CHAPTER 8

Blockchain and AI for network economics

Toward intelligent pricing, transparent enforcement, and decentralized trust in mobile ecosystems

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8.1 Introduction

The exponential growth in mobile connectivity, driven by rising user expectations for flexible, high-quality data access, is reshaping the economics of modern networked systems. With the advent of 5G and the anticipated rollout of 6G, networks are becoming increasingly intelligent and service-aware, supporting diverse verticals such as Internet of Things (IoT), eXtended Reality (XR), autonomous systems, and remote healthcare, with heterogeneous Quality of Service (QoS) requirements. Traditional static pricing models are no longer sufficient to manage the dynamic and decentralized nature of modern mobile ecosystems. Instead, operators are transitioning toward adaptive, real-time pricing strategies that respond to fluctuating network demand, QoS requirements, and user behavior. These models require high levels of transparency, automation, and trust.

Two technological pillars, blockchain and Artificial Intelligence (AI), are emerging as enablers of this shift. AI provides the predictive intelligence required to anticipate demand patterns, detect anomalies, and personalize pricing based on real-time data analytics. Blockchain offers an immutable and decentralized ledger system capable of enforcing pricing policies through smart contracts and distributed consensus.

Recent research has introduced platforms like CREDIT (A Credible Trust Framework for Dynamic Mobile Data Pricing Enforcement), that provide a blockchain-based solution for credible implementation of dynamic pricing policies in mobile data services [1]. The CREDIT framework leverages smart contracts to autonomously enforce user-specific policies and penalize violations without relying on centralized authorities. This approach addresses critical trust issues in dynamic data pricing, particularly in multi-stakeholder environments.

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Simultaneously, we discuss the recent research on how the advent of recent technologies such as embedded Subscriber Identity Module (eSIMs) has disrupted the traditional telecom pricing landscape [2]. eSIM enables users to switch carriers and data plans seamlessly, thereby increasing pricing competition and complicating revenue models. We highlight the role AI can play in managing this complexity by automating pricing decisions, optimizing Quality of Experience (QoE), and enhancing customer retention.

Together, this chapter underscores the transformative potential of combining blockchain and AI to architect the future of network economics. This chapter synthesizes the insights from recent studies in this domain to explore how these technologies can converge to foster transparent, intelligent, and dynamic pricing mechanisms in emerging mobile ecosystems. We investigate their application in dynamic pricing enforcement and eSIM ecosystem optimization, while also addressing deployment challenges and future research directions.

8.2 The evolution of mobile network pricing

Advances in mobile internet technologies have led to the development of a multitude of new applications and use cases supported by advanced networks such as 5G and 6G, the IoT, and edge computing. As a result, there has been an unprecedented increase in mobile data demand, and this demand is growing exponentially. This has led to increasing levels of congestion, making the development and deployment of such networks both imperative and challenging [3]. Digital transformation driven by these technological trends will compel the telecom industry to innovate continuously in order to remain competitive in the market [4]. Whereas network standards are continuously evolving, purely technological solutions for expanding cellular network capacity may not be adequate for future networks aiming to support multifold increases in supported data rates and the number of connected devices. Furthermore, it is unlikely that the rate of growth in the supply of wireless capacity (per unit of investment) will match that of demand in the long term [5]. In light of this demand, Mobile Network Operators (MNOs) are turning to new pricing and penalty mechanisms to manage network demand while matching prices to costs [6]. Given the large-scale investments required for 5G/6G networks and the benefits they offer, the issues of charging and resource allocation become critical for recouping these efforts [7,8].

In Beyond 5G (B5G) and upcoming 6G networks, the landscape of mobile services is increasingly shaped by heterogeneous QoS demands from advanced applications. Services such as Augmented Reality (AR) and Virtual Reality (VR), autonomous vehicles, remote robotic surgery, and industrial IoT each require distinct and stringent QoS parameters, including ultra-low latency, high reliability, massive connectivity, or guaranteed bandwidth [9–11]. For instance, an AR-based live sports experience demands high throughput and low latency for real-time rendering, while a remote medical operation prioritizes Ultra-Reliable Low-Latency Communication (URLLC) to ensure surgical precision. These diverse requirements necessitate flexible service provisioning, where networks must dynamically allocate resources tailored to each application's needs. Consequently, pricing models must also evolve to support differentiated, usage-based, or QoS-aware tariffs that reflect the value and resource intensity of each service. This shift toward granular, on-demand pricing and provisioning is essential to sustainably meet the expectations of next-generation digital services.

Further, the adoption of eSIMs is growing rapidly, with consumer-facing products such as mobile phones and wearable devices leading the way, followed by automobiles and smart meters [12]. It has been predicted that the total number of eSIM smartphone connections will increase to 2.4 billion by 2025 [13]. Furthermore, it is anticipated that eSIMs will replace physical SIM cards in the next decade and that all smartphones will have eSIMs by 2030. Currently, the world's largest OEMs, including Apple, Samsung, Google, and Huawei, are offering dual capability (removable SIM and eSIM) in their commercialized smartphones [14]. In particular, Apple's recent launch of an eSIM-only smartphone could further accelerate eSIM market adoption. With several phone vendors switching to eSIMs and eSIM-only devices launching in the market, a new ecosystem for offering and pricing cellular services will emerge. The eSIM value chain comprises of multiple stakeholders, including MNOs, Mobile Virtual Network Operators (MVNOs), Original Equipment Manufacturers (OEMs), Content Providers (CPs), application developers, third-party profile managers, and regulators, and is inherently complex. In particular, the possibility of seamless switching between operators will result in increased churn and greater competition [15]. Hence, innovative business models and pricing strategies must be explored to exploit the benefits and mitigate the challenges related to eSIMs.

