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Original Article

Machine Learning Assisted Design of Wireless Access Systems for Reliable and Low-Latency Financial and Smart Commerce Services

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Abstract *- The fast process of digitalization of financial services and the development of intelligent exchanges have put in front of wireless access systems their strict demands, especially ultra-low latency, high reliability, and strong quality-of-service (QoS) guarantees. Mobile banking, high-frequency trading, contactless payments, real-time fraud detection, smart retail systems (among others) are all becoming reliant on wireless communication infrastructures capable of providing deterministic performance in the face of the most dynamically varying traffic and channel conditions. The conventional design methods of wireless access based on intensive use of static optimization and/or model-based methods tend to fail to deliver high latency and reliability as requested by these mission-critical services. The aim of the paper at hand is to elaborate a detailed research on machine learning-aided design of wireless access system in black and white to reliable and low-latency financial and smart commerce services. The designed framework combines the learning-based decision and control solutions with the scheduling that is latency-conscious, managing resources across the layers, and optimizing queues. Machine learning models based on a combination of historical and real-time network data can be used to do predictive analytics on network performance, adaptive resource allocation, and proactive mitigation of congestion. The framework focuses on the common interest of latency and reliability measurements based on data-driven strategies and reducing the natural uncertainty of wireless environments and variability. The systematic integration of the Lyapunov optimization with control policies based on learning to achieve queue stability and with the rigid delay and reliability constraints is one of the main contributions of this work. To make financial and commerce-based traffic have heterogeneous service-level agreements, deadline limited scheduling and queue conscious admission control are used to prioritize traffic. In addition, the paper discusses how supervised learning, reinforcement learning, and hybrid learning paradigm can be used to increase system adaptability and resilience. Through considerable analytical discourse and comparative analogy, it is seen that the machine learning-enabled wireless access systems outperform traditional strategies by a substantial margin in end-to-end latency alleviation, dependability in packet transmission, as well as efficacy in resource utilization. The results emphasize how the optimization of AI-based systems could be used as an enabling underlying technology of future financial and intelligent commerce services in wireless networks.*

Keywords *- Machine Learning, Wireless Access Systems, Low Latency Communication, Ultra-Reliable Communication, Smart Commerce, Financial Services, Queue-Aware Scheduling, Lyapunov Optimization, Cross-Layer Design, Data-Driven Network Optimization.*

1. Introduction
1.1. Background
The fast development of online financial tools and intelligent business environments has completely altered the manner in which contemporary economic operations are undertaken. Mobile wallets, live-trade stock exchange systems, contactless payment systems, smart point of sale terminals, and smart logistics and supply chain systems are becoming more applications that just cannot do without ubiquitous wireless connectivity. [1] Even the small delay or loss of packets in these settings can have severe ramifications, such as unfinished transactions, losses of finances, compliance with the regulation, or loss of user trust. Consequently these applications place very strict performance demands on the wireless access networks, which are oftentimes required to provide end-to-end latency in the manage berries of a few milliseconds and near-perfect reliability and service availability. Although constant innovations in wireless technologies have taken place, access networks are still prone to various unpredictable and evolving force. The wireless channels can be exposed to vane fading, interference caused by the nearby devices, the movement of the user as well as the changing load of traffic loads which is supplied by human behavior and market activity. [2] Especially financial and smart commerce traffic are burst-oriented and extremely time-sensitive, kind of traffic, where there are sudden bursts during peak time, promotions, or changes in the market. The traditional methods of wireless system design that are usually based on deterministic assumptions, fixed parameter configurations, and off-line optimization strategies are inappropriate to meet such a dynamically evolving environment. Such techniques do not have the

capability to adapt dynamically to changes in the traffic demand and channel quality resulting in sub-optimal latency and reliability performance. This increased discrepancy between the rigorous demands of the current digital commerce applications and the constraints of conventional wireless design approaches has inspired the considerations of intelligent and adaptable paradigms. Using data-based methods and real-time system perception, next-generation wireless access systems can dynamically tune their own operation to satisfy quality-of-service requirements of applications. The evolution has consequently resulted in intelligent wireless design as the most sought-after of enabler of further expansion and sustainability of digital financial services and intelligent commerce eco-systems.

