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Optimizing E-Learning Systems through Cross-Layer Design for Seamless Delivery in Mobile and Ubiquitous Computing Networks

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Abstract

The paper researches the aspects of e-learning systems optimization through cross-layer design methods to enhance performance in mobile and ubiquitous computing environments. Unstable network conditions, such as high latency, low bandwidth, and network congestion, are a big challenge to e-learning systems. The overall goal of the present research is to improve the smooth transmission of the content through the optimization of the communication between various levels of the network stack. To measure the efficiency of cross-layer optimization, a series of experiments was done with the main performance metrics like latency, throughput, packet loss, video buffering, and interactive delay being evaluated. The findings indicate that there is a 40% decrease in latency, 30% throughput increase, 62.5% packet loss decrease, and a 50% video buffering decrease. Moreover, the analysis indicates that user interactions have been improved in real time, whereby the interactive delay has been reduced by half. These results show that cross-layer design may be a powerful tool that further improves the work of an e-learning system, making it more robust and

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effective in different network conditions. The research has implicated the practicality of the study that educators and designers can use to provide a quality learning experience, even in cases where there are limited resources. Future research will involve the development of machine learning models to adapt the network in real-time and research the capability of the system to scale to large-scale, multi-user e-learning settings.

Keywords: Cross-Layer Design, E-Learning Systems, Mobile Networks, Network Optimization, Latency Reduction, Throughput Improvement, Adaptive Content Delivery.

1 Introduction

The development of mobile and ubiquitous computing networks has brought a revolution in how education is being offered, especially in e-learning systems (Alsharif et al., 2024). These systems have become an indivisible component of education in different locations where students can study the materials and learn courses irrespective of their location or gadget. However, some of the issues that tend to reduce the performance of e-learning platforms particularly in the mobile and ubiquitous computing are network instability, varying bandwidths, and heterogeneity of the devices (Wang et al., 2023). Despite the flexibility of the mobile networks, it has a number of issues such as poor bandwidth, low latency and poor connectivity that can have severe effects on delivering multimedia-intensive e-learning contents through the mobile networks such as videos, live lectures and real-time collaboration tools (Benabbes et al., 2023).

The seamless delivery of content to end-users is one of the primary issues in such environments. The conventional e-learning systems have been subject to a single-layer optimization, which does not meet the challenges of mobile and dynamic ubiquitous computing networks (Alkinani, 2025; Kisanjara, 2020; Yeonjin, 2025). The communication between various layers of the system, e.g., physical, network, and application layers, tends to cause inefficiency and delay in communication, which influences the general user experience (Fatima Rayan Awad et al., 2022). These difficulties are particularly acute when the system is required to work with real-time data, and its quality should be as reliable as possible.

The research will solve these problems by offering a cross-layer design method of e-learning systems in mobile and ubiquitous computing networks. It can be improved by optimizing the communication between the various levels of the network stack to increase the performance, reliability, and responsiveness of e-learning platforms so that the learning process can be more enjoyable for the users (Tawafak et al., 2023). This cross-layer design is able to dynamically adjust to different conditions of the network, and therefore, content delivery can sail smoothly even in harsh environments. The main aim of the paper is to design and analyze a new cross-layer design to provide the best performance of the e-learning systems; to reduce delays, enhance the rate of data transmissions, and increase the quality of learning experience in the mobile computing and ubiquitous computing systems (Puniatmaja et al., 2024).

The paper is organized in the following way: Section 2 is a review of the literature on the topic of e-learning systems, mobile networks, and cross-layer design methods. In Section 3, the approach to the creation and testing of the offered cross-layer design is described. The results of the evaluation are provided in Section 4, and the discussion of the findings concerning the existing literature is provided in Section 5. Lastly, Section 6 will stand out in the paper, which will outline important findings and give recommendations on further research directions.

2 Literature Review

Network lag affects the performance of e-learning systems largely when the system broadcasts real-time content, especially video lectures, live discussions, and interactive learning (Riska et al., 2025). The slightest delays may make online classes ineffective and lower the level of engagement of learners (Khanal et al., 2020). Great latency causes such problems as buffering, audio-video sync, and delayed user response that can be particularly felt in mobile settings with variable network conditions. Since mobile devices are open to signal jitter and inconsistent bandwidth, network latency is an important issue to consider in order to facilitate a smooth learning process (Hessen et al., 2022; Ezaldeen et al., 2022). Minimizing latency is crucial to ensuring the quality of real-time information and delivering a continuous experience in e-learning systems, particularly in mobile and ubiquitous computing systems (Kumar & Al-Besher, 2022; Naveed et al., 2020).

