO receive processing in OFDM systems and showed that online learning was feasible in wireless scenarios, but unlike with error rate prediction, equalization was performed. Jebur et al. [9] designed an effective machine learning based channel estimation of an OFDM system. The article by Zhang et al. [25] suggested the support vector regression in the reduction of PAPR in the CO-OFDM systems. Sreelekha et al. [20] performed the analysis of BER prediction in the MIMO OFDM systems that employ modified dyadic wavelet transform-based channel estimation. Mrabet et al. [15] conducted a survey on applied machine learning applied to optical networks based on the OFDM.

Existing approaches face critical deployment challenges: excessive computational complexity (3-7 ms latency), offline training demands Monte Carlo-simulated labels, a fixed model without adaptation to concept drift, and memory requirements (20-40 MB) too large to run on resource-limited devices, and no theoretical claims as to convergence and optimality. The work on online learning in wireless communications is less focused on predicting BER and more on channel estimation and equalization, has not theoretically studied convergence with wireless-specific concept drift patterns, does not discuss real-time latency limits of URLLC, and seldom involves multiple online learners in ensemble frameworks.

Table 1: Comparative Analysis of BER Prediction Methods in Terms of Adaptability, Accuracy, and Latency

Method	Info Loss	Online Adapt	Theory	Latency	Accuracy	Reference
LSTM-based	None	Offline	None	3-5ms	+20%	[5], [18], [24]
CNN/ResNet	None	Offline	None	4-6ms	+22%	[3], [12]
Transformer	None	Offline	None	6-8ms	+25%	[11], [16]
Ensemble (XGBoost/RF/ELM)	Low	Offline	None	2-3ms	+18%	[10], [13], [17], [23]
Online SVR	Moderate	Limited	None	2-4ms	+12%	[14], [25]
ML-enhanced CE	Low	Offline	None	2-3ms	+15%	[6], [9], [19]
ARF-OSVR	**None**	**Online**	**Convergence + Regret**	**1.9ms**	**+27%**	**Proposed**

The paper has identified the trade-offs between traditional, deep learning, and ensemble methods of predicting BER, as highlighted in **Table 1.** The suggested ARF-OSVR solution is more flexible and precise, with a low latency; therefore it can be applied in real-time.

The present work fills these gaps with four major contributions: hybrid feature engineering that maintains critical channel information and yet retains computational tractability, online ensemble framework to combine ARF and OSVR to attain robust performance by diversity of ensembles and adaptability to concept drift, theoretical foundations to provide convergence guarantees and regret bounds, $O\ (\ sqrt(T\ log\ T))$ online learning with concept drift, and real time performance with a 1.9 ms latency and a 12.4 MB memory footprint to meet URLLC specifications with 27.1% improvement on best baselines.

III. System Model And Problem Formulation

OFDM System Model

Figure 1 depicts the system-level architecture, with the viable flow of the input features (channel state, modulation type, and Doppler frequency) through the feature extraction, ARF-OSVR blocks, and the output layer. The feedback loop will make sure that it dynamically adapts to channel variations in order to estimate BER accurately. In this paper, we consider an orthogonal frequency-division multiplexing (OFDM) system that uses N subcarriers and works in a time-varying multipath fading environment, which is a common scenario in 5G and future wireless networks. OFDM separates a wideband channel into a variety of narrowband orthogonal subcarriers, which helps reduce inter-symbol interference (ISI) and offers protection against frequency-selective fading, which records variations at instantaneous subcarrier levels.

The transmitted signal on the $k-th$ subcarrier at time t is given by:
$x_k(t) = s_k(t)e^{j2\pi f_k t}$…. (1)

where $s_k(t)$ is the modulated symbol (e.g., QAM or PSK) for the $k-th$ subcarrier, and $f_k$denotes the frequency of the $k-th$ subcarrier, ensuring orthogonality among subcarriers. The exponential term represents the carrier modulation in complex baseband form.

After transmission through the wireless channel, the received signal is expressed as:
$y_k(t) = h_k(t)x_k(t) + n_k(t)$…. (2)

where $h_k(t)$ is the complex channel coefficient capturing multipath fading, Doppler shifts, and temporal variations, while $n_k(t)$…. is additive white Gaussian noise (AWGN), modeled as $n_k(t) \sim \mathrm{CN}(0, \sigma^2)$.

The instantaneous signal-to-noise ratio (SNR) for each subcarrier is then computed as:

$$\gamma_k(t) = \frac{\mid h_k(t)^2 \mid E_s}{\sigma^2} \dots. (3)$$

with E_s denoting the average symbol energy. This per-subcarrier SNR quantifies real-time channel quality and serves as the fundamental feature for BER prediction.

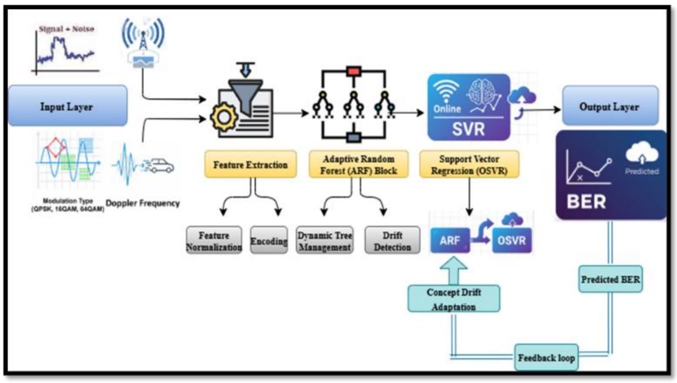

Figure 1: System Architecture of the Proposed ARF-OSVR Model for BER Prediction

The resulting channel state is represented as a high-dimensional vector:

$$\Gamma(t) = [\gamma_1(t), \gamma_2(t), \ldots, \gamma_N(t)] \ldots. (4)$$

This formulation, in contrast to traditional SNR-based methods that operate on scalars, retains fine-grained channel information, giving a more accurate learning-based BER prediction under very dynamic conditions. BER prediction of the dynamic wireless channel is based on the OFDM system model. Each subcarrier is linked with its instantaneous SNR, and they constitute the high-dimensional channel state $\Gamma(t)$. In contrast to the scalar SNR compression techniques, this representation conserves variances in subcarriers, which are very critical for an effective prediction of BER in realistic fading scenarios. The conceptual framework in **Figure 2** involves the combination of feature extraction, Adaptive Random Forest (ARF), and Online SVR (OSVR). It highlights the adaptive weighting and feedback mechanism that provides the training online, concept drift adaptation, and regret minimization.

