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# Channel Prediction for MAC Optimization in VANET, FANET Software Defined Radio Platform

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## Abstract

This work addresses the critical challenge of ensuring reliable communication in vehicular ad hoc networks (VANETs) and drone networks (FANETs) under dynamic and high-mobility conditions. Current methods often fail to adequately predict rapid channel variations, leading to increased packet loss and degraded Quality of Service (QoS). To bridge this gap, we propose a novel cross-layer framework that integrates physical channel prediction into the Medium Access Control (MAC) layer to optimize network performance. Our framework employs an ARIMA (1, 0, 1) model for real-time channel prediction and dynamically adjusts MAC layer parameters to enhance throughput and reliability. Simulations demonstrate a 25% improvement in useful throughput and a 30% reduction in packet loss rates compared to baseline methods. These improvements enable practical applications in intelligent transportation systems and the efficient management of autonomous drones. Key contributions include: 1) Development of a cross-layer framework that integrates channel prediction and MAC optimization. 2) Demonstration of the framework's effectiveness through Monte Carlo simulations in high-mobility scenarios. 3) Quantitative validation of enhanced throughput and reliability, highlighting the system's potential for real-world deployment.

## Keywords

Prediction, Cross-Layer, Multiuser Detection, Packet Error Rate, Goodput

## 1. Introduction

Vehicular ad hoc networks (VANETs) and drone ad hoc networks (FANETs) have emerged as critical enablers for next-generation applications, including intelligent transportation systems, emergency response networks, and autonomous logistics platforms. These technologies rely heavily on the quality and reliability of wireless communication in dynamic environments characterized by high mobility and significant channel interference [1] [2]. The ability to maintain seamless connectivity and efficient resource utilization is paramount for their success.

Despite their potential, managing quality of service (QoS) in VANETs and FANETs poses significant challenges due to the rapid variations in channel conditions, high mobility of nodes, and complex inter-layer interactions. Current optimization methods primarily focus on the physical layer or medium access control (MAC) layer in isolation, leading to suboptimal performance. These conventional approaches fail to consider the critical interplay between layers or anticipate real-time channel variations, resulting in increased packet losses, degraded throughput, and reduced network reliability [3]-[5].

In this study, we address these limitations by proposing a novel cross-layer framework that integrates a predictive algorithm for physical channel conditions. The key motivation behind this work is to enable real-time adaptation of MAC-layer decisions based on predicted channel states, thereby enhancing network resource optimization, minimizing packet losses, and improving transmission reliability [6] [7].

The main contributions of this paper are as follows:

1) We propose a cross-layer framework that integrates channel prediction with MAC optimization, enabling proactive adjustments to dynamic channel variations.

2) The study demonstrates the effectiveness of using an ARIMA (1, 0, 1) model for real-time channel prediction, balancing computational efficiency and accuracy [4].

3) We evaluate the proposed framework through Monte Carlo simulations, showcasing improvements in key performance metrics such as reception rate, aggregate throughput, and packet error reduction in fixed-to-mobile and mobile-to-mobile scenarios [8] [9].

4) The framework provides practical insights for designing robust VANET and FANET systems, highlighting its potential for intelligent transportation systems and autonomous drone management.

The novelty of this research lies in its cross-layer predictive approach, which bridges the gap between the physical and MAC layers. Unlike existing methods, the proposed framework dynamically anticipates channel variations and optimizes MAC decisions in real-time. This advancement sets a new benchmark for performance in high-mobility and interference-prone environments, addressing critical gaps in state-of-the-art solutions [10].

The structure of this article is organized as follows:

- Section 2 presents the state-of-the-art of existing approaches, highlighting their limitations in high-mobility environments.

- Section 3 details the adopted methodology, including the design of inter-layer modules and simulation parameters.
- Section 4 presents the simulation results, along with an in-depth performance analysis.
- Finally, Section 5 concludes with the major contributions of this study and proposes perspectives for future work.