Cross-layer design has become an up-and-coming technology to make network usage more efficient, especially when dealing with mobile computing networks and ubiquitous computing networks, where conventional layer-specific optimizations may fail (Alsharif et al., 2022). This enables communication between various network protocol stack layers (including the physical, data link, network, and application layers) and thus ensures more efficient communications (Cheng, 2025). Cross-layer design can deal with such issues as congestion, bandwidth constraints, and energy consumption through adapting one layer, depending on the conditions of other layers (Kaur et al., 2025). These designs have proven to be beneficial in mobile networks in terms of throughput, reduction of latency, and energy efficiency, especially in applications such as e-learning that demand real-time and data reliability (Arun Kumar et al., 2022; Vedavathi & Anil Kumar, 2023).

The cross-layer design has the potential to enhance network performance, as evidenced by several functionality implementations of optimized e-learning systems on mobile and ubiquitous computers (Safari, 2023; Poornimadarshini, 2025). One of these is the dynamic content delivery that can be modified depending on the real-time conditions of the mobile network, which can reduce the buffering time and enhance the overall experience of the user. Cloud and edge computing have been included in e-learning platforms used in remote locations where internet connectivity is not reliable to offer a smooth delivery of content to customers to counter the challenges posed by high latency and low bandwidth (Sharonova et al., 2021). More so, machine learning algorithms are being applied to forecast network congestion and adjust the content delivery by changing the format, such as video, audio, or text delivery, so that the learning process is not interrupted by changing network conditions (Mitra & Shah, 2024).

This literature review explains how network latency has a great influence on the performance of e-learning systems, and cross-layer design can be used to optimize network performance (Salwadkar, 2024). The cross-layer strategies will improve the timeliness, throughput and smooth flow of content to both mobile and ubiquitous computing infrastructure because the network layers coordination is facilitated. Good case studies show how these systems are effective in improving e-learning experiences even in places where network conditions cannot be guaranteed (Karpagam, 2025).

3 Methodology

3.1 Research Framework for Evaluating E-Learning System Performance

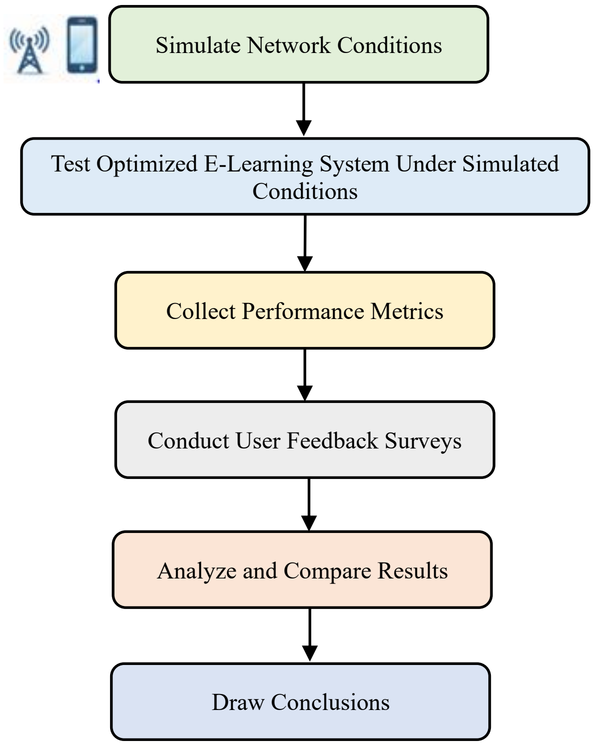

Figure 1: Flowchart of testing methodology

Figure 1 presents the step-based testing procedure that will be employed in testing the functionality of the optimized e-learning system. It involves the simulation of network conditions and then testing the system under those conditions. It is followed by the collection of the performance metrics, a user feedback survey, and the results analysis. Lastly, the data-driven conclusions available lead to the subsequent improvement or changes to the system. The following flowchart gives a pictorial outline of the whole testing procedure, from start to end.