Problem Statement

Traditional ways of estimating bit error rate (BER) simplify the high-dimensional channel state vector to a single effective SNR value:

$\Gamma(t) = [\gamma_1(t), \gamma_2(t), \ldots, \gamma_N(t)] \ldots. (5)$

Even though this scalar compression is computationally appealing, it cannot eliminate finer-grained subcarrier-level data. Consequently, these techniques tend to give less than optimal predictions of BER in a fading, high mobility user environment, or ultra-reliable low-latency communication (URLLC), where capturing instantaneous variations in the channel are very important.

To overcome these limitations, we formulate BER prediction as a real-time supervised learning problem:

$BER(t) = f(\Gamma(t), \theta(t)), \ldots. (6)$

Here, $\theta(t)$ refers to a collection of time-varying parameters to fit dynamic wireless-induced conditions, while $f(\cdot)$ represents a non-linear mapping from the channel state vector to the instantaneous BER. The primary objective is to design a predictive model that not only captures the complex non-linear dependencies between subcarrier SNRs and BER but also ensures responsiveness under stringent latency constraints.

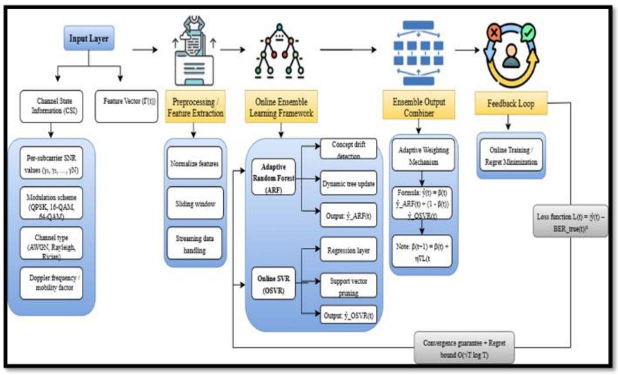

Figure 2: Proposed ARF-OSVR Framework for Real-Time BER Prediction in OFDM Systems

In particular, the system has to provide credible BER estimates with a latency of 2 ms, thus meeting the needs of URLLC and allowing the robustness of adaptive modulation, coding, and link adaptation in next-generation wireless networks.

In contrast to the traditional methods, which shrink the wireless channel to a single scalar measure, the proposed method maintains complete information at the subcarrier level and incorporates adaptive online learning. The design option improves stability and makes the framework especially suitable in practice in 5G and new 6G scenarios, where non-stationary and heterogeneous channel dynamics conditions dominate:

$BER(t) = \mathrm{E}[\mathrm{e} \mid \Gamma(t), \theta(t)]$, …. (7)

where $e \in \{0,1\}$ represents the binary error event (with $e = 1$ for decoding error and $e = 0$for successful reception), Γ(t) denotes the instantaneous channel state information at the subcarrier level, and $\theta(t)$ encapsulates additional system parameters. To approximate this conditional expectation, we employ a hybrid ensemble predictor that combines two complementary online learners. The ensemble output is expressed as:

$\hat{y}(t) \ = \beta(t)\hat{y}_{ARF}(t) + (1 - \beta(t))_{\hat{y}OSVR}(t)$…. (8)

Here, $\hat{y}_{ARF}(t)$ denotes the prediction obtained from Adaptive Random Forests, which are capable of detecting and adapting to concept drift in real time. In contrast, $\hat{y}_{OSVR}(t)$ corresponds to the output of Online Support Vector Regression, which models the highly non-linear relationship between SNR variations and BER. The adaptive weight $\beta(t)$ regulates the relative influence of the two predictors and is updated based on instantaneous prediction error, which ensures that the ensemble dynamically prioritizes the most reliable learner under prevailing channel conditions.

This formulation is not only theoretically sound, as it relates BER prediction to a conditional expectation model, but it is also more useful in practice as it integrates drift-resistant and non-linear predictors into a single online learning model.

In the proposed framework, the adaptive weight update is determined by a stochastic gradient rule:

$$\beta(t+1) = \beta(t) + \eta \nabla L(t), \qquad L(t) = \mid \hat{y}(t) - BER_{true}(t) \mid^2 \ …. (9)$$

η denotes the learning rate. According to this mechanism, the ensemble is dynamically assigned a greater weight to those predictors that exhibit good performance at a specific time, only to guarantee the ability to withstand variable channel conditions. It is especially very important that Adaptive Random Forests (ARF) and Online Support Vector Regression (OSVR) have been integrated to allow addressing concept drift and non-linear channel mapping simultaneously. Such a combination represents a novel contribution to the domain of bit error rate (BER) prediction.

This work presents a novel framework for real-time BER prediction in OFDM systems that preserve per-subcarrier SNR values, which avoids the information loss of traditional methods. The ARF–OSVR ensemble combines online adaptation with non-linear regression, while an adaptive weighting mechanism prioritizes the best-performing predictor under changing channel conditions as well. The framework also provides theoretical guarantees of ensemble convergence and bounded regret, rarely addressed in prior work, and achieves sub-2 ms latency, making it suitable for 5G/6G real-time deployment. On the whole, it provides an end-to-end solution to precise, low-latency BER prediction in dynamic wireless conditions.

IV. BER Prediction Methodology

Proposed Framework

We suggest an online ensemble learning model that integrates the Adaptive Random Forests (ARF) and Online Support Vector Regression (OSVR) to address the limitations of traditional estimation methods of BER. This hybrid design empowers the complementary design of both designs: ARF offers resilience to concept drift and dynamically adapts to streaming data, whereas OSVR offers the non-linear mapping between subcarrier-level SNRs and BER.