8.2.1 Traditional pricing models

8.2.1.1 Static versus dynamic pricing

Various static and dynamic pricing strategies have been proposed in the literature [16]. While static pricing mechanisms such as flat-rate, tiered, and usage-based pricing incur minimal operational overhead, they do not offer any incentive for users to dynamically adjust their demands for better utilization of the network. Dynamic pricing mechanisms such as differential pricing, proportional fair pricing, and game-theoretic pricing take current network conditions into account, resulting in higher responsiveness [17–19]. Despite these benefits, some of these pricing mechanisms do not take QoS into consideration. A number of alternatives, such as QoS-based pricing and congestion-aware pricing schemes, have also been proposed [20–23,25]. Most of these provide differential pricing, with predefined QoS parameters for each QoS class, and focus on exploiting user adaptability by increasing prices based on network congestion to shift usage to off-peak hours. However, such penalty-based pricing mechanisms are not acceptable in a network ecosystem and may negatively impact customers, as they may end up paying more for services due to the operator’s failure to provide sufficient capacity (resulting in congestion and higher prices) [26].

Hence, there is a need for innovative and dynamic pricing strategies that not only help service providers manage the ever-increasing demand but also provide the flexibility and granularity to map costs to the heterogeneous QoS requirements of various user applications.

8.2.1.2 Prepaid versus postpaid subscriptions

The impact of eSIMs is expected to be greater in markets with a majority of prepaid customers than in markets with a majority of postpaid customers. In developing countries, with predominantly prepaid customers, several customers purchase SIM cards from multiple MNOs, resulting in a mobile penetration rate exceeding 100% [15]. As prepaid customers are not contractually bound to their MNOs, they may discontinue service without prior notice, posing unique challenges for operators. The eSIM makes switching easier, further increasing the probability of churn and intensifying competition.

In developed countries, although customer loyalty is driven mainly by device subsidy levels, investments in device subsidization are expected to decrease drastically over the next few years. With eSIMs, customers may also want to maintain a base subscription while holding multiple other subscriptions, which could change market dynamics. Another popular trend in developed countries is the provision of unlimited data plans at a subsidized rate. However, the so-called “unlimited plans” for 5G have capped speeds, and QoS is throttled once a data limit is exceeded. This limit will be reached sooner for applications such as AR and VR with stringent QoS requirements. Hence, to manage the ever-increasing demand for resources in a highly competitive ecosystem with eSIMs, operators will be required to adopt optimal pricing strategies in the near future.

8.2.2 Pricing challenges

Due to heterogeneous requirements in advanced mobile ecosystems, dynamic pricing mechanisms such as congestion pricing, game-theoretic pricing, auction-based pricing, and QoS-based pricing have been proposed and are being considered as replacements for flat-access pricing schemes [16,27–29]. However, none of these have yet been practically adopted by MNOs due to the associated complexity of implementation and psychological issues related to lack of trustworthiness when prices vary in response to network congestion [30].

The enforcement of real-time dynamic pricing mechanisms must consider the accounting architecture, incentive compliance, price variation, and security, as well as challenges related to QoS management and scheduling. However, a lack of credibility could arise when prices vary due to dynamically varying QoS in response to network congestion. Users prefer a degree of certainty in prices and control over their usage, such as choosing different QoS levels based on application requirements or waiting for discounted periods for non-critical applications in time-dependent data plans. Furthermore, the lack of validated methods for users to demonstrate service quality variation and to claim Service Level Agreement (SLA) violations further challenges this. For instance, consider the scenario where an MNO offers congestion-based pricing, i.e., the price increases in case of congestion to maintain the same QoS for the user [26]. This is done to mitigate congestion by encouraging users to shift their usage to off-peak hours. However, it would be unfair if the user is charged a higher price but his QoS requirements are not met (e.g., due to insufficient network capacity or unpredictable demand spike). Therefore there is a requirement for a trustworthy framework for automated enforcement of such pricing mechanisms, as well as a credible mechanism for auditing service quality.

Moreover, as the adoption of eSIM technology is accelerating rapidly and is anticipated to prevail over conventional physical SIM cards in the next few years, innovative business models and pricing strategies must be explored to exploit the benefits and mitigate the challenges related to eSIMs. The eSIM value chain comprises multiple stakeholders and is inherently complex [31]. The rise of the IoT, provision of QoS subscriptions, flexibility of network slicing, and upcoming enhancements available with B5G/6G networks will further add to the complexity of this ecosystem [32]. In particular, the possibility of seamless switching between operators will result in increased churn and greater competition [15].