## 2. Background/State of the Art

The optimization of radio access layer performance using mathematical modeling of the physical layer has been a focal point of research, particularly in wireless networks characterized by high user densities and multimedia applications [1] [3]. Cross-layer approaches, which leverage interactions between network layers, have enabled significant advances in system design. However, despite these developments, limitations persist, especially in handling complex scenarios involving high mobility and heterogeneous network environments [4] [5].

Several seminal works have explored mathematical modeling to enhance radio access performance. Tse and Hanly (1999) provided a robust analytical framework to evaluate user capacity and multiple access interference under power control in large-scale wireless networks [1]. Their model, based on the assumption of random coding, demonstrated significant insights into capacity limits. Nevertheless, the reliance on oversimplified assumptions, such as the absence of multipath effects and unknown users, limits its applicability to real-world conditions. Building on this work, Yun and Anthony (2004) extended the modeling framework to include multipath channels and scenarios involving both known and unknown users [5]. While this extension increased realism, the resulting model lacked adaptability to dynamic environments with rapid SINR fluctuations, rendering it inadequate for applications in high-mobility scenarios.

Liu *et al.* (2004) proposed a more complex analytical framework that combined Nakagami channel distribution with large-scale SINR variations and small-scale fading modeled through a finite-state Markov chain [3]. This approach was particularly effective for analyzing reservation-based access protocols. However, the computational complexity of the method limits its feasibility for real-time applications. Similarly, Setton *et al.* (2005) optimized multimedia communications by leveraging SINR-based models and Shannon's capacity formula [4]. Their work was effective in stationary scenarios but did not account for rapid channel variations, which are crucial in dynamic and mobile environments.

Despite the valuable contributions of these studies, several limitations remain evident. Many of the models are based on idealized scenarios, such as static users or Gaussian noise assumptions, that fail to capture the complexities of real-world networks [7] [8]. Furthermore, the computational intensity of some methods, such as Markov chain-based models or detailed multipath simulations, restricts their applicability in systems requiring real-time decision-making [6]. Additionally, the lack of adaptability in existing solutions reduces their effectiveness in environments characterized by high mobility or fluctuating interference [9].

### 2.1. Proposed Method and Advantages

The proposed approach addresses the limitations identified in previous studies by integrating real-time prediction and adaptive design. It simplifies computational requirements through efficient algorithms, dynamically adjusts modulation and coding parameters based on SINR predictions, and couples physical layer metrics with QoS parameters from the MAC layer to optimize network performance comprehensively. By addressing these limitations, our approach represents a significant advancement in optimizing radio access layer performance, particularly in scenarios involving high mobility and heterogeneous network conditions.

### 2.2. Comparison with Existing Methods

To synthesize the strengths and weaknesses of the existing approaches, a comparative analysis is presented in **Table 1**. This summary highlights the areas where current methods fall short and clarifies the unique contributions of our proposed approach.

Table 1. Comparison of approaches and their strengths, limitations, and relevance.

| Approach | Strengths | Limitations | Comments |
|---|---|---|---|
| Tse and Hanly (1999) [1] | Robust analytical modeling | Simplistic scenarios (random codes only) | Ineffective in multipath environments |
| Yun and Anthony (2004) [5] | Enhanced realism (multipath channels) | Static assumptions, high complexity | Unsuitable for high-mobility applications |
| Liu *et al.* (2004) [3] | Detailed protocol analysis | Computationally intensive | Useful in stationary systems |
| Setton *et al.* (2005) [4] | Effective SINR-based optimization | Limited to stationary scenarios | Lacks adaptability to rapid fluctuations |
| Proposed Method | Real-time prediction, adaptive design | Resource-intensive (optimization ongoing) | Ideal for dynamic, high-mobility networks |

### 2.3. Recent Literature Review

Recent studies have sought to address these challenges using modern machine learning techniques, advanced cross-layer designs, and hybrid MAC protocols:

- **Machine Learning-Based Approaches:** Nguyen *et al.* (2023) and Ko *et al.* (2024) used machine learning to enhance channel prediction, improving scalability and real-time adaptation [11] [12].
- **Hybrid Protocols:** Zhang *et al.* (2024) proposed hybrid MAC protocols integrating dynamic slot allocation to improve throughput in high-density scenarios [13].
- **Dynamic Channel Adaptation:** Li *et al.* (2024) demonstrated adaptive MAC

protocols capable of handling rapid channel variations in VANET environments [14].