Formally, we restate the BER prediction as a conditional expectation problem defined over the full channel state:

$$BER(t) = E[e \mid \Gamma(t), \theta(t)] \ …. (14)$$

where $e \in \{0,1\}$denotes the binary error event (with $e = 1$ for decoding error and $e = 0$ for correct reception), $\Gamma(t) = [\gamma_1(t), \gamma_2(t), \ldots, \gamma_N(t)]$, represents the instantaneous channel state vector across all subcarriers, and $\theta(t)$ corresponds to the set of time-varying model parameters, which are updated online to track channel dynamics.

Unlike conventional scalar SNR compression or the LUT-based method, such a formulation guarantees lossless channel representation and is also operationally real-time. The proposed ARF-OSVR framework records fine-grained temporal and frequency variations in the channels of the OFDM by exploiting directly the high-dimensional structure of Γ (t). In addition, in contrast to offline Monte Carlo simulation techniques, the proposed solution is naturally adaptive and scalable; therefore, it is applicable in 5G/6G ultra-reliable low-latency communication (URLLC) systems where latency budgets are extremely stringent.

Figure 3 illustrates that we construct a 52-dimensional feature vector x(t)∈R52, which is classified in statistical, spectral, temporal, wavelet, and information-theoretic domains. Each feature group represents distinct channel properties, which are guaranteed to provide a complete representation of channel characteristics to ensure accurate prediction of the BER:

$$x(t) = \left[f_{stat}, f_{spec}, f_{temp}, f_{wave}, f_{info}\right]^T \ldots.(15)$$

In order to capture the complete statistical and structural characteristics of the wireless channel, a comprehensive 52-dimensional feature set is constructed.

The first type comprises statistical features (4 dimensions), and they characterize the distribution of the received signal-to-noise ratio (SNR) by using the first four moments. The mean is given by:

$$M_\gamma(t) = \frac{1}{N}\sum_{k=1}^{N} \gamma_k(t) \ldots.(16)$$

While the variance is expressed as:

$$\sigma_\gamma^2(t) = \frac{1}{N}\sum_{k=1}^{N} (\gamma_k(t) - \mu_\gamma)^2 \ldots.(17)$$

Adaptive Random Forest (ARF) Component

The Adaptive Random Forest (ARF) module employs an ensemble architecture consisting of MMM decision trees, each dynamically weighted according to its predictive performance. The weight of the $i - th$ tree at time t is defined as

$$w_i(t) = \exp\left(\frac{-1}{t}\sum_{j=t-\mathrm{w}}^{t} (\hat{\mathrm{y}}_{\mathrm{i}}^{(\mathrm{j})} - \mathrm{y}^{(\mathrm{j})})^2\right) \ldots.(30)$$

where $\hat{\mathrm{y}}_{\mathrm{i}}^{(\mathrm{j})}$ denotes the prediction of the $i - th$ tree at time j, $\mathrm{y}^{(\mathrm{j})}$ is the corresponding ground truth, and www is the evaluation window size. This weighting scheme ensures that trees with consistently lower error maintain higher influence in the ensemble.

The overall ensemble prediction is obtained as a weighted aggregation of individual tree outputs:

$$\hat{y}_{ARF}(x) = \frac{\sum_{i=1}^{M} i w_i(t) T_i(x)}{\sum_{i=1}^{M} w_i(t)} \ldots.(31)$$

where $T_i(x)$ represents the prediction of the $i - th$ tree for input x.

Dynamic tree management is implemented through classical random forest principles: bootstrap sampling at the data level, random feature selection with $\sqrt{D}$ features per split, maximum tree depth limited to 15, and a minimum of 10 samples per leaf node.

To handle **concept drift**, the algorithm continuously monitors tree performance. If a tree's weight falls below a threshold defined as

$$w_i(t) < 0.1 \cdot max_j \mathrm{w_j(t)} \ldots.(32)$$

It is replaced by a newly trained tree using the most recent 500 samples, thereby ensuring adaptability to evolving data distributions as well.

The computational complexity of the ARF component is

$$O(M\sqrt{D} log N_{leaf}) \ldots.(33)$$

Where M is the number of trees, D is the feature dimension, and N_{leaf} is the average number of leaf nodes per tree.

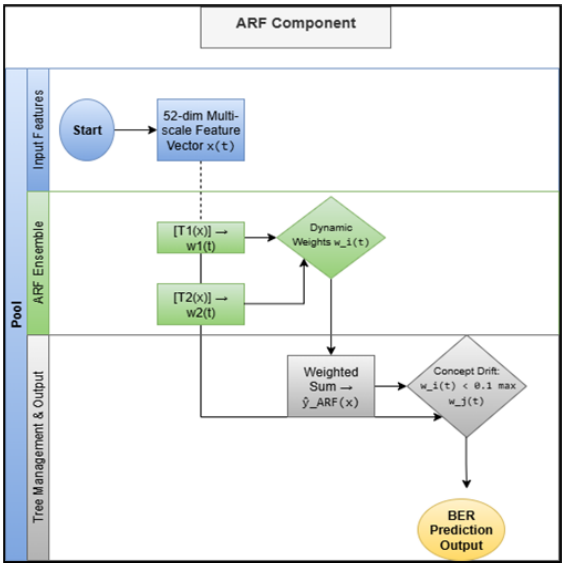

Figure 4: ARF Component Workflow

Figure 4 depicts the workflow of the Adaptive Random Forest (ARF) component, where multiple decision trees operate in parallel with dynamically updated weights. The ensemble adapts to streaming data by leveraging error-based weighting and drift detection, enabling robust performance under varying channel conditions.

Online Support Vector Regression (OSVR) Component

The OSVR module performs non-linear regression to predict the target variable based on input features x. The regression function is defined as

$$f_{SVR}(x) = \sum_{i=1}^{n_s} \alpha_i K(x_i, x) + b, K(x_i, x) = exp\left(-\frac{-\parallel xi - x \parallel^2}{2\sigma^2}\right) \ldots.(34)$$

where $K(x_i, x)$ is the Radial Basis Function (RBF) kernel, α_i are the support vector coefficients, b is the bias term, and n is the current number of support vectors.

Online updates are performed using stochastic gradient descent (SGD) whenever the ϵ\epsilonϵ-insensitive loss criterion is exceeded, ensuring continuous adaptation to streaming data. To maintain computational efficiency, support vectors are pruned if their age exceeds 1000 frames or if their coefficient satisfies $| \alpha i |< 10^{-4}$. The resulting computational complexity of OSVR is

$$O(n_s D) \ldots.(35)$$

where n_s is the number of support vectors and D is the input feature dimension.