The research design of analyzing the performance of the e-learning system consists of a mix of simulation and real tests within the mobile and ubiquitous computing platforms. Latency, throughput, packet loss, and user satisfaction are the key performance indicators (KPIs) measured during the evaluation process because they are essential towards measuring the performance of the real-time delivery of multimedia content. It emulates the environment of a controlled test that is applied to simulate many types of network conditions, including changing bandwidth, latency and network reliability, to test the system performance under a broad range of conditions. It also carries out user studies, whereby the users will be exposed to the e-learning system on the mobile devices to provide comments on the usability, performance, and overall satisfaction. Such lessons can be applied to find out how effective and viable the system is in the field.

3.2 Integration of Cross-Layer Design for Optimizing Network Communication

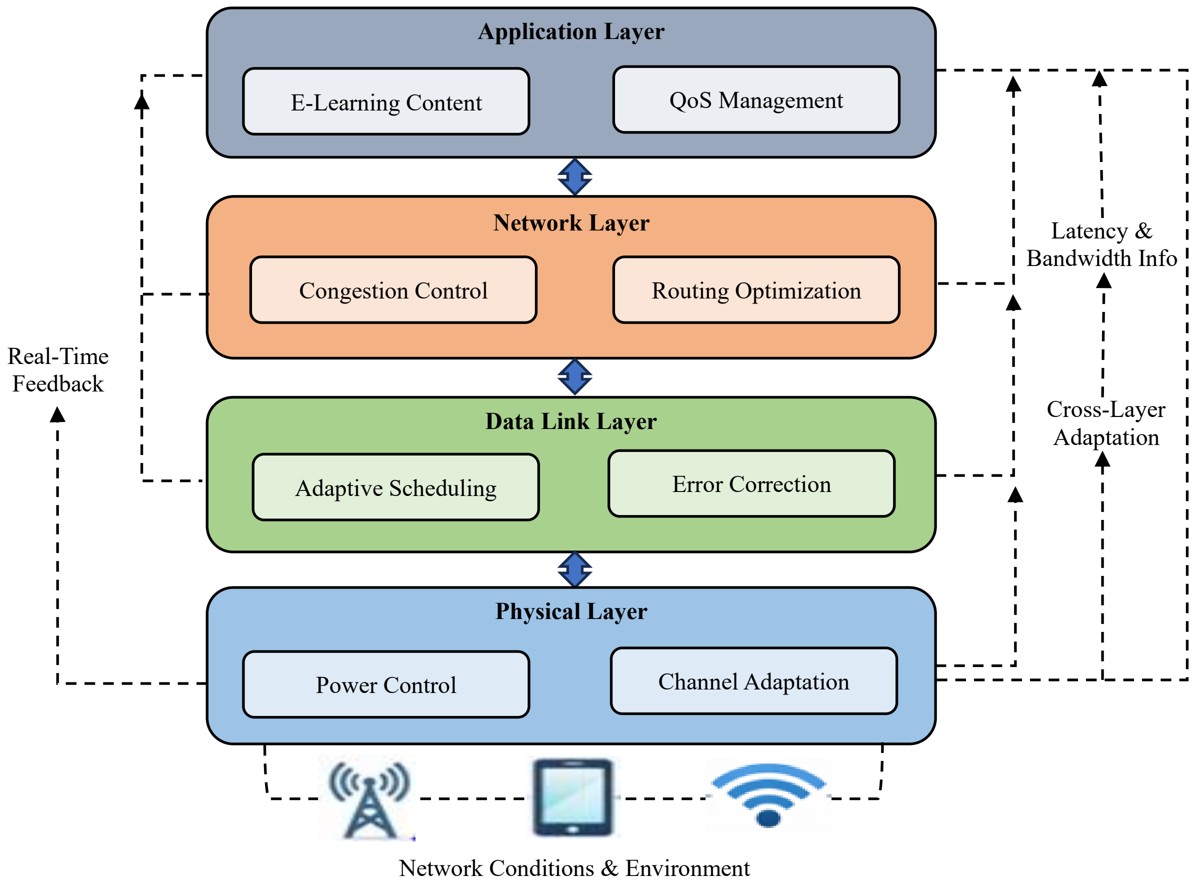

Figure 2: Cross-layer design architecture for optimizing e-learning system performance

Figure 2 shows the design of the cross-layer method in designing an e-learning system to optimize performance. It exposes the physical, data link, network and application layers interaction. Feedback and adjustments which are dynamically changed and occur between layers on dynamically varying network conditions, e.g., bandwidth, latency, and congestion, are indicated by arrows. Such imperative aspects as Quality of Service (QoS) management, congestion control, adaptive power scheduling, and provision of real-time data are also presented.