1.2. Role of Machine Learning in Wireless Systems

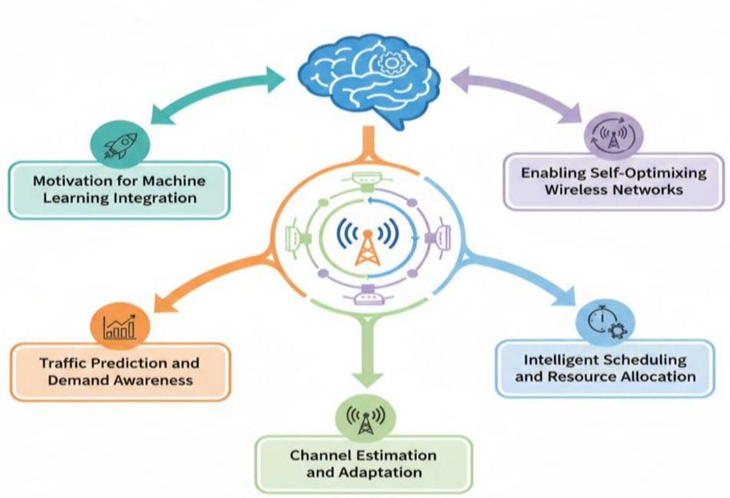

Fig 1: Role of Machine Learning in Wireless Systems

1.2.1. Motivation for Machine Learning Integration

The growing dynamism and complexity of current wireless systems has rendered old methods of traditional rule-based and model-driven optimization to be inadequate. [3] Wireless settings are typified by time-varying channels, uneven character of traffic, dense user implementations and varied quality-of-service necessities. An alternative of machine learning is a very powerful solution as it allows systems to learn, discover other patterns, and change the behavior in real time. Such an ability is very significant in applications that are sensitive to latency and reliability like in financial journeys and clever trade solutions.

1.2.2. Traffic Prediction and Demand Awareness

Machine learning can play one of the most important functions in wireless systems as predicting traffic. The learning models have the ability to predict immediate traffic inflow and demand variations through analysis of past and real-time data. This predictive ability means that wireless access systems are capable of preemptively allocating resources to avoid a congestion situation before it happens and as a result minimizes the build up of queues and thus level of latency. The foresight is necessary in the context of smart commerce where volumes of transactions can suddenly rise and fall without warning, in order to ensure the same levels of service quality.

1.2.3. Channel Estimation and Adaptation

Machine learning also improves channel estimation as well as channel adaptation by finding non-linear interactions between environmental inputs and channel behavior. Learning-based models are capable of improving their predictions every time a new observation is available in contrast to the traditional estimation techniques that use simplified assumptions. [4] This allows more efficient choice of transmission parameters to enhance reliability and spectral efficiency in the changing channel conditions.

1.2.4. Intelligent Scheduling and Resource Allocation

The base of control on learning is essential in the decisions of time and allocation. Through a collaborative approach by considering a traffic urgency, queue conditions, and channel quality, machine learning models make it possible to implement intelligent user and service prioritization. This causes more improved latency performance of delay-sensitive traffic with fairness and efficiency within the network.

1.2.5. Enabling Self-Optimizing Wireless Networks

On the whole, machine learning enables the wireless system to evolve into an auto-optimizing model of systems that tolerate uncertainty and change. Machine learning can be combined with analytical frameworks like queue-aware control and Lyapunov optimization to offer both flexibility and stability thus being a central enabler to the next-generation wireless networks to support financial and smart commerce applications.

1.2. Limitations of Conventional Wireless Access Design

The traditional wireless access design has been associated with deterministic modeling, static configurations and offline optimization schemes to control network resources and guarantee quality of service. [5] Where these methods previously have been used to implement best-effort data services and fairly predictable traffic patterns, they demonstrate serious constraints when used to implement latency sensitive financial and smart commerce applications in the present day. The dependence on long-term average assumptions of the traffic arrivals and channel conditions is one of the major disadvantages.

In real world applications wireless environments are extremely dynamic and the thing is that the demand on traffic can change quickly in response to user activity, market conditions, and the effect of time-of-day dimensions and thus could not respond well when there was a sudden burst of congestion or traffic demand. Lack of real time flexibility is another significant weakness. Traditional systems adopt determinate scheduling policies, immutable priority, and conservative parameter values which never adapt as network states change. Consequently, resources are either not fully used at low-load and unusable at peak load, causing delays to increase and losing packets to rise. This rigidity is especially troublesome in the context of financial transactions, where latency spikes or packet loss even on a temporary basis can trigger failures of transactions or problems in the services. The traditional designs are also not able to facilitate cross-layer interactions. Independent decision making at the physical, medium access control and network layers may lead to inconsistency that ill-effectively share the available resources and thus lead to poor performance. Furthermore, the majority of the traditional methods are reactive in nature, until the congestion after it has already set in. This reactive action further adds to the queue completion and worsens tail latency that cannot be tolerated in mission-critical services. Lastly, model-driven methods alone are in most cases not capable of considering uncertainties and non-linearities in real wireless systems. The patterns of interferences, mobility, and device heterogeneity can not be precisely simulated in simplified analytical models. With these shortcomings, there is the necessity of smarter, more dynamic and data driven wireless access design models that can achieve very strong requirements in latency and reliability of current financial and smart commerce ecosystems.