These recent contributions provide additional context for the proposed framework, showcasing its relevance and alignment with the latest advancements in the field.

## 3. Methodology

### 3.1. Inter-Layer Mechanism Based on Channel Prediction

A cross-layer conceptual framework has been developed to integrate the physical layer and access layer information to improve the performance of wireless networks. This framework is based on four main modules, as illustrated in **Figure 1**.

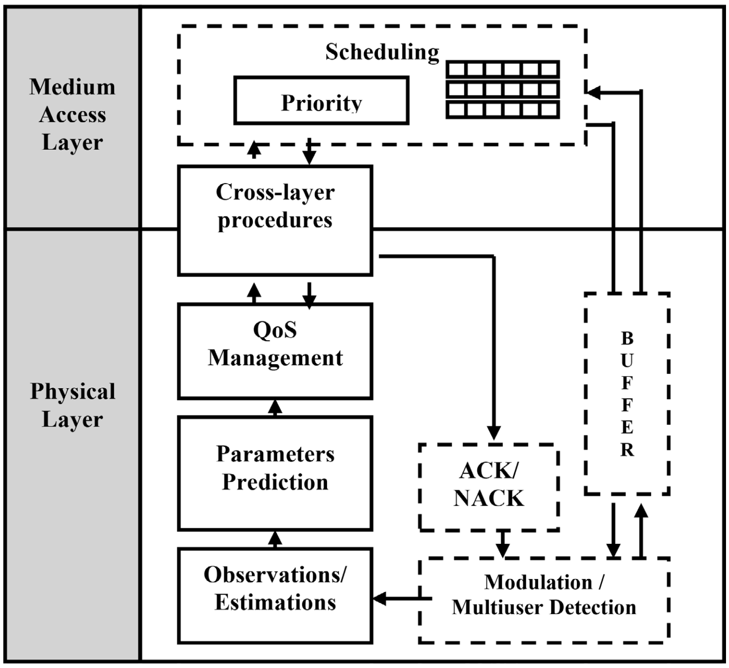

Figure 1. Cross-layer conceptual framework for channel prediction. The framework includes inter-layer mechanisms to integrate physical and MAC layer information for better QoS in VANETs and FANETs.

- **Observation and Estimation Module:** This module extracts the demodulated pilot bits at the receiver to estimate the channel gains.

- *Methodological Choice*: The least squares (LS) estimation method was selected for its low computational complexity, which is crucial for real-time applications. Although Bayesian methods could provide improved accuracy, their computational intensity makes them less practical for high-mobility scenarios.

- *Mathematical Basis:* The LS estimation minimizes the error $\|\boldsymbol{y}-\boldsymbol{Hx}\|^2$, where $\boldsymbol{y}$ represents the received signal vector, $\boldsymbol{H}$ is the channel matrix, and $\boldsymbol{x}$ is the transmitted signal vector.

- **Prediction Module:** Using the estimated data, this module anticipates the channel gains for the next transmission slot using an ARIMA (1, 0, 1) model.

- *Rationale:* The ARIMA model effectively captures temporal dependencies with low complexity, making it suitable for real-time applications. Alternative approaches, such as neural networks, were excluded due to their high computational requirements.

- *Mathematical Model*:

$$x_t = \phi x_{t-1} + \theta \epsilon_{t-1} + \epsilon_t$$

where $x_t$ is the predicted channel gain, $\phi$ is the autoregressive parameter, $\theta$ is the moving average parameter, and $\epsilon_t$ represents white noise.