In light of the above challenges, the successful deployment of dynamic pricing mechanisms in advanced mobile ecosystems hinges on the development of credible, transparent, and user-centric frameworks. While theoretical models such as congestion-based, game-theoretic, and QoS-aware pricing offer promising solutions, their real-world adoption remains hindered by issues of trust, enforceability, and user perception. The shift toward eSIM-based connectivity, multi-operator access, and the advent of B5G/6G technologies only amplifies these challenges, introducing greater churn, competition, and service complexity. In this evolving landscape, mobile network operators must not only innovate pricing strategies but also ensure that these strategies are supported by robust enforcement mechanisms such as blockchain-based smart contracts, and intelligent quality validation, through AI-driven analytics [33–35]. Only with such trusted, auditable, and adaptive infrastructures can dynamic pricing become viable and widely acceptable, balancing economic incentives with user satisfaction and fairness.

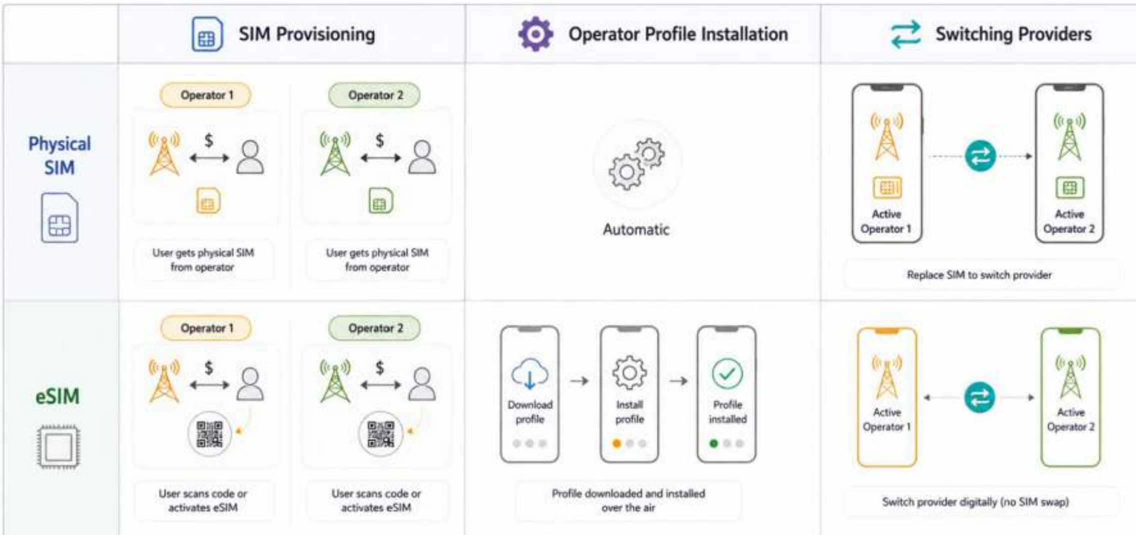

Figure 8.1:
SIM provisioning and switching: physical SIMs vs. eSIMs.

8.3 eSIM services and their economic impacts

eSIM is a combination of an embedded Universal Integrated Circuit Card (eUICC) and an operator profile. It performs the same function as conventional physical SIM cards. eSIMs allow for over-the-air provisioning of MNO or MVNO profiles based on users' location and requirements, resulting in the digitization of the consumer experience. A profile consists of the operator's credentials, subscription-related data, and SIM-based applications. After setting up a contract with the desired MNO, a user can activate the eSIM service using Quick Response (QR) codes, manual activation codes, or operator applications to connect the device to the MNO's Remote SIM Provisioning (RSP) system [36]. The eSIM-based RSP architecture for consumer and Machine-to-Machine (M2M) scenarios has been standardized by GSMA [37]. Unlike physical SIM cards, where users are required to acquire SIM cards from a new operator and physically swap the cards to connect to a new network, eSIMs allow users to download multiple operator profiles and flexibly switch between them, as illustrated in Fig. 8.1. eSIMs are a means of meeting the growing demand for flexible connectivity as the industry moves into the 5G era. They also enable cellular connectivity for devices (e.g., laptops and wearable devices) that do not typically have physical SIMs.

Since being first introduced in 1991 with the evolution of Global System for Mobile (GSM) communications, the SIM cards have evolved considerably in terms of size, storage capacity, and supported functionality. Although the size has shrunk from credit-card-sized SIM cards to eSIMs, the main functionality of identifying and authenticating customers on the mobile network remains the same. However, eSIMs offer several additional benefits, including

Table 8.1: Challenges and opportunities for players in eSIM eco-system.

Stakeholder	Key Challenges	Key Opportunities
User (Consumer)	New on-boarding process Lack of universal support and awareness	Simplified subscription management Seamless switching between providers Multi-device connectivity
Network Provider (MNO / MVNO / OEM)	Increased competition and price pressure Reduced retail channel control and power Higher customer churn New investments for 5G and IoT Lack of standardization in some areas	New revenue via bundles and multi-device plans Wholesale opportunities and reduced OPEX Lower entry barriers for new operators and IoT players New target segments (e.g., expats, IoT users) Improved customer experience and retention
Content Provider (OTT / Digital Services)	Increased competition from other OTT players Dependency on connectivity quality Uncertain future business models	Broader reach via seamless connectivity Higher quality of service (QoS) Opportunities for bundled and value-added services
Regulatory Authorities (Regulators)	Need for new regulatory frameworks for Disruptive technologies and players Cross-border and roaming regulation complexity	New Regulations for disruptive eSIM and co-existing technologies such as IoT, 5G (network slicing)

the ability to simultaneously subscribe to multiple operators, ease of switching networks, temporarily changing networks, enhanced security, and saving space on mobile devices by eliminating the need for a physical SIM. These benefits and opportunities have made the eSIM value chain inherently complex, as it comprises multiple stakeholders from enablement to management stages. Although MNOs will still play a pivotal role, numerous other players will seek to exploit new market dynamics. Furthermore, the use of eSIMs implies that the mobile industry value chain will be reconfigured owing to potential negotiations between chipset manufacturers and OEMs. The eSIM-related opportunities and challenges for different players have been summarized in Table 8.1.