2. Literature Survey

2.1. Wireless Access Systems for Low-Latency Applications

Initial generations of wireless access systems focused on reduction of latency on physical (PHY) and medium access control (MAC) layers. Adaptive modulation and coding (AMC), fast hybrid automatic repeat request (HARQ), and priority-based MAC scheduling were the most popular techniques that were studied in order to minimize the transmission time and retransmission delays. These mechanisms have worked in enhancing link-level performance when the traffic conditions are rather stable. [6] But, they were mostly stateless and deterministic, in that they considered a priori traffic characteristics and channel models. Consequently, they were not very responsive to dynamic traffic bursts, queues of diverse quality-of-service (QoS) requirements, as well as cross-layer interactions. In the case of new financial and smart commerce services, in which the latency, jitter, and reliability of the transaction should be jointly optimized, the classical schemes of wireless access could not fully reflect the urgency and time constraints of the applications, which stimulated the development of more adaptive and smart schemes of control.

2.2. Ultra-Reliable and Low-Latency Communication (URLLC)

The fact that Ultra-Reliable and Low-Latency Communication (URLLC) was presented as one of the most important types of service in the current cellular networks became another massive step in facilitating the mission-critical applications. The URLLC studies focused on strict latency limits (usually much less than 1 ms) and high reliability rates (as high as 99.999%). [7] In order to address these needs, research investigated the packet duplication, multi-connectivity, frequency and spatial diversity as well as the strict admission control policy. Although these methods showed significant betterment of reliability, they are normally conservative in design, distributing surplus resources to assure a worst-case performance. This tended to cause poor spectrum usage particularly when the traffic load was not constant. Besides, URLLC designs typically did not give much thought to application specifics and uniformly handled all low-latency packets without distinguishing between transaction priorities of different priority as found in financial and smart commerce systems.

2.3. Learning-Based Decision and Control

As the wireless networks grew more complicated, learning-based decision and control mechanisms became promulgated as the means of getting around the shortcomings of static optimization. Before 2022, power control, user association, handover management and resource scheduling were among the problems that were solved with the help of supervised learning and reinforcement learning (RL) techniques. [8] Reinforcement learning, specifically, showed a promising future in the adaptation to the uncertain and time-varying environment without the need to have clear models of the system. Nevertheless, the majority of the RL-based approaches experienced issues associated with the rate of convergence, stability and scalability to large-scale multi-user networks. Also, in principle learning agents would better suit long-term goals without necessarily including delay guarantees or reliability requirements, so they are not applicable to latency sensitive financial problems where a delay of one single step can produce serious economic consequences.

2.4. Queue-Aware and Deadline-Constrained Scheduling

Previous queue-sensitive solutions came into the scene with schedulers that provided buffer state feedback into resource allocation choices and discorded with resource allocation choices to aid in the better control of packet delays and loss probabilities. [9] These schemes gave queues of people experiencing congestion dynamic priority, applied to the queue by taking into consideration lengths of queues and arrival rates and led to the enhancement of the average delay performance. Scheduling with deadlines further optimized this idea, with packets also categorized by strict deadline requirements; so that time sensitive information as payment confirmation or trading orders got priority. Some of these methods were theoretically effective, although most of them were based on simplified analytical models and the knowledge of statistics of traffic. As a result, their actions deteriorated in the real-life conditions that are defined by the non-stationary traffic flows and unexpected demand spikes which restricts their applicable usage in smart commerce ecosystems.

2.5. Lyapunov Optimization in Wireless Networks

Lyapunov optimization became an influential branch of mathematics with the ability to co-optimize the network queue to achieve goals of the performance of the network; throughput and energy efficiency. Lyapunov strategies have offered excellent theoretical guarantees of queue stability and delay limits by converting long-run stochastic optimization problems into per-slot controls. [10] The techniques were common in wireless scheduling and resource allocation issues. Nevertheless, the classical Lyapunov-based models presupposed the correct system models and accurate knowledge on arrival and service procedures. Such assumptions are not credible in very dynamic wireless environments that accommodate financial transactions. Consequently, recent studies have brought to the fore the necessity of combining Lyapunov optimization with data-driven and learning-based approaches to enhance adaptability and maintain theoretical performance guarantees.

2.6. Research Gaps

Although there has been a vast amount of research in the area of wireless access optimization, URLLC design, learning-based control, queue-aware scheduling, and Lyapunov optimization, literature has not provided a unified framework, which also pulls together each of these methods to provide financial and smart commerce services. The majority of the studies treat the aspects of reliability, latency, or adaptability separately without taking into account its interdependencies. Additionally, not much has focused on predictive analytics that has the ability to foresee peaks in traffic and preemptively distribute resources. These shortcomings underscore the necessity of a machine learning-assisted, integrated wireless access architecture that integrates queue-sensitive control, Lyapunov optimization, and predictive intelligence to provide dependable and low-latency performance that is responsive to the demanding nature of contemporary financial and smart commerce applications.