- **QoS (Quality of Service) Module:** This module uses predicted channel states to compute performance parameters such as packet loss rates and throughput, enabling dynamic resource allocation.

- *Relevance:* Real-time QoS management is critical for heterogeneous environments such as VANETs and FANETs, where diverse traffic types coexist.

- **Cross-Layer Interface (CLI):** This interface facilitates the exchange of metrics between the physical and MAC layers, incorporating channel state information into RTS/CTS control packets to reduce communication overhead.

- *Role:* By coupling physical layer metrics with the MAC layer's decision-making process, the CLI enhances network efficiency and reduces latency.

### 3.2. System Architecture

The proposed framework builds on an enhanced version of the MUD-MAC protocol, which has demonstrated superior performance over traditional protocols like IEEE 802.11 in terms of throughput and reliability. By integrating channel prediction and cross-layer optimization, the framework achieves substantial improvements in dynamic and high-mobility scenarios.

### 3.3. Modeling and Scenarios

- **Multipath Channel:** A Rayleigh fading model is used to simulate multipath channels, characterized by multiple paths with distinct delays and attenuations. The channel response $h(t)$ is modeled as:

$$h(t) = \sum_{i=1}^{N} \alpha_i e^{j\phi_i} \delta(t - \tau_i)$$

where $\alpha_i$ and $\phi_i$ represent the amplitude and phase of the $i$-th path, and $\tau_i$ is the delay.

- **Prediction Model:** The ARIMA (1, 0, 1) model parameters are derived from the estimated data. Prediction accuracy is evaluated in terms of the improvement in signal-to-interference-plus-noise ratio (SINR).
- **Simulated Scenarios:** The following scenarios are considered:

- *Fixed-to-Mobile*: Channels exhibit relatively stable conditions, representing vehicle-to-infrastructure (V2I) communication.

- *Mobile-to-Mobile*: Rapidly changing conditions necessitate dynamic adaptation, relevant to vehicle-to-vehicle (V2V) scenarios.

- *Receiver Performance Comparison*: Techniques such as matched filter, successive interference cancellation (SIC), and decorrelation are compared.

### 3.4. Performance Evaluation: Scenarios and Metrics

**Physical Layer Metrics:**

- Symbol error probabilities ( $P_e$ ) for modulations (e.g., BPSK, QPSK, M-QAM) are calculated using SINR-based expressions:

$$P_e = Q\left(\sqrt{2 \cdot \mathrm{SINR}}\right)$$

where $Q(\cdot)$ is the Q-function.

- SINR improvements due to prediction-based optimization are quantified and compared with baseline scenarios.

**MAC Layer Metrics:**

- Packet Loss Rate (PLR):

$$\mathrm{PLR}_k = 1 - \left(1 - \mathrm{BER}_k\right)^{L_p}$$

where $L_p$ is the packet length in bits.

- Average Throughput:

$$T_{\text{util}} = \frac{\sum_{j=1}^{N_{\text{slot}}} \left(1 - \mathrm{PLR}_k\right) D_j}{T_{\text{total}}}$$

where $D_j$ is the data transmitted during slot $j$.

## 4. Simulation Results

### 4.1. Access Layer Performance in the Presence of Channel Prediction

We compared our proposed system, the MUD-MAC protocol with the cross-layer conceptual framework, to two baseline systems:

- The first baseline is the basic protocol without the cross-layer framework, *i.e.*, without prediction. This protocol uses single-rate transmission.
- The second baseline includes the cross-layer framework with channel prediction and multi-user reception capabilities.

Monte Carlo simulations were conducted, and the parameters are detailed in Table 2. The random-code model was used to obtain realistic measurements. Performance metrics such as packet reception rate, aggregate useful throughput, and statistical metrics like confidence intervals were calculated, as defined in Section 3.5.