Currently, most M(V)NOs offer similar plans for both SIMs and eSIMs. However, owing to differences in service provisioning, changing market dynamics, and increased competition, this may change in the future. Hence, to harness the opportunities and innovations enabled by 5G and eSIMs, mobile data pricing strategies should be designed carefully [25]. The different factors to be considered for pricing eSIM-based services are summarized in Fig. 8.2.

8.3.1 Optimal pricing for churn management

eSIMs allow users to simultaneously subscribe to multiple network providers, allowing them to switch operators flexibly. This implies that, in addition to traditional churn, where consumers switch between different MNOs, *soft churn*, where consumers dynamically switch

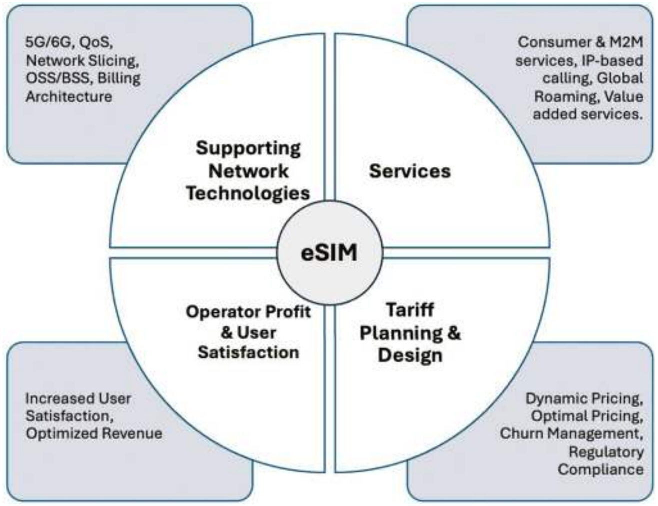

Figure 8.2:
Underlying factors for pricing eSIM-based network services.

among multiple plans from multiple providers, must also be considered. Soft churn can be triggered by several factors, such as short-term promotions, network coverage and quality, pricing strategies, technology, advertising, reward programs, and complaint resolution. The eSIM-triggered churn among operators is likely to be higher in prepaid ecosystems [15]. However, this does not necessarily imply that customers who are not contractually bound will spend less or churn networks more frequently. As QoS demands increase, consumers may still prefer acceptable QoS and a superior user experience, and satisfied consumers are expected to remain loyal to their MNOs, similar to contractually bound consumers. The issue of customer churn is a major concern for global telecommunications companies and is especially critical in mature markets, with annual churn rates ranging from 20% to 40% for most global MNOs. Hence, MNOs and MVNOs should offer appropriate service quality and adopt optimal pricing strategies that are dynamic and flexible to retain their customer base and attract new customers in a highly competitive environment.

8.3.2 Emerging pricing trends

Emerging pricing trends in the eSIM ecosystem reflect shifts in pricing strategies, shared data offerings, global roaming models, and customer acquisition strategies. Table 8.2 summarizes key trends and their implications for M(V)NOs and end users.

8.4 Blockchain for credible pricing enforcement

As mobile data pricing evolves toward dynamic, personalized, and context-aware models, the need for credible enforcement mechanisms becomes paramount. Traditional enforcement

Table 8.2: Emerging Pricing Trends in eSIM eco-system.

Pricing Trend	Key Points	Implications
Wholesale Service Provisioning and Pricing	eSIMs reduce entry barriers for MVNOs; MNOs can offer wholesale services to optimize revenue. OEMs may also act as MVNOs by purchasing connectivity from MNOs.	Leads to increased competition and reduced subscriber loyalty. Volume-based pricing limits MVNO flexibility in offering high-volume or unlimited plans.
Shared Data Plans	eSIMs allow connectivity across multiple devices (IoT, wearables, laptops, etc.) under one subscription. Each device has an independent connection but shares a master plan.	Facilitates innovative pricing models and enhances customer experience through bundled services.
Global Roaming Tariffs	eSIMs enable users to switch to local networks while traveling. MVNOs can offer tailored plans for specific user groups such as expats.	Puts downward pressure on roaming prices; increases transparency may reduce operator revenues. Competitive pricing expected to increase.
Promotional Pricing	Temporary discounts to attract or retain customers. eSIMs enable easier switching, making this tactic more viable.	Improves short-term customer acquisition and perceived value but may reduce long-term profitability and affect perceived service quality.
Try and Buy	Allows users to test services before committing. eSIMs simplify trial provisioning.	Encourages user adoption, especially for advanced services (5G, AR/VR). Supports QoS-based differentiation and can increase conversion rates.

approaches often rely on centralized authorities or operators, which can lead to opacity, inconsistency, and a lack of user trust. Existing pricing plans are typically implemented using AAA (Authentication, Authorization, and Accounting) protocols such as RADIUS and DIAMETER for user authentication, access control, and accounting; and the Policy and Charging Rules Function (PCRF) for implementing policy and charging control functionalities, including dynamic policy enforcement, QoS management, traffic steering and optimization, and real-time charging. These traditional charging mechanisms do not offer sufficient flexibility and agility [38,39]. In multi-stakeholder environments, such as those involving MNOs, service providers, and consumers, there is a growing demand for transparent, automated, and tamper-proof pricing policy enforcement. These challenges can be addressed by leveraging blockchain technology and smart contracts [40–43]. It enables the adoption of dynamic pricing models while ensuring that both the provider and the user are held accountable to predefined service policies. By encoding these policies into smart contracts on a blockchain, it can be ensured that pricing rules are executed autonomously and verifiably, without the need for centralized arbitration.