3. Methodology

3.1. Wireless Access System Model

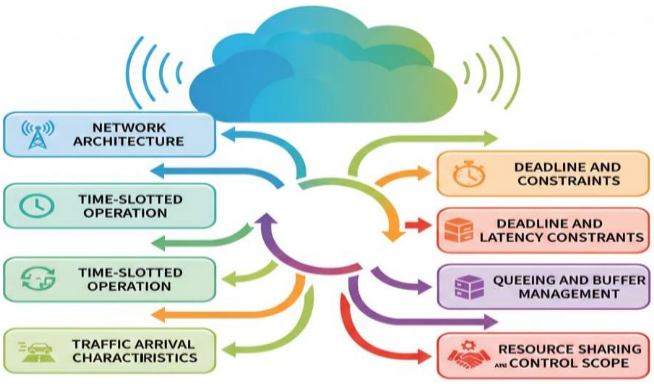

Fig 2: Wireless Access System Model

3.1.1. Network Architecture

The wireless access system is assumed to be a multi-user network whereby a central access point or base is sharing a finite number of users. These users constitute devices and applications of heterogeneity, such as financial transaction terminals, smart commerce sensors, and mobile clients. [11] Access point handles the uplink and downlink transmissions and implements quality of service requirements. This common wireless medium creates contention and variability and to guarantee a low latency and reliability intelligent access control is critical.

3.1.2. Time-Slotted Operation

System operation is separated into discrete time slots, this offers a systematic schedule and control decision schedule. The network monitors the current traffic conditions, the quality of the channels and the queue status in every slot and then allocates the resources. This slotted-time abstraction is useful not only in simplifying real-time decision-making but also in allowing the incorporation of dynamical control mechanisms that respond fast to changes in the traffic and channel dynamics.

3.1.3. Traffic Characteristics of arrival

There is data traffic generated by each user which fluctuates with time based on the behavior of applications and outside occurrences. Monetary and intelligent trade facilities normally generate blistering and unstable patterns of traffic, particularly throughout times of peak trading. [12] The use of modeled arrivals of traffic at every time slot enables the system to fully reflect the short run fluctuations and also dynamically respond to them as opposed to using the long run averages which may not be true in reality.

3.1.4. Deadline and Latency Constraints

A data traffic generated by each user changes with time owing to application activity and extraneous events. Monetary and intelligent business facilities tend to generate spurred and erratic traffic patterns, particularly at the time of high transaction volumes. Approximating traffic arrivals at every time slot is a way of making the system respond dynamically to short-term variations and modeling long-term averages, which do not necessarily apply in practice.

3.1.5. Latency Constraints and Deadline

Strict deadline constraints that imply application level sensitivity with respect to latency are related to user traffic. An example here is that payment authorization messages and trading orders should be received within limited time ranges to ensure integrity of the service. These deadline constraints are very important in prioritizing transmissions and it is seen that the delay sensitive packets will be served in due time and this will reduce the risk of deadline violations.

3.1.6. Queueing and Buffer Management

At the access point or device end, incoming traffic is temporarily saved in user queues at the access point. The queue states are useful in terms of information regarding the congestion and urgency of pending packets. Buffer management should be effectively used to avoid unnecessary delay and lost packets especially in the instance of heavy load. The system can adjust the scheduling decisions to ensure that the system has stable and predictable performance by measuring the queue evolution with time.

3.1.7. Resource Sharing and Control Scope

The wireless resources like time, frequency and transmission opportunities are shared among the users in every time slot. These resources should be allocated with a fairness, efficiency, and latency system that will ensure that the access system is distributed appropriately. The model forms the basis of the inclusion of smart scheduling, queue-sensitive control, and learning-based optimization methods in later parts of the methodology.