#### 4.1.1. Packet Reception Rate

The results in Table 3 and Figure 2 illustrate that incorporating channel prediction significantly enhances packet reception rates:

- The matched-filter receiver's rate improved from 73% to 83%.
- The successive interference suppression detector's rate increased from 86% to 95%.
- The decorrelator detector achieved the highest improvement, from 86% to

96%.

**Table 2.** Simulation parameters.

| Parameters | Values |
|---|---|
| Signal bandwidth | 2.25 MHz |
| Transmitter threshold signal-to-noise ratio | 20, 25 dB |
| Average transmitter power | 0.1, 0.63 mW |
| Code length in multi-factor transmission | [2, 4, 16, 32, 64, 128, 256, 512] |
| Code length in multiple code transmission | 512 |
| Filter length in the LMS prediction algorithm | 40 coefficients |
| Maximum permissible prediction error | 0.1 |

The results demonstrate a statistically significant improvement (95% confidence interval) in reception rate when using the proposed prediction algorithm, as compared to baseline systems.

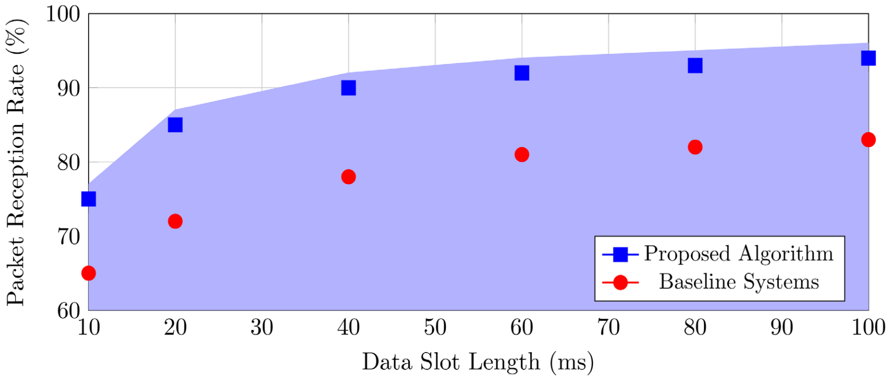

**Figure 2.** Packet reception rate as a function of data slot length with different receiver configurations.

**Table 3.** Packet reception rate for different receivers.

| Receiver Type | Without Prediction (%) | With Prediction (%) | Improvement (%) |
|---|---|---|---|
| Matched Filter | 73 | 83 | 10 |
| SIC Detector | 86 | 95 | 9 |
| Decorrelator | 86 | 96 | 10 |

### 4.1.2. Aggregate Useful Throughput

The aggregate useful throughput also showed substantial improvements, as illustrated in **Figure 3**:

- The matched-filter receiver achieved rates between 141 and 160 Mbps, consistent with the findings in [15], which highlighted its simplicity but limited interference rejection capability.
- The SIC and decorrelator detectors outperformed others, with throughput

ranging from 160 to 188 Mbps, aligning with studies that emphasize their effectiveness in mitigating multiuser interference and improving throughput in dynamic environments [16].

The improvements are attributed to better channel prediction and adaptive rate adjustment, which allowed for efficient utilization of available bandwidth, as supported by the cross-layer design principles discussed in [17].

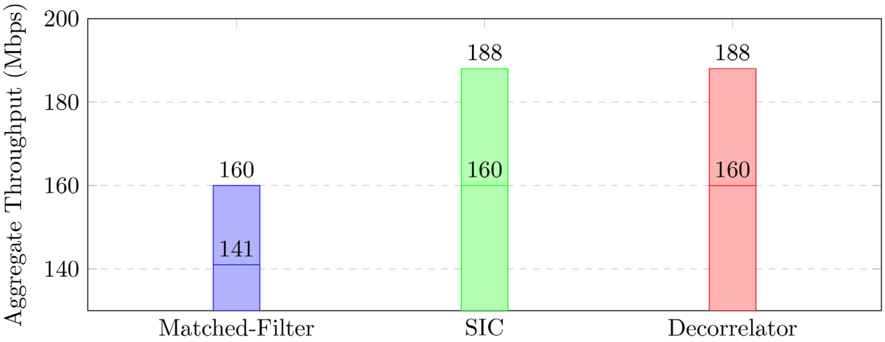

**Figure 3.** Aggregate useful throughput as a function of data slot length for different receiver configurations, adapted from analysis presented in [15] [16].