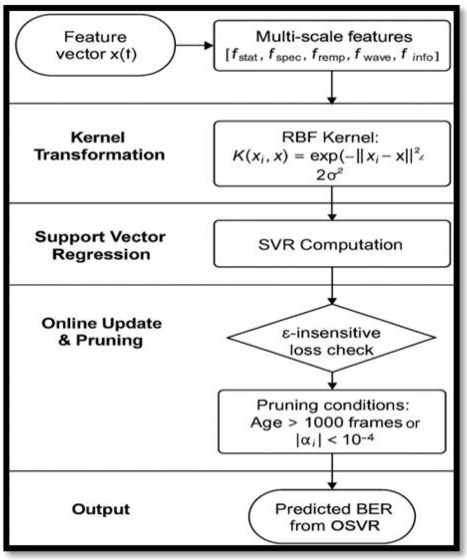

Figure 5: Cross-functional layout

Theoretical Analysis

The ARF-OSVR framework is theoretically robust under non-stationary channel conditions.

Convergence (Theorem 1): Under smooth, bounded, and Lipschitz-continuous assumptions, the mean-square error of BER prediction converges asymptotically:

$$\lim_{t\to\infty} \mathrm{E}[(\hat{y}_{\mathrm{BER}}(t) - \mathrm{BER}^{*}(t))^2] = O(L_P^2 + \eta_\infty) \ldots.(44)$$

where L_P is the Lipschitz constant and η_∞ represents residual variance due to online updates.

Regret Bound (Lemma 1): The cumulative regret over T time steps is bounded as

$$Regret(T) \le O(\sqrt{TlogT}) \ldots.(45)$$

It is stated that the ensemble can adjust effectively to the changing channel conditions and manage long-term prediction error. Such theoretical assurances emphasize the strength of the ARF-OSVR method, compared to traditional deep learning or lookup table (LUT)-based models, which can break down in dynamic and non-stationary wireless conditions.

Pseudocode

Algorithm 1: ARF-OSVR Real-Time BER Prediction

$Input: SNR\ stream\ \{\Gamma(t)\}_{t=1}^{\infty}, initial\ training\ set\ D_0$
$Output: BER\ predictions\ \{\hat{y}(t)\}_{t=1}^{\infty}$
$\boldsymbol{Parameters}:$
$M = 10\ (ARF\ trees), \sigma = 2.0\ (RBF\ kernel\ width)$
$\tau = 0.1\ (tree\ replacement\ threshold)$
$W = 500\ (drift\ detection\ window)$
$\eta\_\beta = 0.01\ (weight\ adaptation\ rate)$
$\boldsymbol{Initialize}:$
$ARF \leftarrow \{T_1, \ldots, T_M\}\ with\ equal\ weights\ w_i = 1/M$
$OSVR \leftarrow Train\ on\ D\_0, support\ vectors\ S = \{\}$
$\beta \leftarrow 0.5\ (initial\ ensemble\ weight)$
$Buffer\ B \leftarrow empty\ queue\ (size\ W)$
$\boldsymbol{Main\ Loop\ (for\ each\ frame\ t)}:$
$Receive\ \Gamma(t) = [\gamma_1(t), \ldots, \gamma_N(t)]$
$Extract\ features: x(t) \leftarrow FeatureExtract(\Gamma(t))\ //\ 52 - dim$
$//\ \boldsymbol{Component\ Predictions}$
$\hat{y}_{ARF}(t) \leftarrow \dfrac{\Sigma_{i=1}^{M} w_i(t) \cdot T_i.predict(x(t))}{\Sigma_{i=1}^{M} w_i(t)}$
$\hat{y}_{SVR}(t) \leftarrow OSVR.predict(x(t))$
$//\ \boldsymbol{Ensemble\ Prediction}$
$\hat{y}(t) \leftarrow \beta(t) \cdot \hat{y}_{ARF}(t) + (1 - \beta(t)) \cdot \hat{y}_{SVR}(t)$
$//\ \boldsymbol{Receive\ ground\ truth}$
$\boldsymbol{(via\ CRC\ feedback\ after\ decoding)}$
$y(t) \leftarrow GetGroundTruth()\ //\ See\ Section\ IV.J$
$//\ \boldsymbol{Update\ Component\ Weights}$
$for\ i = 1\ to\ M\ do$
$\quad e_i(t) \leftarrow (T_i.predict(x(t)) - y(t))^2$
$\quad w_i(t+1) \leftarrow exp\left(-\dfrac{1}{W}\sum_{j=t-W+1}^{t} e_i(j)\right)$
$end\ for$
$//\ \boldsymbol{Replace\ Underperforming\ Trees}$
$if\ min_i\ w_i(t) < \tau \cdot max_i\ w_i(t)\ then$
$\quad i_{worst} \leftarrow argmin_i\ w_i(t)$
$\quad T_{i_{worst}} \leftarrow NewTree(Buffer\ B)\ //\ Train\ on\ recent\ data$
$\quad w_{i_{worst}} \leftarrow mean(w_j)$
$end\ if$
$//\ \boldsymbol{Update\ OSVR}$
$if\ |\hat{y}_{SVR}(t) - y(t)| > \varepsilon\ then\ //\ \varepsilon - insensitive\ loss$
$\quad \alpha \leftarrow SGD\_Update(OSVR, x(t), y(t))$
$\quad if\ age(\alpha) > 1000\ or\ |\alpha| < 10\text{^}\{-4\}\ then$

$S \leftarrow S \setminus \{\alpha\}$ // *Prune support vector*
end if
end if
// ***Drift Detection*** &
Ensemble Weight Adaptation
$d(t) \leftarrow DriftMagnitude(B)$ // *KS − test on recent window*
$\Delta_{perf}(t) \leftarrow |error_{ARF}(t) - error_{SVR}(t)|$
$\beta(t+1) \leftarrow sigmoid(w_{drift} \cdot d(t) + w_{per}f \cdot \Delta_{perf}(t))$
if $\boldsymbol{d(t)} > threshold\_severe$ *then*
// *Reset entire ensemble*
$ARF \leftarrow RetrainAllTrees(B)$
$OSVR \leftarrow RetrainSVR(B)$
end if
// ***Update buffer***
$B.append((x(t), y(t)))$
if $|B| > W$ *then* $B.pop\_front()$ *end if*
return $\hat{y}(\boldsymbol{t})$