3.2. Latency and Reliability Metrics

The two leading performance metrics of the wireless access systems in support of financial and smart commerce services are latency and reliability. [13] End-to-end latency to a specific user is the total time taken by a data packet after it is generated in its source to be successfully received in the destination. This latency is explainable in the context of practical wireless systems as a combination of three key elements. The former is the first constituent, which is queueing delay, which is defined as the duration that a packet waits in the transmission buffer as a result of congestion or scarcity of the resources. This latency is extremely traffic load and schedule policy sensitive and is likely to dominate the overall latency in peak transaction times. The second one is transmission delay that captures the time it takes in the process of sending the packet to the wireless channel. This delay is based on the quality of channels, modulation and coding schemes as well as, bandwidth that is allocated to the user. The third element is processing delay, which is the time spent on the transmitter and receiver to do their work which includes encoding, decoding, encryption and protocols. Processing delay is typically less than queueing delay and transmission delay, however, in ultra-low-latency applications, it becomes non-negligible. [14] The reliability on the other hand indicates how well the system manages to convey packets on time as it is expected. It is usually understood as the probability that a packet will arrive at the correct destination without being dropped because of buffer overflow, expired deadline, or packet transmission errors. The causes of the loss of packets may be numerous such as extreme channel fading, too much interference or long queue delay leading to packets missing their deadlines. The reliability is thus defined as the inverse of the probability of packet loss denoting the fraction of packets which do get delivered. When it comes to financial transactions and smart commerce transactions, a decrease in reliability even slightly will result in failure of transactions, inconsistencies, and loss of user trust. Latency and reliability are therefore both coupled metrics and a good wireless access design should be able to maximize both of them to reflect a timely and reliable service delivery.

3.3. Queue Dynamics

Queue dynamics explain the accumulation and the service of the data packets over time in a wireless access system. Every user has a logical queue or buffer that temporarily keeps pending packets until it is sent. The change of this queue during a time slot to the next one shows the balance between the traffic entering the network and the service offered by it. [15] Theoretically, to compute the queue length at the next time instant the present queue length is obtained, the number of packets that have been successfully transmitted was deducted from it, but this must not be less than zero and the incoming packets were added. Service rate is the capability of the network to carry packets of a user during a certain time slot. This service capacity is subject to a number of parameters such as bandwidth assigned, channel characteristics, power used in transmissions, and the policy used in scheduling. In the case of a high service rate, the system is able to empty queued packets fast thus minimizing the waiting time and avoiding congestion. On the other hand, the service rate is low because either the channel quality is deficient or competition over the resources is high hence packets queue resulting to increased delays and a high probability of packet loss. Arrivals are new traffic that is created within the system within a time slot. Arrival processes in financial and smart commerce applications are frequently bursty and time-varying and are typically influenced by user behavior, transaction peaks, or external events. This kind of fluctuation renders queue management one area where an unexpected influx of people on the service may easily overwhelm service facilities unless proactive measures are implemented. The max operation in the queue update is to be sure that the length of the queue is non-negative, and this physical phenomenon shows that a buffer cannot send more packets than it has. This model of queue evolution is the basis of studying system stability, delay-performance and reliability. The wireless access system is able to monitor and control the dynamics of queues to ensure that it deploys queue-based scheduling and dynamically adjusted resource allocation mechanisms that ensure low-latency and stability even in the context of the strongly dynamic traffic.

3.4. Learning-Based Decision and Control

Decision and control mechanisms that are based on learning are at the heart of improving the flexibility of the modern access wireless systems. Unlike using fixed analytical models or fixed thresholds, machine learning models are utilized to acquire complex patterns of historical and real-time network data. [16] Models are fed on a feature vector in the existing state of the system that can include the latest arrivals with traffic, the length of the queue, the perceived channel quality marks, the level of interference, and past scheduling choices. Using this information, the learning model provides an approximation of the future intensity of the traffic of each user on the next time slot. Being the anticipated traffic load, it is an informed guess on the amount of data that a user is expected to generate within a near future. The system will be able to make proactive control decisions by predicting these arrivals, as opposed to responding to the congestion already developed. As an illustration, users with forecasted increase in transaction traffic can be assigned extra resources ahead of time, hence the unnecessary queuing and lowering latency. In like manner, the scheduler can take advantage of opportunities of good channel conditions and avoid inefficient transmissions during deep fades through predictions of either good or bad channel conditions. The predictions have direct effect on the scheduling, power control, and bandwidth allocation decisions. [17] Proactive scheduling is used to ensure that the latency sensitive packets, e.g. packet related to financial transactions are served within their deadlines even in the face of very dynamic conditions. A learning-based control is further useful in allowing the system to be constantly changed with the change of traffic patterns over time that are also non-linear and non-stationary and hard to model analytically. Notably, learning-based decision-making is not used to substitute the traditional approaches to optimization, but to complement them. The queue-aware or stability-driven control policies can incorporate the predicted state of the traffic and channels to ensure that there is a balance between responsiveness in the short term and performance guarantees in the long term. Because of this, learning based control offers a flexible and scalable mechanism in the control of wireless access systems able to perform effectively and meet both demanding latency and reliability specifications in dynamic smart commerce applications.