In assessing blockchain platforms for the implementation of dynamic pricing through smart contracts, several key factors come into play. Ethereum, renowned for its expansive developer community and comprehensive documentation, stands out as the preferred choice [44–46]. Although other alternatives, such as Binance Smart Chain, offer lower transaction fees and faster confirmations, they sacrifice decentralization, a key tenet of blockchain technology. Cardano, with its emphasis on security and scalability, is promising but still in the early stages of ecosystem development. NEO's faster transactions and language support are notable, but its ecosystem lags behind Ethereum. Tezos prioritizes on-chain governance but has a smaller developer community. Ethereum, despite slightly higher fees, excels in overall ecosystem maturity, developer support, and compatibility [47,48].

This section explores how blockchain, through the lens of the CREDIT framework, can be used to reinforce trust in mobile data markets by creating a credible and enforceable pricing architecture. It leverages Ethereum smart contracts to encode and enforce SLAs between MNOs and users [49–51]. It introduces a decentralized auditor mechanism, in which randomly selected user auditors verify whether the guaranteed QoS has been delivered. This process ensures fairness and discourages collusion through randomized selection and a reward-penalty structure based on auditor truthfulness. A key strength of CREDIT lies in its game-theoretic foundation, which proves that truthful behavior by auditors leads to strong Nash equilibria, making the system inherently credible and self-enforcing.

8.4.1 Use case

Consider a cellular network scenario consisting of an MNO offering mobile data services to its users. Today's cellular networks, such as 5G/6G, are designed to be multiservice networks capable of supporting different applications with heterogeneous QoS requirements over a single integrated network platform [52]. Therefore assume that MNO offers different levels of QoS and that users can choose them based on their application requirements. Let us also assume that appropriate scheduling mechanisms are implemented at the base station to ensure QoS guarantees based on user-subscribed plans.

The MNO implements dynamic pricing mechanisms where users are charged based on instantaneous network conditions. Each user selects a subscribed QoS level Q_{Plan} according to their service requirements, and the price varies dynamically in response to user demand and network congestion. Under no congestion, the user pays a base price p proportional to Q_{Plan}, while during congestion, the price p' depends on the adopted pricing strategy. For example, in congestion pricing [26], $p' > p$ to shift demand to off-peak periods, whereas in differential pricing models [53], $p' < p$ as users are compensated for degraded QoS. Since pricing is dynamic, it becomes essential to detect SLA violations caused by congestion. Currently, detection is centralized with the MNO, offering users no verifiable proof of SLA breaches

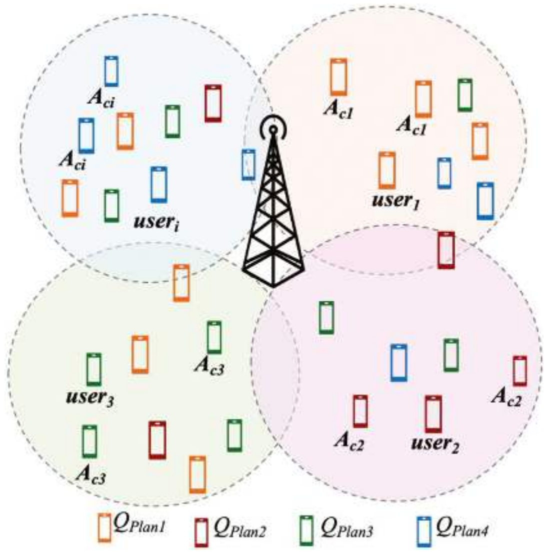

Figure 8.3:
System overview.

(i.e., when actual QoS is less than Q_{Plan}). To address this, an auditor entity is introduced, and the users subscribed to the MNO who voluntarily act as validators of the achieved QoS in exchange for rewards. From a decentralized pool, N auditors are randomly selected to verify the QoS delivered to a user over a service duration T_{srv}, with participants incentivized to maximize truthful SLA validation.

The achieved QoS in wireless networks depends on multiple factors (e.g., distance from the base station, height of the antenna, frequency and directional characteristics of the antenna, physical obstructions, beam switching, network load, transmission power, etc.), and on the user subscription class Q_{Plan}. Considering these factors, it is assumed that users close to the given user $user_i$ at any given time will experience a similar QoS and hence be good candidates for validating the SLA between $user_i$ and the MNO. Therefore the area within radius r from $user_i$ is defined as $zone_i$, as indicated in Fig. 8.3. A_{ci} represents the candidate auditors for validating the SLA between $user_i$ and the MNO. The set of auditors for validating the service agreement between the MNO and $user_i$ must be selected from the auditor pool comprising the users in $zone_i$ at the time instance t, subscribed to the same Q_{Plan}, and willing to provide this validation for some rewards. At the end of the service duration, the SLA ends with two possibilities (i.e., network service violation or no violation) determined based on the response forming the majority in the auditor evaluation. Consequently, MNO, user, and auditors are compensated based on the SLA, as illustrated in Fig. 8.4.