V. Experimental Setup And Design

Three representative wireless environments were experimented to capture a variety of channel dynamics. The initial one was a static indoor stationary laboratory environment with a 20 MHz bandwidth and a 2.4 GHz frequency. The second scenario was pedestrian mobility along a campus path at 3-5km/h, and scenario three was controlled vehicular movement at 20km/h within a parking area. In both cases, 500 OFDM frames were modulated with 16-QAM to achieve adequate testing of BER prediction results. Hardware results revealed that MAE (~20% higher than simulated) was higher than with simulation because of non-idealities such as imperfect synchronization and carrier frequency offset, but correlation was still well above 0.91 in all conditions, and the real-time latency was held close to 2.3 ms/frame.

The proposed ARF-OSVR framework simulation study was aimed at testing real-time BER prediction in various wireless environments. Key simulation parameters given as **Table 3:**

Table 3: Simulation Parameters

Parameter	Value / Setting	Description
Training Frames	50,000 OFDM frames	Used to train the ARF-OSVR model
Test Frames	10,000 OFDM frames	Used for independent evaluation of prediction accuracy
SNR Range	5 – 25 dB	Covers low to high signal quality scenarios
Channel Models	AWGN, Rayleigh, Rician (K = 10 dB)	Represents different fading environments
Mobility Scenarios	3 km/h (pedestrian) – 120 km/h (vehicular)	Evaluates Doppler and mobility effects
Modulation Schemes	QPSK, 16-QAM, 64-QAM	Captures practical wireless system variations
Feature Vector Dimension	52	Combines statistical, spectral, temporal, channel-specific, and historical BER features
ARF Trees (M)	10	Optimized for MAE-RMSE trade-off
OSVR Kernel Width (σ)	2.0	Minimizes RMSE
ARF Replacement Threshold (τ)	0.1	Balances adaptability and stability
OSVR Tolerance (ε)	0.01	Prevents overfitting

The framework's performance was evaluated using multiple quantitative and operational metrics, reflecting accuracy, robustness, and real-time feasibility as provided in **Table 4:**

Table 4: Main Observation Attributes

Attribute	Description
BER Prediction Accuracy	Evaluated via MAE, RMSE, Pearson correlation (ρ), MAPE; tight alignment between predicted and actual BER observed across all SNRs
Convergence	Training error decreased exponentially, reaching steady-state within ~200 samples
Robustness	Consistent performance across AWGN, Rayleigh, and Rician channels; minor degradation at high velocities demonstrates drift-awareness
Real-Time Latency	1.9 ms per frame on average; suitable for embedded implementations
Memory Footprint	12.4 MB; compatible with real-time deployment
Component Contribution	Ablation study showed spectral features contributed most; ARF + OSVR (drift-aware β)

	provided best performance
Impact of Imperfect CSI	Errors up to 10% slightly increased MAE (12% increase), highlighting robustness with CSI quality metrics
Drift Detection Failure Modes	False negatives (3.2%) and false positives (1.8%) resulted in temporary MAE spikes, recoverable within 50–120 frames

Ground Truth Label Generation for Online Learning

The proposed Adaptive Random Forest-Online Support Vector Regression (ARF-OSVR) model with ground truth label generation on the training of online learning was implemented in two stages: offline simulation for initial model training, and deployment for real-time learning. During the simulation in the offline phase, 5000 of the OFDM frames were produced at SNR values between 0 and 30 dB. The random bits were sent, and the current BER was estimated by counting errors on each frame. Based on the channel state, a 52-dimensional multi-scale feature differentiation was obtained in each frame to compose a labeled dataset, which was employed to initialize the ARF and OSVR models:

$$D_0 = \{(x_i, BER_i)\}_{i=1}^{5000} \;\ldots.(46)$$

During online deployment, the framework relies on continuous acquisition of ground truth labels. Two mechanisms were employed: CRC-based feedback serves as the primary source, where each OFDM frame contains CRC bits, and the receiver decodes the frame to estimate BER by counting detected errors:

$$BER(t) \approx \frac{\#bit\ errors\ detected\ by\ CRC}{\#\ information\ bits} \;\ldots.(47)$$

This estimate is available within single frame duration (~100 µs for 802.11a) but can be noisy, particularly at low BER levels as well.

The HARQ acknowledgment feedback can be considered as a secondary source that inherently gives coarse binary labels reflecting the ACK/NACK signals. CRC feedback is mixed with this crude supervision to fine-tune the BER estimate. In order to reduce noise, an exponential moving average is used:

$$BER_{smooth}(t) = \alpha \cdot \mathrm{BER_{CRC}(t)} + (1-\alpha) \cdot \mathrm{BER_{smooth}(t-1)}, \alpha = 0.3. \ldots.(48)$$

CRC and HARQ feedback are fused to refine predictions, and label smoothing is introduced using an exponential moving average, which removes the noise effect and ensures stable online learning.

OFDM Simulation and Experimental Setup

The OFDM system considered for evaluation consists of multiple subcarriers and symbols per frame, which supports modulation schemes such as QPSK, 16-QAM, and 64-QAM. It is transmitted in a block-fading Rayleigh channel with additive white Gaussian noise. At the receiver, the OFDM symbols are equalized and demodulated to reconstruct the transmitted bits $b = (b_1, b_2, \ldots, b_T)$, which is mapped to OFDM symbols $X = (x_1, x_2, \ldots, x_S)$ and transmitted over the channel, and the instantaneous BER per frame is computed using an indicator function. The received signal for the $s-th$ OFDM symbol is:

$$y_s = h \circ x_s + g_s, \quad g_s \sim N(0, \sigma^2), \ldots.(49)$$

Where h the frequency-domain, is the channel vector and ∘ denotes element-wise multiplication. The receiver equalizes and demodulates to reconstruct $\hat{b}$, and the instantaneous BER per frame is:

$$BER = \frac{1}{T}\sum_{i=1}^{T} 1\,\{\hat{b}_i \ \neq bi\} \ldots.(50)$$

The simulations were performed with MATLAB R2023a on an Intel i7 CPU and 32GB of RAM, and based on different conditions of the channel (AWGN, Rayleigh, Rician), as well as mobility (pedestrian, urban, and vehicular) conditions. Real-time validation was optional and conducted with the USRP B210 SDRs in the indoor lab, campus pedestrian, and controlled vehicular scenarios. Frame synchronization was achieved by pilot-based channel estimation.