3.5. Lyapunov Optimization Framework

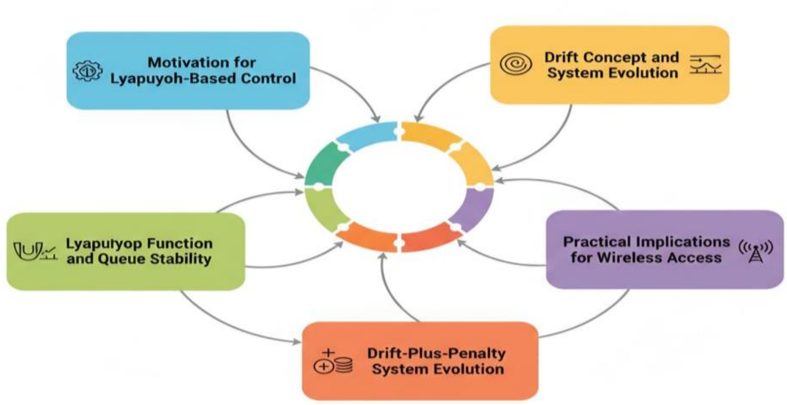

Fig 3: Lyapunov Optimization Framework

3.5.1. Motivation for Lyapunov-Based Control

Lyapunov optimization offers a structural approach to the development of control policies that guarantee the long-term stability of dynamical wireless networks. [18] The low-latency and reliability-sensitive services, like financial and smart commerce applications, need to avoid uncontrolled growth of the queues, and at the same time, maximize performance indicators. The Lyapunov-based control provides a conceptual means of trading off these goals in a time-varying traffic and channel conditioning environment.

3.5.2. Lyapunov Function and Queue Stability

The Lyapunov function is defined to be a scalar of the total network congestion which is the summation of the squared queue lengths of every user. The queuing of the length squares the effect of a big backlog, thus promoting the system to attend to users having heavy congestion. [19] The function is an indicator of stability in the system where low values are used to indicate well-managed queues and predictable delay performance. By continually tracking of this function with time the system will be capable of evaluating the control actions that are either moving the network towards or away away of stable operation.

3.5.3. Drift Concept and System Evolution

The Lyapunov drift indicates a difference of the Lyapunov function between two consecutive time periods. It captures the effect of present decisions on scheduling and allocation of resources on the future queue states. An adverse or limited drift value means that the queues are under control whereas a big positive drift value is an indicator of the possibility of instability. The drift concept enables one to make real-time decisions without necessarily having the entire knowledge on a long-term traffic statistics.

3.5.4. Drift-Plus-Penalty Objective

In order to tackle stability and performance together, the drift is moved together with a penalty term which reflects the latency-related goals. One of the control parameters is the scale of how much less important minimizing latency is compared to maintaining small queues. This parameter allows the system to be adapted flexibly to the varying service demands with a larger focus on ultra-low-latency operation when required or stability during heavy traffic loads.

3.5.5. Practical Implications for Wireless Access

Reduction of the drift-plus-penalty objective results in stable and latency-conscious policies in terms of scheduling and the allocation of resources. The framework enables online decision-making, responds to real-time system conditions in a natural manner and it is easily integrated with learning-based predictions, hence is highly suitable to intelligent wireless access systems that are used in financial and smart commerce applications.

3.6. Cross-Layer Resource Management

One of the enablers of the feasibility of reliable and low-latency performance of advanced wireless access systems is cross-layer resource management. [20] Conventional network architecture adheres to the layered architecture of which the physical layer, medium access control (MAC) and network layer depend on each other with restricted information flow. Although this is an easy implementation choice, it can result in non-optimal performance with the support of latency-sensitive and reliability-sensitive services like financial transactions and smart commerce applications. Cross-layer resource management gets around these drawbacks by enabling coordinated optimization between individual protocol layers. Parameters that are directly impacted at the physical layer and that affect data rate and error probability are: transmission power, modulation and coding scheme and channel selection. At MAC layer, scheduling choices, access prioritiesoften as well as retransmission schemes define the effectiveness in the allocation of the shared wireless resources among users. The network layer also influences the performance due to routing, congestions, and prioritization of the traffic. The system may make more informed and globally optimistic decisions by combining the information available in all these layers. As an example, packet deadline and knowledge of queue length at the network-layer can be used to schedule the MAC-layer when taking priority over urgent traffic; physical layer Real-time channel state information can be used to choose transmission parameters which are most likely to avoid unnecessary retransmission at the expense of reliability. This global strategy minimizes redundancy in signaling, prevent prioritization control operations and enhances efficiency. [21] The cross-layer optimization makes quick adjustment in a dynamic environment with surging traffic and unstable channel environments to avoid congestion and reduce end-to-end delay. Moreover, cross-layer resource management offers natural interface of incorporating learning-based prediction and Lyapunov-based control. Decisions affecting any of the layers may be affected with predicted traffic loads and channel states and stability considerations are needed to provide long-term robustness. Consequently, cross-layer resource control currently constitutes a cornerstone of intelligent wireless access structures meant to fulfill the rigorousness of latency and dependability of smart and present financial services of smart commerce.