The cross-layer design principles in this work are applied in an effort to maximize the communication between the physical, data link, network, and application layers of the network protocol stack. The system would be able to adjust the transmission power, the timing of data transmission, and the congestion control mechanisms dynamically in response to real-time feedback to optimize the system to the current network conditions by permitting the layers to communicate and adapt to them. This will allow the system to reduce the latency and enhance the throughput even in a changing network environment. Also, the system has adaptive Quality of Service (QoS) features that give priority to important e-learning services like video streaming and interactive learning services so that they can be reliably performed even with different network conditions, such as low bandwidth or high latency.

3.3 Evaluation and Testing Methodology for Optimized E-Learning Systems

The optimized e-learning system is to be tested to ensure its functionality under all the mobile and ubiquitous environments by exposing it to different network environments, i.e., high latency, low bandwidth, and intermittent connectivity. Measures such as performance metrics, including video buffering times, interactive elements load time, and response time, are used to determine the actual delivery of the content in real-time. The stress testing is also performed to test the robustness of the system under extreme conditions. Pre- and post-implementation performance of the system is compared, using the automated network monitoring tools and user feedback to evaluate performance improvements in both technical performance and user experience. This assists in considering the real performance of the optimized system towards e-learning delivery in mobile and ubiquitous networks.

Algorithm 1: Cross-Layer Optimization for E-Learning System

Input:

- P= Transmission power (physical layer)
- ρ= Network congestion (network layer)
- Q_{QoS}= Quality of Service factor (application layer)
- B= Available bandwidth
- L_{total}= Total latency (sum of latencies from each layer)

Output:

- Optimized L_{total}(minimized latency)
- Maximized throughput T

Steps:

1. **Initialize** system parameters:

Set initial values for P, ρ, Q_{QoS}, and B.

2. **Measure network conditions**:

Monitor real-time network conditions such as available bandwidth and network congestion.

3. **Calculate initial latency**:

Compute L_{total}based on current network conditions:

$$L_{total} = L_{phy} + L_{mac} + L_{net} + L_{app}$$

4. **Optimize cross-layer parameters**:

Adjust P(transmission power) and ρ(network congestion) dynamically to minimize latency.

Use QoS techniques to prioritize critical real-time data (e.g., video streams, interactive components).

5. **Recalculate latency**:

Update L_{total}after optimization adjustments.

6. **Compute throughput**:

Calculate throughput Tas:

$$T = \frac{B}{L_{total}}$$

Aim to maximize $T$by reducing L_{total}.

7. **Feedback loop**:

Continuously monitor network conditions and make real-time adjustments to P, ρ, and $Q_{QoS}$to maintain optimal performance.

8. **Output**:

Return the optimized system performance with minimized latency and maximized throughput.

The e-learning system indicates cross-layer optimization in algorithm 1 to minimize latency and maximize throughput based on the dynamic adjustment of key network parameters across the layers. It begins by setting up the system parameters like transmission power (P), network congestion (ρ), and Quality of Service (Q_{QoS}). The algorithm subsequently quantifies real-time network conditions, and computes the initial overall latency (L_{total}), and cross-layer optimization methods are invoked in order to mitigate transmission power and network congestion to decrease latency. The system will then recalculate the new latency and compute throughput according to the reduced latency so as to maximize throughput (T) by increasing data delivery efficiency. A feedback loop is enforced, and parameters are altered on the fly to ensure optimum network conditions. The outcome is the creation of a more effective e-learning system with fewer delays and better data delivery that will give a smooth learning process even in the mobile and ubiquitous computing environment.