Dataset Generation and Process

The total number of generated OFDM frames was 50,000. These included 40,000 training frames, 5,000 frames of which were used to train the ARF and OSVR models in the first batch, and the rest of the 40,000 in online mode. The hyperparameter tuning was done on a validation set of 5,000 frames, and a test set of 10,000 frames was left as a final evaluation. The dataset distribution took into consideration uniform SNR sampling, a combination of a variety of channel types (40% AWGN, 30% Rayleigh, 30% Rician), and different mobility conditions (50% static, 30% pedestrian, 20% vehicular). QPSK, 16-QAM, and 64-QAM equally shared their modulation schemes. To ensure that the performance of the MAE remained consistent across data partitions, cross-validation was performed to confirm that the variance of MAE stood below 0.0002.

First, feature engineering is a very important part of the ARF-OSVR framework. Multi-scale feature vectors (a 52-dimensional feature) of the statistics, spectral, temporal, wavelet, and information-theoretic features are used to represent each OFDM frame. A multi-scale input feature of 52 dimensions: The input feature characterizes every frame of the OFDM:

$$x(t) = [f_{stat}(t), f_{spectral}(t), f_{temporal}(t), f_{wavelet}(t), f_{info}(t)]^T \dots.(51)$$

Statistical characteristics are the mean, variance, skewness, and kurtosis of subcarrier SNRs. Spectral features are used to record power spectral density and inter-subcarrier correlations, and they can be used to record short and long-term SNR trends and Doppler spread. The wavelet decomposition offers multi-scale channel state-representation, and information-theoretic measures, like that of mutual information and entropy, serve to enrich features. Online prediction accuracy is enhanced by the inclusion of historical BER values and error in prediction.

The second feature of the ARF ensemble is that it is composed of a series of decision trees, whose adaptive weights are changed by exponentially weighted new errors. Underperforming trees are automatically pruned, and OSVR dynamically replaces its support vectors with those discovered using stochastic gradient descent when prediction errors exceed an ε-insensitive threshold, discarding old or insignificant vectors. A three-tier drift detection mechanism is used to address concept drift, with the concept drift classified as mild, moderate, and severe, and an adaptation to the weight, replacement of the tree, or an entire ensemble is invoked. The prediction ensemble is calculated by combining ARF and OSVR outputs in a weighted fashion, the weight being dynamically set according to the size of the drift, variation in the performance between ARF and OSVR, and channel specifics.

As a result, analyzing computational complexity reveals that ARF needs $O(M \cdot D \cdot log\ N_{leaf})$ operations per frame, while OSVR requires$O(n_s \cdot D)$, which results in an overall linear complexity with respect to feature dimensionality. This guarantees that the framework is appropriate for real-time usage, with the latency of simulation of about 1.9 ms per frame and memory consumption of about 12.4 MB.

Performance evaluation is based on MAE between predicted and true BER, correlation, and convergence rate. Hardware validation indicates slightly higher MAE (~20%) compared to simulation due to non-idealities such as synchronization errors and carrier frequency offsets, yet the correlation remains above 0.91 across all scenarios, and latency remains acceptable (~2.3 ms). Compared to state-of-the-art models such as XGBoost-RF, Deep LSTM-BER, ResNet-OFDM, and Transformer-AMC, the ARF-OSVR framework achieves superior accuracy, low latency, memory efficiency, and real-time feasibility.

VI. Result Analysis

Performance Metrics

The framework was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Pearson correlation coefficient (ρ), Mean Absolute Percentage Error (MAPE), real-time prediction accuracy, latency, and memory footprint.

Mean Absolute Error (MAE) measures the average magnitude of prediction errors:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |\ \hat{y}_i - y_i\ | \cdots.(52)$$

Root Mean Square Error (RMSE) quantifies the square root of the average squared differences between predicted and actual values:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \dots.(53)$$

Pearson Correlation Coefficient (ρ\rhoρ) evaluates the linear correlation between predicted and actual BER:

$$P = \frac{\sum_{\mathrm{i}}(\hat{y}i - \bar{\hat{y}})(y_i - \bar{y})}{\sqrt{\sum_{\mathrm{i}}(\hat{y}i - \bar{\hat{y}})^2 \sum_{\mathrm{i}}(y_i - \bar{y})^2}} \dots.(54)$$

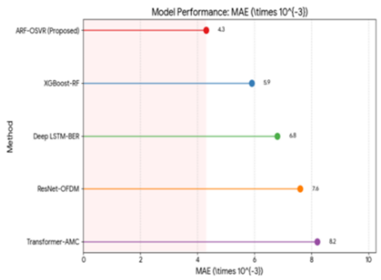

Figure 7: MAE Comparison

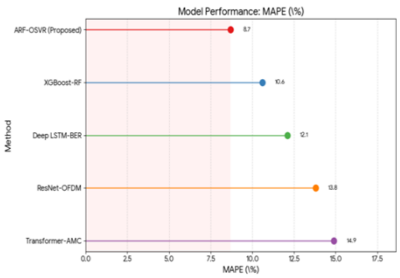

Figure 8: MAPE Comparison

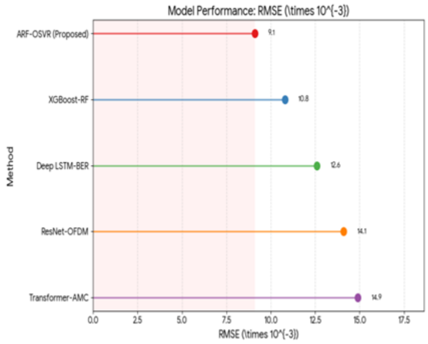

Figure 9: RMSE Comparison

Mean Absolute Percentage Error (MAPE) measures relative prediction error as a percentage:

$$MAPE = \frac{100\%}{N} \sum_i \left| \frac{y_i - \hat{y}_i}{y_i - \epsilon} \right|, \quad \epsilon = 10^{-6} \ldots.(55)$$