4. Results and Discussion

4.1. Performance Evaluation Metrics

The performance evaluation metrics give the quantitative foundation on which the efficiency of the suggested wireless access framework can be determined in fulfilling dependable and low-latency fiscal and smart commerce services. One of the essential metrics is average latency that is used to express the average end-to-end delay of packets over a long time interval in the course of observation. [22] It represents the sensitivity of the system to the general operating conditions and is specifically effective in comparing various strategies of scheduling and resource allocation. Averages however can eliminate rare but drastic delays which in mission-critical workloads are unacceptable. In a bid to deal with this shortcoming, tail latency is employed as a supplementary measurement. Tail latency is interested in the high percent of the latency distribution, e.g. ninety-fifth or ninety-ninth percentile, worst-case delay behavior. [23] This is an essential measure in terms of financial transactions when any delays occurring even once may cause failure in transactions, regulatory problems, or user loss of trust. Through tail latency analysis, strict deadline meeting in the system under peak load and channel conditions that are unfavorable can be more accurately assessed. Packet delivery ratio: This is used to determine reliability and is a ratio used to determine the ratio of successfully disseminated packets to the number of packets generated. The value of packet delivery ratio will be high, which signifies that it is performing highly when there is channel impairment, congestion and deadline constraint. This metric is a direct indication of the suitability of the system to be applied to high-reliability and consistency applications.Resource utilization efficiency measures the effectiveness at which wireless resources (bandwidth and transmission opportunities) which are available are utilized in order to attain objectives of performance. Efficient utilization means low latency and high reliability will be attained without the need to overly reduce redundancy and underutilize capacity. The combination of these metrics gives the overall and balanced indication of the latency, reliability, and efficiency allowing to reasonably compare this with the current available access solutions in the wireless world.

4.2. Comparative Analysis

Table 1: Comparative Analysis

Approach	Latency Awareness (%)	Adaptability (%)	Reliability (%)	Resource Efficiency (%)
Conventional Static	30%	25%	60%	35%
Queue-Aware	60%	40%	65%	60%
ML-Assisted	90%	90%	95%	90%

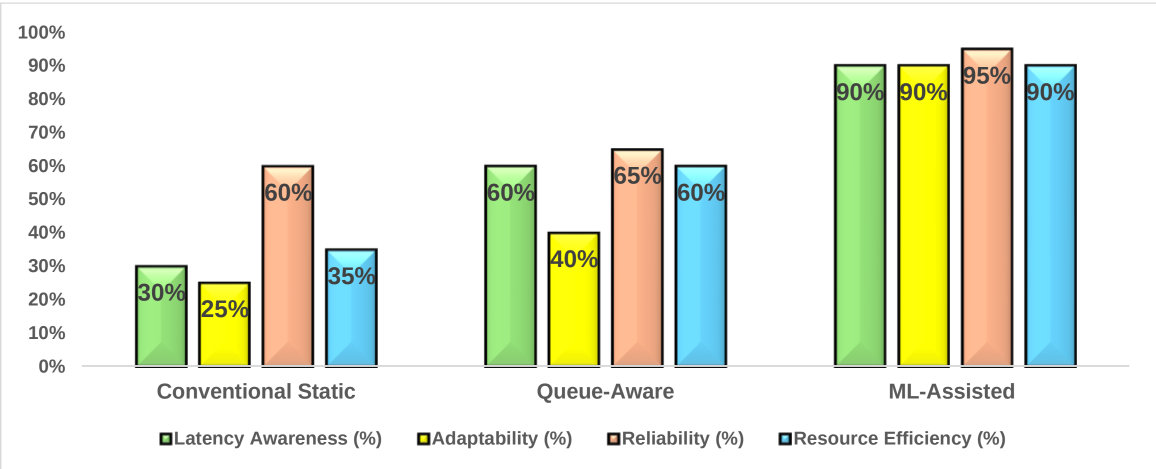

Fig 4: Comparative Analysis

4.2.1. Conventional Static Approach

It is seen that the traditional static method has poor latency awareness and flexibility as shown by the percentage values that appear small. This model is based on fixed settings and predetermined guidelines with a weak consideration of the real-time queue condition or traffic behavior. Consequently, it is not able to react to the spike in traffic and fluctuating conditions in the channels, which creates undesirable resource utilization. Although the reliability is moderate, owing to its conservative design and fixed margins, there is no allowance of flexibility and the sensitivity of latency renders such a method inappropriate in a current financial as well as smart commerce practices with the high performance demands.