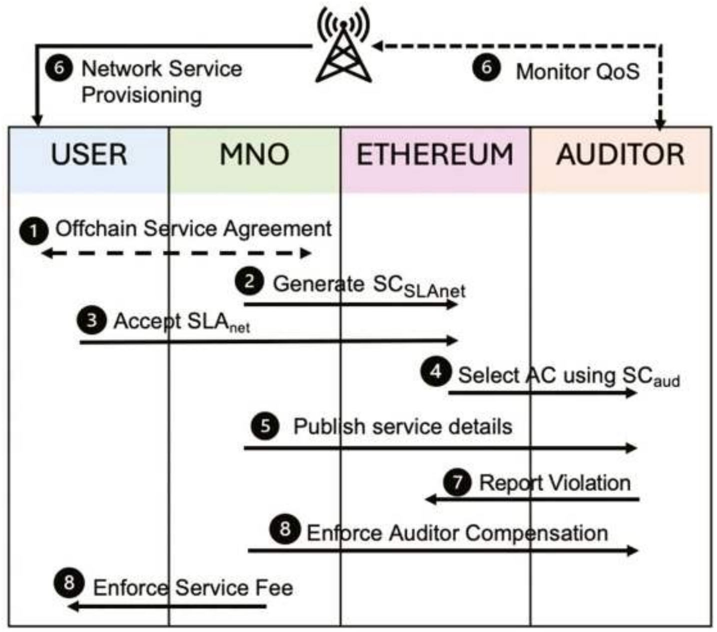

Figure 8.4:
SLA enforcement in CREDIT.

8.5 AI for intelligent pricing and optimization

In this section, we will discuss how AI can be leveraged to design personalized plans that achieve high user satisfaction while optimizing revenue for operators. Further, we will illustrate how recommender systems can be used to provide optimal plan recommendations based on historical usage data from different users.

8.5.1 Personalized pricing

In the current prepaid ecosystem with traditional SIM cards, switching between different operator plans is not straightforward; hence, it is very difficult for users to differentiate between operators' low-profitability plans (to attract more customers) and high-profitability plans (to increase their revenue). Moreover, since they can use only one plan at a time, they cannot leverage the flexibility to choose the right plan at the right time. With eSIMs, manual switching is no longer required, and the processes of optimization (choosing the best plan at any point in time) and switching can be easily automated. Consequently, operators are obliged to adopt inventive pricing mechanisms, such as personalized pricing, since they have no choice but to offer optimal pricing to stay competitive.

To illustrate the benefits of personalized pricing for users as well as MNOs, it is compared to traditional pricing, where operators offer fixed tiered plans in terms of data allowance, time validity, and QoS level. Let us consider a traditional pricing approach, where a customer purchases a plan at a certain level of service quality q for a total of d bytes of data and for a period of time t. The cost of providing such a plan to the customer is denoted as $C(q, d, t)$. Note that C is a nondecreasing function of q, d, and t, since the resource requirements (cost) increase with each of these factors. Over the duration of this plan, denote the actual usage of these by $\bar{q} \le q$, $\bar{d} \le d$, and $\bar{t} \le t$. For example, $\bar{q}$ may be lower because of congestion periods, $\bar{d}$ may be lower if the user runs out of time before running out of data, and finally $\bar{t}$ may be lower if the user runs out of data before running out of time. Therefore $C(\bar{q}, \bar{d}, \bar{t}) \le C(q, d, t)$. Note that the user's historical data usage can be used to estimate values for $\bar{q}$, $\bar{d}$, and $\bar{t}$ for each upcoming subscription purchase in the case of personalized pricing.

The price of the plan should reflect the cost of the resources that are allocated to fulfill the service request, as well as the desired profit margin ρ. In a competitive environment, it is important that an appropriate value of ρ is chosen. This is a typical price-elasticity issue [23]. If ρ is too high, this leads to high prices and the operator will attract few customers, resulting in a low total profit. In contrast, if ρ is too low, then, although they may attract many customers, the low profit per customer will also produce a low total profit. Assuming that the optimal value of the profit margin ρ^* is known, the price charged by the traditional provider would be $(1+\rho^*)C(q, d, t)$ which is higher than the price charged by the personalized pricing operator which would be $(1+\rho^*)C(\bar{q}.\bar{d}, \bar{t})$. Therefore the traditional pricing provider is likely to lose customers to the personalized pricing operator. If they instead reduced their price to match that of the personalized pricing operator, their profit margin would drop below the optimal value. Therefore, in either case, the operator offering personalized pricing is better off.

AI can be leveraged to analyze historical user data and behavioral patterns to accurately predict expected usage parameters $\bar{q}$, $\bar{d}$, $\bar{t}$ and dynamically adjust pricing in real time. Machine learning models can also estimate optimal profit margins based on user responsiveness and price elasticity, enabling operators to fine-tune personalized offers that maximize both customer satisfaction and revenue [24].