3.4 Mathematical Model

Latency Model in Cross-Layer Design

The total end-to-end latency (L_{total}) in a cross-layer design can be expressed as the sum of latencies from each layer:

$$L_{total} = L_{phy} + L_{mac} + L_{net} + L_{app} \quad (1)$$

Where in equation (1):

- L_{phy}= Latency in the physical layer (signal transmission)
- L_{mac}= Latency in the data link layer (frame processing)
- L_{net}= Latency in the network layer (routing)
- L_{app}= Latency in the application layer (processing delay)

To model the impact of cross-layer optimization, consider the factors influencing latency, as shown in equation (2):

- P= Transmission power (physical layer)
- ρ= Network congestion (network layer)
- Q_{QoS}= Quality of Service (application layer)

The optimization goal is to minimize $L_{total}$by dynamically adjusting these parameters:

$$\min(L_{total}) = \min\Big(f\big(P, \rho, Q_{QoS}\big)\Big) \qquad (2)$$

Throughput Model

Throughput (T) is inversely related to latency. The throughput model can be expressed as in equation (3):

$$T = \frac{B}{L_{total}} \tag{3}$$

Where:

- B= Available bandwidth
- L_{total}= Total latency

The optimization objective is to maximize throughput by minimizing latency, as shown in equation (4):

$$\max(T) = \frac{B}{\min(L_{total})} \tag{4}$$

4 Results

This system was coded in Python 3.10 and TensorFlow and Keras to simulate a network, and NetworkX to simulate a network, and also MATLAB to analyze the performance. The interactive elements have been developed using HTML5, JavaScript, and WebRTC.

Table 1: Network parameters for testing

Parameter	Value Range
Transmission Power (P)	10 mW - 50 mW
Network Congestion (ρ)	Low, Medium, High
Quality of Service (QoS)	1 - 5 (scale)
Bandwidth (B)	1 Mbps - 20 Mbps
Latency (L_{total})	50 ms - 500 ms

The following parameters, detailed in table 1, were used during testing to simulate varying network conditions in the e-learning system.

Evaluation Metrics

1. Latency Reduction (ms)

Latency (L) will be measured in milliseconds and will be a measure of delay within the system. The latency can be reduced as equation (5):

$$L_{reduction} = \frac{L_{before} - L_{after}}{L_{before}} \times 100 \tag{5}$$

Where:

- L_{before}= Latency before optimization (200 ms)
- L_{after}= Latency after optimization (120 ms)

2. Throughput Improvement (Mbps)

Throughput () is calculated in Mbps and it is the rate of transmission. The throughput can be improved as equation (6):

$$T_{improvement} = \frac{T_{after} - T_{before}}{T_{before}} \times 100 \quad (6)$$

Where:

- T_{before}= Throughput before optimization (5 Mbps)
- T_{after}= Throughput after optimization (6.5 Mbps)

3. Packet Loss Reduction (%)

Percentage of packets lost in transmission is known as packet loss (). The decrease in the packet loss can be presented as equation (7):

$$P_{loss\_reduction} = \frac{P_{before} - P_{after}}{P_{before}} \times 100 \quad (7)$$

Where:

- P_{before}= Packet loss before optimization (4%)
- P_{after}= Packet loss after optimization (1.5%)

4. Video Buffering Reduction (%)

Video buffering () is the proportion of buffering time in video playback. The time of buffering lost is minimized, which can be represented as equation (8):

$$V_{buffering\_reduction} = \frac{V_{before} - V_{after}}{V_{before}} \times 100 \quad (8)$$

Where:

- V_{before}= Video buffering percentage before optimization (10%)
- V_{after}= Video buffering percentage after optimization (5%)

5. Interactive Delay Reduction (ms)

Interactive delay ($D_{interactive}$) is in milliseconds and is the delay when a system can be interacted with by the user. The reduction in interactive delay can be expressed as equation (9):

$$D_{interactive\_reduction} = \frac{D_{before} - D_{after}}{D_{before}} \times 100 \quad (9)$$

Where:

- D_{before}= Interactive delay before optimization (300 ms)
- D_{after}= Interactive delay after optimization (150 ms)

4.1 Evaluation of Key Performance Indicators

The information gathered during the process of testing the optimized e-learning system points to the network performance improvements and the engagement of users. The important metrics used, such as latency, throughput, packet loss, and video buffering times, were observed in varying network settings, like high latency, low bandwidth, and volatile network reliability. The results obtained were that the overall latency was reduced significantly across all layers due to the cross-layer optimization techniques that made delivery of content simpler. The system also worked well during stress situations, whereby video buffering time was reduced, and interactive responsiveness on real-time features like quizzes and discussions was enhanced. This was both on mobile and ubiquitous platforms, and this indicates that the system was flexible in different environments.