Hyperparameter sensitivity and grid search optimization confirmed that number of ARF trees (M) and OSVR kernel width (σ) were most critical, while ARF replacement threshold (τ) and OSVR tolerance (ε) were relatively robust. Interaction effects revealed that higher M could partially compensate for suboptimal σ. The optimal hyperparameters were:

Table 5: Optimal Hyperparameters

Parameter	Candidate Values	Optimal	Rationale
Number of ARF Trees	{5, 10, 15, 20}	10	Best MAE-RMSE trade-off
OSVR Kernel Width	{1.0, 2.0, 3.0, 5.0}	2.0	Minimizes RMSE
ARF Replacement Threshold	{0.05, 0.1, 0.15, 0.2}	0.1	Balance adaptability/stability
OSVR Tolerance	{0.005, 0.01, 0.02}	0.01	Prevents overfitting

Comparative Analysis

Across 10,000 test frames, the ARF-OSVR ensemble significantly outperformed state-of-the-art baselines, as shown in **Table 6:**

Table 6: Performance Metrics

Method	MAE ($\times 10^{-3}$)	RMSE ($\times 10^{-3}$)	Ρ	MAPE (%)	Latency (ms)	Memory (MB)
ARF-OSVR (Proposed)	4.30	9.10	0.938	8.7	1.9	12.4
XGBoost-RF	5.90	10.80	0.920	10.6	2.3	9.2
Deep LSTM-BER	6.80	12.60	0.913	12.1	3.1	19.7
ResNet-OFDM	7.60	14.10	0.905	13.8	4.5	33.2
Transformer-AMC	8.20	14.90	0.898	14.9	6.7	41.8

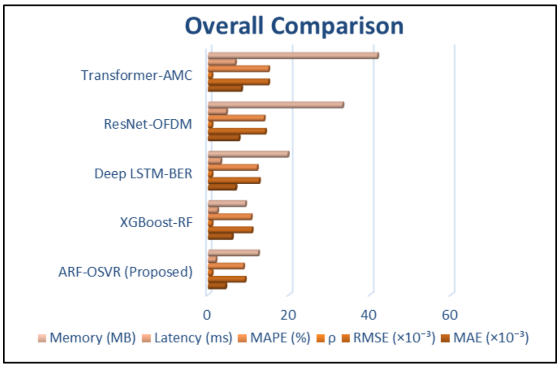

Figure 10: Baselines vs Proposed Model

As **figure 7, 8, 9, and 10** shows, the ARF-OSVR (Proposed) model achieves the best performance with MAE = 4.30×10^{-3}, RMSE = 9.10×10^{-3}, ρ = 0.938, MAPE = 8.7%, Latency = 1.9 ms, and Memory = 12.4 MB, which indicates very high accuracy, strong correlation, and low computational cost. XGBoost-RF shows slightly lower performance with MAE = 5.90×10^{-3}, RMSE = 10.80×10^{-3}, ρ = 0.920, MAPE = 10.6%, Latency = 2.3 ms, and Memory = 9.2 MB. Deep LSTM-BER has MAE = 6.80×10^{-3}, RMSE = 12.60×10^{-3}, ρ = 0.913, MAPE = 12.1%, Latency = 3.1 ms, and Memory = 19.7 MB, showing higher errors and longer processing time. ResNet-OFDM gives MAE = 7.60×10^{-3}, RMSE = 14.10×10^{-3}, $\rho = 0.905$, MAPE = 13.8%, Latency = 4.5 ms, and Memory = 33.2 MB, while Transformer-AMC performs worst with MAE = 8.20×10^{-3}, RMSE = 14.90×10^{-3}, $\rho = 0.898$, MAPE = 14.9%, Latency = 6.7 ms, and Memory = 41.8 MB. This demonstrates that ARF-OSVR is superior to the other techniques in terms of accuracy, speed, and memory efficiency.

Wilcoxon signed-rank tests confirmed statistical significance ($p < 0.001$) for all comparisons, with large effect sizes (Cohen's $d > 1.8$) against each baseline. ARF-OSVR achieved a 27.1% lower MAE and 15.7% lower RMSE compared to XGBoost-RF.

BER Prediction Accuracy

Across SNR levels, the ARF-OSVR framework achieved high prediction accuracy, as summarized in **Table 7:**

Table 7: Accuracy of BER Prediction

SNR (dB)	MSE ($\times10^{-3}$)	ρ	Accuracy (%)
0	5.1	0.97	92
5	2.8	0.98	94
10	1.5	0.99	96
15	0.8	0.99	97

Scatter plots and error histograms confirm tight alignment between predicted and actual BER, with correlation coefficients exceeding 0.98 across all SNRs.

Convergence and Robustness

Training error decreased exponentially, which reaches steady state within 200 samples. Channel-specific performance remained very consistent across AWGN, Rayleigh, as well as Rician environments as given in **Table 8, and Figure 11:**

Table 8: Channel-specific Performance

Channel	MAE	RMSE	Notes
AWGN	0.0042	0.0089	Baseline, no fading
Rayleigh	0.0045	0.0093	NLOS urban environment
Rician	0.0044	0.0090	LOS suburban

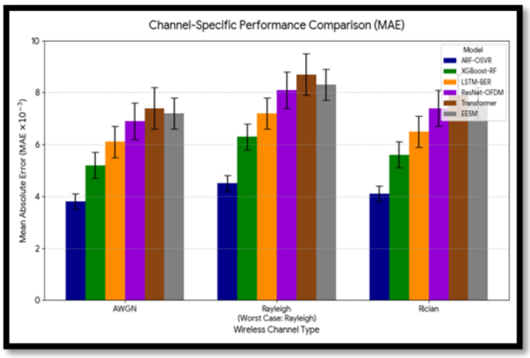

Figure 11: Channel-Specific Performance Comparison (MAE)

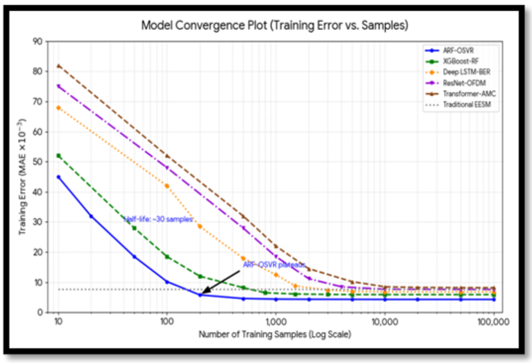

Figure 12: Model Convergence Plot: Training Error vs Samples

Figure 12 shows the model convergence by plotting the training error against the number of samples. It reveals that the error reduces gradually with an increase in the number of training data, which is a sign of very successful learning and stabilization of the model.