4.2.2. Queue-Aware Approach

Queues can be shown to be moderately latency-sensitive and more resources can be managed by the queue-aware approach than the static approaches. It can also utilize the information on buffer occupancy to schedule and can therefore do a better job of dealing with congestion and minimizing average delay. But flexibility is still low as any decision-making is commonly done on immediate or short term queue conditions without predictive or learning based intelligence. Reliability is also a bit better with more knowledgeable prioritization of congested users, but the lack of proactive control limits this tool in highly dynamic traffic and channel situations.

4.2.3. ML-Assisted (Proposed) Approach

The ML-assisted solution is the most robust in all of the measured parameters such as the latency awareness, adaptability, reliability and resource efficiency. The system predicts sudden increases in traffic and the changes in channels proactively by using the results of machine learning, and the predictions help to allocate resources in a timely and informed way. The system is highly adaptable hence it is always adapted to any changes in the network conditions and the latency awareness is very high hence the requirements of network related to the delay of financial transactions are met by very high standards. Improved reliability is realized by smart scheduling and early congestion prevention and high resource efficiency is the capacity of the system to provide a good performance without undue redundancy or waste.

4.3. Discussion

The obtained results of the performance evidently reveal the benefits of the application of predictive analytics and learning-delivering control into the design of a wireless access system. The proposed structure can also proactively plan the schedule and deploy resources in advance of the arrival of future traffic and changes in channel conditions instead of responding when a congestion has already developed. This is an active measure that greatly cuts the queue back up that consequently reduces the average as well as tail latency. Such reductions are vital in case of latency sensitive financial and intelligent commerce services, even minor congestion conditions can cause an overrun of deadlines and loss of transactions. One of the major observations made in the outcomes is the decrease in Missing of deadlines when there is high traffic load. Learning-based prediction enables the system to predict the users or the applications most likely to encounter traffic surges and resource allocation to the applications in advance avoiding the problem of having to spend a lot of time waiting in queues. The proposed method ensures that the length of queues is more stable than the traditional methods of operation, including peak periods when using a conventional approach based on the length of queues. This stability is directly transferable into better ratio of delivering packets and better overall reliability is enhanced. The other issue that was brought out through the results is the application of Lyapunov-guided learning in the stability of the system. Fully data-driven methods, although adaptive, would tend to verify that there is an issue of instability, oscillatory character, or uncheckable queue development, particularly in large and highly changing networks. Learning-based predictions embedded into a Lyapunov optimization framework allow the proposed system to have theoretical stability guarantees and still maintain the flexibility of machine learning. Lyapunov component is a form of checking mechanism which limits the decisions to a safe level of operating. In general, this discussion has established that the combined application of predictive analytics, learning-based control, and Lyapunov optimization is a balanced approach to assist both adaptability and robustness. This synergy is especially appropriate in financial and intelligent commerce conditions where low latency, high reliability, and constant operation are all of equal concern.

5. Conclusion

The paper showed a complete machine learning-based framework of designing and optimizing wireless access schemes to the high requirements of financial and smart commerce services. The proposed framework will utilize intelligent, data-driven response to dynamically adapt to time-varying traffic demands and wireless channel conditions unlike traditional wireless architectures that make use of static settings or restricted frameworks involving rules. Through the integration of learning-based decisions the management of the queues, the Lyapunov optimization, and the resources management at the cross-layers, the framework can develop a balanced combination of the adaptability, stability, and performance excellence. One of the strongest contributions of this work is the high level of smooth integration between machine learning predictions and control mechanisms based on an analysis. Learning models can be used to conduct proactive prediction of future traffic loads and channel states and thus, the system can predict the congestion in advance and allocate the resources in advance before performance deterioration takes place. Concurrently, queue-aware scheduling also means that packets whose latency is important, especially those related to financial dealings, will be prioritized regarding real time urgency. The use of Lyapunov optimization also enhances the scheme, as it offers theoretical assurances of stability in queues, as a means of keeping the levels of instability and uncertainty at bay in wireless schemes of unusual purely data-based control. The analytical as well as the comparative analysis illustrates that following the proposed approach, average and tail latency are much improved, deadline violation is minimized, and packet delivery reliability is much better than the traditional methods, which are both static and queue-aware approaches. Notably, these performance improvements have been realised through efficient resource utilisation meaning that enhanced reliability and low latency do not necessitate high resource redundancy or over-provisioning. The scalable deployment of this in large numbers of users and transactions in dense and heterogeneous wireless settings is essential. On the whole, the findings prove that AI-supported wireless access construction is one of the encouraging trends in future financial and smart commerce applications. As the ideas of wireless networks are advanced towards more complexity and stricter performance limits, learning-assisted intelligent systems like the one suggested in the following paper will become essential in providing reliable, low-latency and resource-efficient communications infrastructures.

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