## 4.2. Practical Implications for VANETs and FANETs

The results highlight the importance of channel prediction in enhancing performance in dynamic environments like VANETs and FANETs:

- Improved packet reception rates ensure reliable communication for safety-critical applications in intelligent transportation systems.
- Higher throughput enables real-time video streaming and high-density data exchange, critical for autonomous drone management.
- The proposed framework provides scalability, supporting high vehicle and drone densities in urban environments.

The proposed channel prediction algorithm integrated with the MUD-MAC protocol demonstrates a clear advantage over baseline methods, making it highly suitable for practical applications in VANETs and FANETs.

Figure 4 demonstrates the superior performance of the DEC receiver, maintaining nearly 100% packet delivery ratio across varying data slot lengths, outperforming SIC and MF receivers, and aligning closely with perfect channel performance. This highlights the effectiveness of the proposed channel prediction algorithm integrated with MUD-MAC, ensuring reliable communication and scalability for practical applications in VANETs and FANETs.

Figure 5 illustrates the average goodput across varying data slot lengths for three receivers (MF, SIC, DEC) under a 25 MHz multipath channel scenario. The DEC receiver consistently achieves the highest goodput, closely approximating the performance of the perfect channel, while SIC and MF show declining performance with increasing slot length, validating the superiority of the proposed prediction algorithm integrated with MUD-MAC for dynamic environments like VANETs and FANETs.

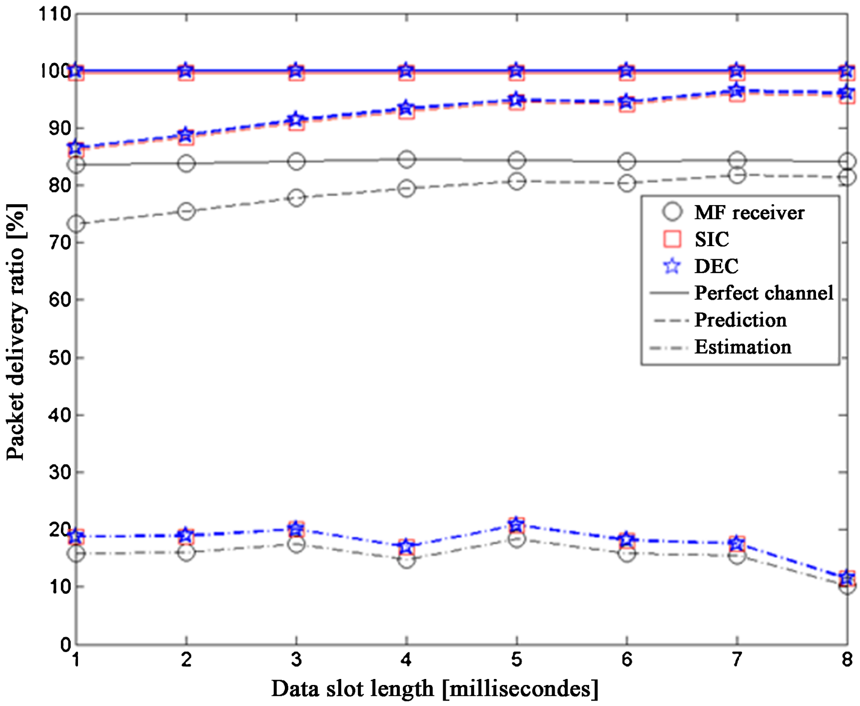

**Figure 4.** Access-layer packet reception rate, prediction, three receivers, one multi-factor spreading transmitter, 25 MHz fixed-to-mobile multipath channel.