8.5.2 Optimal plan recommendation

In the previous section, we discussed the benefits of an optimized customer-specific plan. Since such plans are presently unavailable, in this section, we illustrate the process of finding the best available plan for a customer. Assume that we have access to customers' historical data, and plans available from all operators in the customers' location, and their

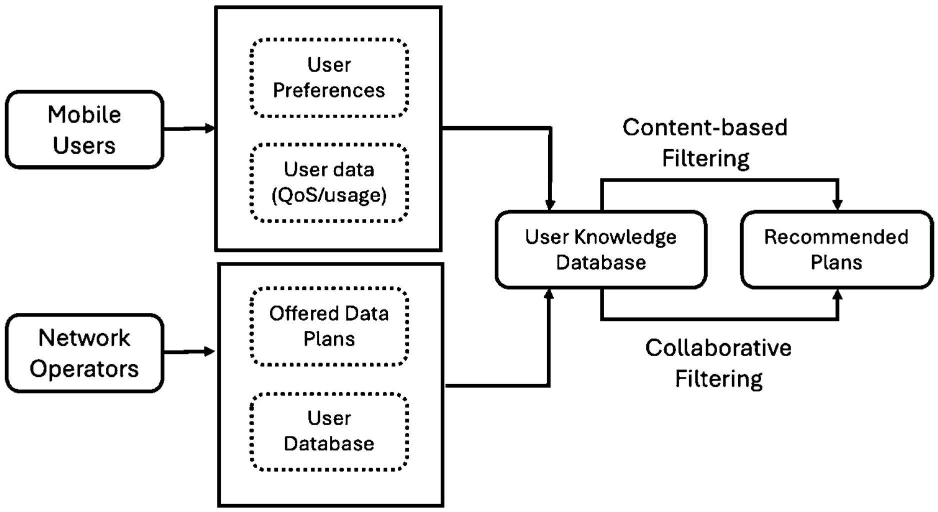

Figure 8.5:
Hybrid recommender system for optimal plan recommendation.

costs ($C_i(q_i, d_i, t_i)$ of plan i). The objective is to determine the plan with the lowest cost for the resources required by the user. For a given plan i, the utility provided by this plan to the customer can be obtained from the plan quality q_i times the maximum number of transferred bits, i.e., $q_i \max\{d_i, dt_i/t\}$. Therefore the lowest cost for the offered utility (i.e., the optimal plan i^*) is given by

$$i^* = \underset{i|q_i \geq q}{\operatorname{argmin}} \left\{ \frac{C_i(q_i, d_i, t_i)}{q_i \max\{d_i, dt_i/t\}} \right\}. \tag{8.1}$$

Note that, for a personalized plan, $d/t = d_i/t_i$ so that the precise resources are available while maximizing the denominator. The associated cost (the numerator) would also be minimal because minimal resources will be provided at the lowest possible quality q. Hence, if such a plan were to be offered, it would be chosen, as one would expect.

This approach depends on the availability of sufficient historical usage of the customer. Since users may potentially switch plans depending on their needs and budget, this estimation is not straightforward, and AI techniques can be leveraged, as illustrated in Fig. 8.5. A knowledge database can be constructed from the collection of mobile data plans, historical user subscription data, and usage data. For customers with significant historical data, content-based filtering can be applied to determine parameters such as data quantity and quality. If insufficient customer data is available for a robust estimate, collaborative filtering (i.e., using data from similar customers) can be used to improve the estimates. Furthermore, operators will offer different benefits for different plans, such as plan sharing, unused-data credits, discounts, and special offers. These factors must also be taken into account.

Therefore a recommender system can be developed to assist in parameter estimation and the determination of the optimal plan, while accounting for additional constraints.

As we move towards the adoption of optimal pricing strategies, AI plays a crucial role in transforming pricing dynamics as it can be applied to automate plan selection, predict user behavior, and optimize operator pricing strategies based on real-time data [54,55]. The key use cases can be summarized as follows:

- Historical Usage Prediction: AI models can analyze users' historical data usage patterns to accurately estimate $\bar{q}$, $\bar{d}$, and $\bar{t}$, the actual service quality, data, and time likely to be used, thus enabling operators to tailor personalized plans that match real usage rather than over-provisioning
- Dynamic Plan Recommendation: AI can continuously monitor network conditions and user activity to recommend or automatically switch to the most cost-effective plan (based on predicted usage and operator pricing) at any given time, leveraging the flexibility enabled by eSIMs
- Profit Margin Optimization: AI can model price elasticity using past consumer behavior and market trends to determine the optimal profit margin ρ^*, helping MNOs balance competitive pricing with sustainable revenue
- Congestion-Aware Adjustments: AI can forecast congestion periods and adjust expected QoS levels ($\bar{q}$) accordingly, helping personalize pricing in a way that reflects realistic service delivery
- Segmentation and Personalization at Scale: AI clustering and classification algorithms can group users based on usage habits, preferences, and device profiles to offer targeted pricing tiers that are more attractive than fixed-plan competitors.