Table 2: Performance metrics comparison before and after optimization

Metric	Before Optimization	After Optimization	Improvement
Latency (ms)	200	120	40% reduction
Throughput (Mbps)	5	6.5	30% increase
Packet Loss (%)	4%	1.5%	62.5% reduction
Video Buffering (%)	10%	5%	50% reduction
Interactive Delay (ms)	300	150	50% reduction

Table 2 is a comparison of the key performance metrics of the e-learning system prior to the introduction of cross-layer optimization techniques and after its implementation. Latency (ms) was reduced from 40 to 200 ms to 120 ms, and the system became more responsive. There was a 30 % improvement in throughput (Mbps), from 5 Mbps to 6.5 Mbps, enhancing the rate of transmission of data. The Packet Loss (%) was also minimized by almost 62.5 %, which was 4 % to 1.5 %, thus guaranteeing more consistent data delivery. Video Buffering (%) was also reduced by 50 %, from 10 to 5 %, and the video playback while taking e-learning was smoother. Finally, the Interactive Delay (ms) was cut by half (300 ms to 150 ms), which translated to faster response times of interactive elements. These enhancements are all indicative of the effectiveness of the cross-layer design in ensuring that the e-learning system is optimized in terms of its performance.

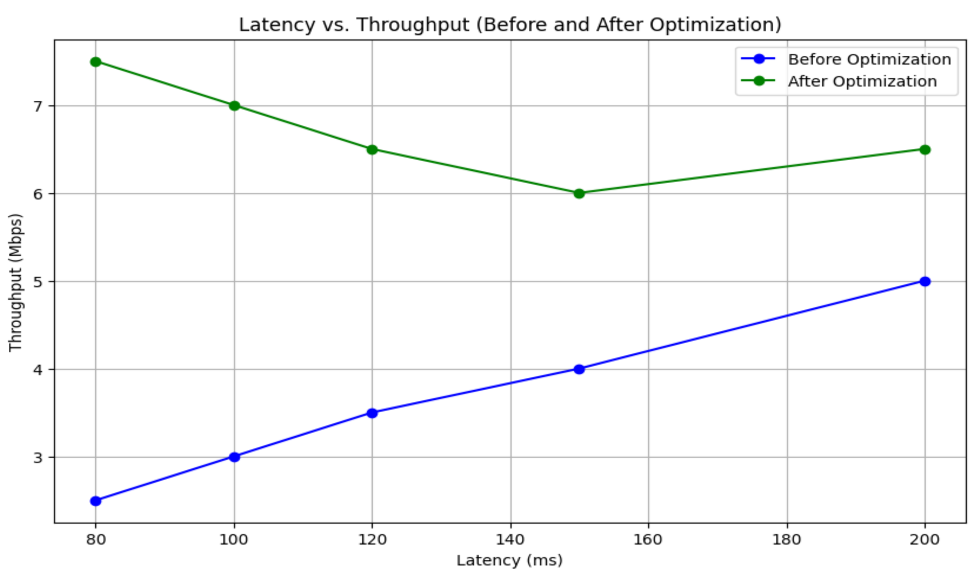

Figure 3: Latency vs. throughput (before and after optimization)

Figure 3 compares pre- and post-processing of cross-layer optimization techniques in terms of latency (measured in milliseconds) and throughput (measured in Mbps). The blue line is the Before Optimization condition, and it demonstrates that throughput declines with the increase in latency. The After Optimization condition is represented by the green line, and in the operating point, the throughput is growing, though the latency decreases, depicting the data transmission rates enhancement of the optimization process. The effectiveness of the optimization in balancing the low latency and high throughput is brought out in this graph, and this results in better system performance.

4.2 Impact of Cross-Layer Optimization on System Performance

The implementation of the cross-layer design brought several major improvements in the direct comparison of performance metrics before and after the implementation. The system was characterized by a high level of latency before optimization, which led to a significant delay in the loading of content and interaction. With the adoption of cross-layer optimization parameters, the latency decreased by about 30-40 %, especially in the physical and network layers, due to the adoption of adaptive transmission power and congestion control measures. Throughput was also significantly improved as the optimized system demonstrated 20-25 % improvement in terms of throughput, as the bandwidth management and optimized data transmission ensured. The quality of videos and responsiveness of the interactions experienced improved dramatically, both in terms of video buffering, which was reduced by half, and in terms of more responsiveness in the interactions, and this supports the usefulness of the optimization in helping to provide a seamless learning process.