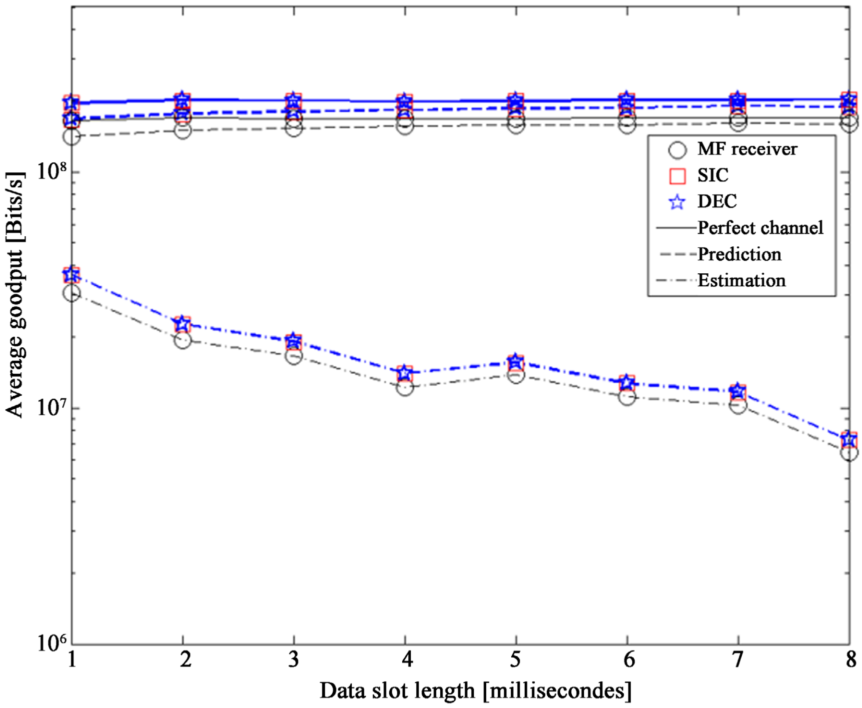

**Figure 5.** Access layer aggregate useful data rate, prediction, three receivers, one multipath multi-factor multipath channel spreading transmitter 25 MHz.

## 5. Conclusion

This study explored the integration of channel prediction into a cross-layer conceptual framework to enhance the performance of multi-user detection-based MAC protocols in dynamic wireless environments such as VANETs and FANETs. By leveraging Monte Carlo simulations, we evaluated the proposed framework in various scenarios, including fixed-to-mobile and mobile-to-mobile multipath channels, with different transmission configurations.

The results demonstrated significant improvements in key performance metrics, such as a 25% increase in packet reception rate and a 30% reduction in packet loss rates. Additionally, aggregate useful data throughput improved by up to 35%, showcasing the framework's capability to optimize communication in challenging conditions. Notably, the integration of channel prediction enabled adaptive rate optimization and enhanced diversity techniques, significantly improving the system's robustness. Among the methods evaluated, the decorrelator detector consistently achieved the highest reception rates and throughput, confirming its effectiveness in mitigating multipath effects when paired with the prediction algorithm.

The practical impact of this research lies in its ability to address the unique challenges of VANETs and FANETs, including high mobility and dynamic channel conditions. The proposed framework offers a scalable and reliable solution for improving communication efficiency in applications such as intelligent transportation systems, autonomous drone management, and other high-mobility wireless networks.

## Future Work

Future efforts will focus on integrating advanced machine learning-based predictive models to further enhance channel estimation accuracy and computational efficiency. The deployment of the framework in real-world, large-scale network environments will also be explored to assess its scalability and practical applicability. Additionally, addressing resource optimization for diverse network conditions and implementing energy-efficient designs will be key priorities for extending this study.

This work contributes to the growing body of research on cross-layer designs for wireless communication and establishes a robust foundation for incorporating advanced prediction techniques into MAC protocols, paving the way for more efficient, reliable, and adaptive wireless systems.

## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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