8.6 Convergence of blockchain and AI

The combination of Blockchain and AI opens up powerful new possibilities for mobile data pricing, transforming how network services are offered, consumed, and enforced [56–58]. AI can aid in predictive user analytics, demand forecasting, and real-time dynamic pricing optimization, while blockchain ensures secure, transparent, and automated enforcement of dynamic pricing methods. As mobile networks evolve with the adoption of eSIM, IoT, and 5G/6G, traditional pricing models face increasing challenges. The combined use of AI and blockchain offers robust solutions for dynamic pricing enforcement, trust management, personalized user experience, and automated transactions [59–61].

Below are practical examples and use cases that demonstrate how AI and blockchain can be applied to enable transparent, adaptive, and efficient pricing strategies across mobile data networks:

- Intelligent Real-Time Pricing Models: AI enables personalized, context-aware pricing by analyzing user behavior, network conditions, and historical usage. It can implement usage-based or QoE-driven models. For example, AI can offer discounts during off-peak hours or adjust pricing based on predicted user demand
- Predictive Demand Management: AI models forecast traffic spikes and usage trends to inform real-time pricing strategies. Blockchain ensures these changes are visible, tamper-proof, and enforceable, reducing the risk of disputes and unfair billing
- Automated Dispute Resolution: Smart contracts can automate the enforcement of rules and penalties in the event of policy violations. AI helps detect anomalies and misuses in network activity, triggering blockchain-based resolutions without human intervention
- Decentralized Marketplace for Data Plans: Blockchain can allow users to securely buy, sell, or lease unused mobile data in a peer-to-peer marketplace. AI can facilitate matchmaking and dynamic pricing between data buyers and sellers, based on demand and network conditions
- eSIM Profile Management and Pricing Optimization: eSIM technology enables users to switch carriers easily. AI can automate the selection of the best network based on price, QoS, and user preferences. Blockchain can ensure that subscription changes and contracts across carriers are securely executed and verifiable
- Cross-Border Roaming and Multi-Operator Interoperability: With eSIM-enabled global roaming, AI can help the user to choose optimal networks in real time. Blockchain can enable transparent roaming agreements and settlements between operators, avoiding overcharging or fraudulent practices
- Integration with IoT and M2M Economy: As wearables and IoT devices proliferate, AI can cluster usage patterns across devices to recommend or automate shared pricing plans. Blockchain can support a secure, autonomous M2M data economy, where devices can purchase connectivity as needed
- Tokenized Incentives and Rewards: Operators can introduce blockchain-based token systems to reward users for behavior such as off-peak usage or contributing to reduced congestion. AI can optimize these incentive models based on network analytics and user responsiveness
- Autonomous Agent-Based Pricing Systems: In the future, AI agents on user devices can autonomously negotiate and purchase data access. Blockchain smart contracts can ensure that these agents follow transparent rules, enforce SLAs, and log transactions immutably
- Decentralized Identity (DID) for eSIM Users: Blockchain enables secure, user-owned digital identities. Linked with eSIM profiles, DID can allow users to control their subscriptions and personal data. AI can personalize offers and manage preferences without compromising privacy

- Next-Generation Service Provisioning (5G/6G): AI is crucial for real-time resource optimization and network slicing in 5G and beyond. Blockchain can support the enforcement and auditing of pricing across slices and operators, ensuring transparency in shared infrastructure
- Edge AI and Federated Learning for Pricing: Edge AI models can make on-device pricing decisions with minimal latency. Federated learning allows collaborative model training without sharing raw data, while blockchain provides coordination and proof of participation
- Sustainability-Driven Pricing Models: AI can analyze data usage and its environmental impact, promoting energy-efficient behaviors. The blockchain can reward sustainable usage through green tokens or discounts, aligning mobile pricing with global climate goals.

8.7 Conclusion and future directions

The evolution of 5G and the anticipated rollout of 6G, along with the emergence of eSIM technology, is radically transforming the mobile network landscape. Traditional static pricing models are becoming increasingly inadequate in managing the diverse QoS demands and dynamic service usage patterns of modern users. In this context, AI and blockchain offer a powerful synergy: AI enables predictive analytics, real-time personalized pricing, and intelligent plan recommendation, while blockchain ensures transparent, tamper-proof enforcement of dynamic pricing mechanisms and SLAs. The convergence of these technologies unlocks novel business models such as decentralized data marketplaces, tokenized incentives, and autonomous agent-based pricing systems. In particular, personalized pricing models powered by AI can significantly reduce resource over-provisioning and improve customer satisfaction, while blockchain-based smart contracts can automate and validate service quality and transaction integrity without relying on centralized authorities.

Future work should explore the following key directions:

- Developing scalable AI-Blockchain models that can operate efficiently in federated or edge environments to support real-time pricing decisions without compromising user privacy.
- Creating interoperable blockchain frameworks that support seamless multi-operator coordination, especially for multi-network slicing in 5G/6G.
- Developing new business models based on tokenization and micro-transactions, enabling fine-grained, usage-based service payments and incentive structures in multi-stakeholder environments.

- Advancing toward autonomous, decentralized network economics, where intelligent agents negotiate service access, enforce contracts, and manage resources without centralized intervention.
- Exploring sustainability-aware pricing models where AI assesses environmental impact and blockchain issues green tokens to reward energy-efficient behavior.
- Ensuring regulatory alignment and ethical deployment of personalized pricing to prevent discriminatory or exploitative practices.

Ultimately, the intelligent integration of AI and blockchain is not just a technological enhancement; it is a foundational shift toward transparent, flexible, and equitable network economics in the age of digital hyperconnectivity.

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