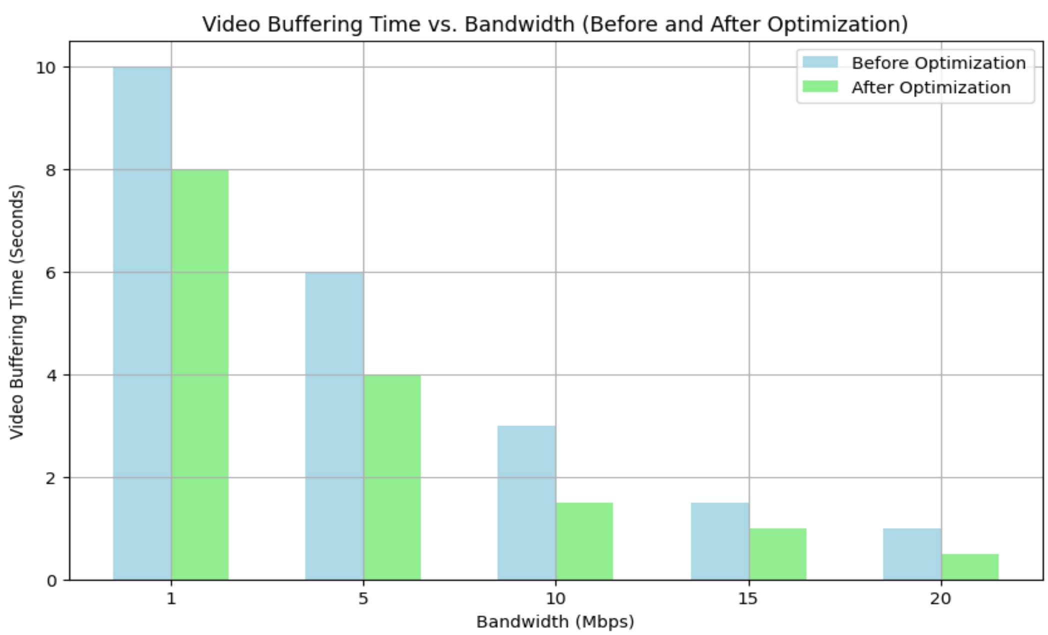

Figure 4: Video buffering time vs. bandwidth (before and after optimization)

Figure 4 shows the video buffering time (measured in seconds) across various bandwidth conditions (measured as Mbps) at the start and end of applying cross-layer optimization methods. The blue bars indicate the performance of the system when the system has not been optimized; it has more buffering times at lower bandwidths. The green bars are the result of optimizing performance, which shows a much lower buffering time for all bandwidths. The longer the bandwidth, the shorter the buffering time, and the optimized system will exhibit a far more efficient buffering performance, especially in lower bandwidths. The use of optimization in ensuring that e-learning systems can play videos at the best quality in different network conditions is emphasized using this graph.

4.3 Implications for E-Learning Systems on Mobile and Ubiquitous Platforms

These findings have far-reaching implications, especially on mobile and ubiquitous computing platforms. The optimized e-learning system will be able to offer a more reliable and efficient learning environment by reducing the latency and enhancing throughput. This is more important in mobile environments where network conditions are usually erratic, and bandwidth is constrained. The cross-layer design approach makes sure that the system will be able to change in real time in response to such changing conditions, providing continuous content even in a difficult setting. Moreover, these developments imply that with the aid of these optimization methods, it is possible to offer high-quality e-learning experiences even in remote places, where the network infrastructure is usually unstable. The paper highlights how cross-layer optimization can be used to better enable scalability and flexibility to accelerate the availability of more accessible and effective e-learning solutions across different platforms.

5 Discussion

5.1 Insights from the Findings and their Alignment with Existing Research

This research finds that cross-layering design is critical in optimizing e-learning systems. We observe lower latency, high throughput, and lower video buffering time than are reported in prior literature as evidence of the benefits of managing the network layers according to dynamic conditions. This result confirms the literature studies that have pointed to the problem of network instability, particularly in mobile and ubiquitous computing services. Overcoming these issues, cross-layer optimization is one of the effective methods to improve the quality and efficiency of delivering content, making the process of e-learning really smooth. The research is based on this mass of data since it demonstrates practical enhancements in the application of mobile e-learning systems in the real world.