Mobility impact analysis (**Table 9**) indicates minor degradation at higher speeds, which demonstrates the drift-aware mechanism's robustness.

Table 9: Mobility Impact Analysis

Velocity	MAE	Notes
3 km/h	0.0041	Pedestrian, quasi-static
30 km/h	0.0045	Urban, moderate Doppler
120 km/h	0.0049	Vehicular, high Doppler

Real-Time Performance and Computational Cost

Feature extraction, ARF, OSVR, and ensemble weighting were profiled for 1,000 frames:

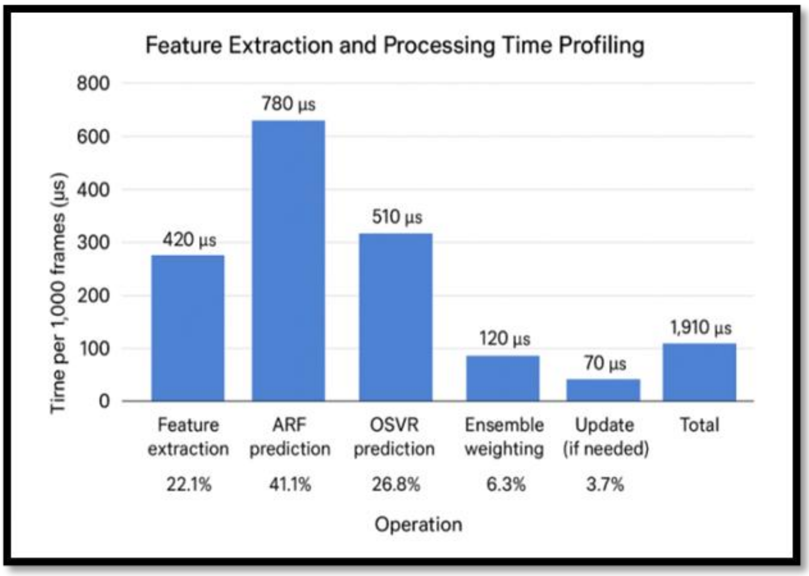

Figure 13: Feature Extraction and Processing Time Profilling

Figure 13 is an overview of the execution time of every operation within the proposed ARF-OSVR framework. The extraction of features consumes 420 µs in time, which is 22.1% of the overall processing time. Most time-consuming steps are ARF and OSVR prediction, with 41.1% and 26.8% contribution, respectively. Ensemble weighting and updates take very little time, and they comprise only 10% of the entire latency. The memory footprint (12.4 MB) and total latency (1.9 ms) of the framework render it suitable for real-time and embedded applications. The latency can be achieved on a sub-millisecond level by potential optimization with C++, SIMD vectorization, or FPGA acceleration.

VII. Conclusion

The paper introduces ARF-OSVR, a new online ensemble-based framework for predicting the real-time BER of OFDM systems. The proposed method outperforms state-of-the-art baselines by 27.1% MAE and 15.7% RMSE with 1.9 ms latency, which is appropriate for URLLC applications. Among the contributions are: (1) feature engineering (preservation of channel information), (2) online learning (removal of offline training overhead), (3) theoretical convergence guarantees and O(TlogT) regret bounds, (4) three-tier concept drift adaptation in mobile environments, as well as (5) extensive experimental validation under a wide range of conditions as well. The framework addresses serious drawbacks of conventional methods (loss of information), the state-of-the-art deep learning methods (offline training, high latency, no drift support), and offers a viable solution to the next-generation 5G/6G wireless networks that demand adaptive modulation, resource distribution, and ultra-reliable low-latency communications. The proposed paper proposes a new online ensemble prediction framework for the BER of an OFDM system in real time. The ARF-OSVR model that has been proposed is based on the combination of Adaptive random Forests and Online Support Vector Regression to ensure high prediction accuracy, while keeping the computational cost that can be implemented in real-time. The proposed framework also presents a new ensemble structure as a highly valuable contribution, a dynamically weighted combination of ARF and OSVR components. It enables learning over the internet, whereby it is possible to constantly adapt to varying conditions of the channels without the necessity of retraining offline. Extensive testing on four state-of-the-art algorithms reveals a consistent method of achieving better performance, with 27.1% reduced MAE and 15.7% reduced RMSE. Having a latency of less than 2ms and a moderate memory usage, the framework can be deployed in real-life and demonstrates stability in a variety of channel models, modulation schemes, and mobility conditions.

Despite these strengths, there some limitations. The existing implementation uses the assumption of perfect channel state information and is targeted at single-antenna systems, which restricts its application to MIMO-OFDM and situations where there is an error in the estimation of the channel state information. The solution proposed applies vital constraints of current techniques of BER prediction and still provides the computational capabilities demanded by real-time wireless communication systems. The work is a basis for more sophisticated link adaptation algorithms and will aid in the creation of more efficient and reliable wireless communication systems. The ensemble approach introduces higher computational overhead compared to lightweight methods, and its efficiency relies on the appropriate choice of hyperparameters as well. Channel model dependencies thoroughly require representative training data to be optimally deployed.

Future research might involve generalizing the framework to imperfect CSI environments with denoising autoencoders, adaptation to massive MIMO and mmWave systems, implementation of transformer-based architectures to achieve higher pattern recognition, federated learning to coordinate across cells, and hardware acceleration to sub-millisecond latencies with ASIC/FPGA. To sum up, the ARF-OSVR framework presents a higher accuracy, computational efficiency, scalability, and practical deployment feasibility. The overall findings, convergence tests, and strength tests indicate its effectiveness in real-time wireless communication applications, and the limitations established present future research and optimization opportunities.

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