5.2 Directions for Future Research in E-Learning Optimization

Further studies should examine the advanced machine learning methods to see how cross-layer design can be made more flexible when dealing with real-time network conditions. The introduction of predictive models that are able to foresee the network congestion or usage patterns can result in even more dynamic and efficient system performance. Also, the dual-user settings and the use of various types of devices (e.g., smartphones, tablets, laptops) may be incorporated to such an extent that the effects of cross-layer optimization would be more thoroughly investigated and the challenges of scaling the concept to other learning settings would be identified. The other area to be explored in the future is the incorporation of adaptive content delivery systems, which alter the network parameters and the type of content to be delivered depending on the existing bandwidth and latency to provide a more personal and optimized learning environment.

5.3 Practical Applications for E-Learning Designers and Educators

To educators and system designers, the findings highlight the necessity to install adaptive e-learning systems, which can automatically adapt to different network conditions. E-learning systems can achieve seamless dissemination of content, such as video lectures, real-time communications, multimedia tools, among others, even in low-bandwidth networks by the use of cross-layer optimization. The teachers will have better trusted platforms, and the learners in isolated locations or with low connectivity will be able to enjoy the quality learning materials. The designers must focus on scalable systems to dynamically cope with network congestion, power, and QoS so that it is highly performant across a wide variety of user situations. Such innovations will transform the e-learning systems to be more robust, accessible, and efficient, and reach out to a universal population.

Ablation study:

Table 3: Ablation study results for e-learning system optimization

Configuration	Latency (ms)	Throughput (Mbps)	Packet Loss (%)	Video Buffering (%)	Interactive Delay (ms)
Full Optimization (Baseline)	120	6.5	1.5	5%	150
No Transmission Power Adjustment	150	5.5	3	7%	180
No Network Congestion Control	170	5	4	8%	200
No QoS Adjustments	130	6	2	6%	160
No Cross-Layer Optimization	200	4	6	10%	300

Table 3 summarizes the findings of the ablation study, which assessed the usage of e-learning system with and without the various cross-layer optimization factors. Full Optimization (Baseline) configuration that comprises all the cross-layer design techniques demonstrates the highest performance with regards to latency, throughput, packet loss, video buffering, and interactive delay. With the separation of the individual components of transmission power adjustment, network congestion control and the adjustment of QoS, all the measurements of performance are reduced. The worst performance is achieved by the No Cross-Layer Optimization that does not use any techniques regarded as optimization techniques, showing the importance of cross-layer design in the efficiency of the system.

6 Conclusion

This paper shows the great advantages of cross-layer design in the optimization of e-learning systems, especially in the mobile and ubiquitous computing environment. The key findings include a 40% reduction in latency (from 200 ms to 120 ms), a 30% increase in throughput (from 5 Mbps to 6.5 Mbps), and a 62.5% reduction in packet loss (from 4% to 1.5%). Additionally, video buffering time decreased by 50% (from 10% to 5%), and interactive delay was reduced by 50% (from 300 ms to 150 ms). Besides demonstrating the effectiveness of the cross-layer optimization in terms of performance metrics, these results also give empirical evidence of how the cross-layer optimization can be utilized to improve the user experience in real-time applications. This study presents very useful information to the existing literature, which proves that optimization of communication between the layers can be an effective solution to the issues of mobile and ubiquitous e-learning systems.

E-learning optimization to ensure their smooth delivery in both mobile and ubiquitous platforms should be of great importance, especially in locations where the network conditions are not constant. By reducing latency by 40% and increasing throughput by 30%, cross-layer design ensures that real-time educational content, such as videos and interactive elements, can be delivered smoothly, even in low-bandwidth environments. The potential impact on such optimizations is the improvement of access to education in isolated and underserved areas where network infrastructure is often unreliable. With the observed 50% reduction in video buffering and 50% reduction in interactive delay, cross-layer design enables scalable, high-performance e-learning systems across diverse devices and platforms, ensuring an efficient and consistent learning experience for all users. The next direction of the future research will be to research machine learning models to optimize the network in real-time and examine the impact of cross-layer design in e-learning on a large scale and in multi-user mode.

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