Adaptive Hybrid Rollups: AI-Guided Routing between ZK and Optimistic Verification

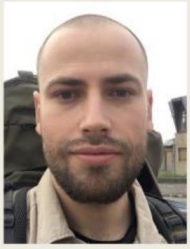
Mykola Malenko[1]

[1]Kyiv National University of Construction and Architecture,
Air Force Ave., 31, Kyiv, Ukraine, 03037
[1]malenko.mv@knuba.edu.ua, https://orcid.org/0000-0002-7360-7749

Received 07.10.2025, accepted 28.11.2025
https://doi.org/10.32347/st.2025.4.1206

Abstract. This article examines the limitations of existing hybrid rollup solutions and presents an adaptive L2 architecture model that leverages artificial intelligence mechanisms. It is shown that current approaches to combining optimistic and ZK verification are largely based on static rules or manual mode selection, which prevents them from effectively accounting for load dynamics, risk profiles, and domain-specific properties of applications. Based on an analysis of optimistic, ZK, and hybrid rollups, an adaptive hybrid rollup model with AI-based transaction routing is proposed. This model combines transaction classification, GNN-based decision making, LSTM-based network condition forecasting, a dual-path execution system, and a continuous learning module. The article describes a Predictive Routing Algorithm that performs proactive selection between ZK and optimistic paths, taking into account cost, latency, security, and risk profile, as well as a Dynamic Resources Allocation mechanism that dynamically redistributes resources between the paths. The proposed multi-criteria optimization framework demonstrates the ability to tune objective weights to the specifics of different classes of DeFi and Web3 protocols. It is shown that the implementation of such a model is promising for systems with high transactional intensity, as it enables a shift from manual configurations to automated, data-driven policies for resource and risk management in hybrid rollup architectures.

Keywords: web3, adaptive hybrid rollups, artificial intelligence, blockchain.



Malenko Mykola
Post Guarduate Student,
department of cyber security
and computer engineering

INTRODUCTION

Contemporary blockchain networks face a fundamental scalability challenge that limits their widespread adoption in the global digital economy. The Ethereum network is capable of processing only 15-30 transactions per second at the base layer [1, 2], while centralized payment systems demonstrate throughput that exceeds this metric by several orders of magnitude [1]. Limited throughput leads to network congestion and significant increases in transaction costs [2], creating a barrier to mass adoption of blockchain technology.

Layer-2 solutions, particularly rollups, successfully reduce the load on the main blockchain, offering more scalable infrastructure [3]. Among rollup technologies, optimistic rollups and zero-knowledge proof rollups have gained the widest adoption [4]. Optimistic rollups, including Arbitrum and Optimism, provide full compatibility with the Ethereum Virtual Machine and low transaction costs ranging from $0.10 to $0.30 [4, 5], however they have a significant limitation in the form of a seven-day waiting period for final confirmation [6, 7]. ZK-rollups, such as zkSync Era and StarkNet, ensure faster transaction finality and efficient data compression [8, 9, 10, 11], but the generation of cryptographic proofs requires significant computational resources, which is reflected in higher transaction costs [5].

Analysis of existing solutions reveals a fundamental shortcoming in the form of absence of mechanisms for adaptation to the specifics of individual transactions and

dynamic network conditions. Both optimistic and ZK-rollups apply a single verification strategy to all operations regardless of their value, urgency, or security requirements [1]. Initial attempts to overcome these limitations are represented by static hybrid architectures, however these systems remain constrained by predefined routing rules and are unable to dynamically adapt to changes in network load [12, 13, 14].

Systematic reviews demonstrate successful application of machine learning methods for optimizing various aspects of blockchain systems, including consensus mechanisms and dynamic optimization of resource allocation [15, 16, 17]. However, the potential for applying artificial intelligence for intelligent routing between different verification mechanisms in rollups remains insufficiently explored in scientific literature [18].

The objective of this work is a systematic analysis of the possibilities and prospects for creating adaptive hybrid rollup systems that utilize artificial intelligence for dynamic routing of transactions between zero-knowledge verification and optimistic verification mechanisms. The research is aimed at developing a conceptual architecture of an adaptive hybrid system, analyzing the possibilities of its practical application, theoretical prediction of efficiency, and evaluation of the technology's development prospects.

REVIEW OF ROLLUP TECHNOLOGIES

Optimistic Rollups

Optimistic rollups represent a second-layer scaling technology based on the assumption of network participant honesty. Unlike traditional approaches that require active verification of each transaction, optimistic rollups proceed from the presumption of operation correctness until proven otherwise [19]. This architectural feature provides a significant increase in throughput while maintaining an acceptable level of security through the fraud proof mechanism.

The architecture of optimistic rollups presupposes the presence of two key roles: sequencers, responsible for collecting and processing transactions, and verifiers, who oversee the network and initiate challenge procedures upon detection of incorrect operations [20]. Sequencers ensure the batching of a significant number of transactions into batches, which are subsequently published in the main blockchain together with a new state root. A critical feature of this process is that sequencers must deposit collateral to participate in the network, which can be confiscated in case of detection of malicious behavior [20]. The fraud proof mechanism constitutes a fundamental element of optimistic rollup security. After publication of a transaction batch, a challenge period begins, during which any network participant can initiate a procedure to verify the correctness of proposed state changes [6]. Modern implementations of optimistic rollups utilize interactive fraud proofs, which require several rounds of interaction between the sequencer and challenger to determine the specific instruction that caused the error [21]. This approach significantly reduces the cost of verification compared to non-interactive proofs, which require re-execution of all batch transactions on the first layer. The challenge period traditionally amounts to approximately seven days in leading optimistic rollups, including Arbitrum, Base, and Optimism [6, 7, 19, 20]. This duration is necessitated by the need for protection against economic censorship attacks, where an attacker may attempt to block challenge submission through bribing block producers [21]. Research shows that to ensure successful completion of the challenge period in the presence of economic censorship, the period duration must exceed one week, proceeding from the assumption that the Ethereum community will implement a social response in the form of a hard fork of the chain within this timeframe [21].

The main advantage of optimistic rollups is their compatibility with the Ethereum Virtual Machine and relatively low transaction costs. Following the implementation of the EIP-4844 upgrade, which introduced specialized data storage space in the form of blobs, the average transaction cost in optimistic rollups decreased to a range from $0.10 to $0.30 [22]. This is

achieved due to the fact that optimistic rollups do not require generation of complex cryptographic proofs for each transaction batch, which reduces computational costs and accelerates the processing procedure [6].

However, optimistic rollups have significant limitations that constrain their widespread adoption in time-sensitive applications. The most critical problem is the delay in final transaction confirmation, which can reach seven days as a result of the necessity to wait for completion of the challenge period [7]. This creates difficulties for users when withdrawing funds from the second layer to the main blockchain and limits the technology's applicability for cases requiring rapid finality. An additional limitation is dependence on the presence of honest network participants capable of detecting and challenging fraudulent transactions, which creates additional requirements for decentralization and verifier activity [6]. Contemporary research, particularly the Dynamic Fraud Proofs protocol, proposes the possibility of applying dynamic fraud proofs to reduce the challenge period under ideal conditions [23]. This approach presupposes adaptive modification of the challenge period duration depending on verifier activity and absence of disputes, which could potentially improve user experience without compromising system security. However, full implementation of this concept requires additional research regarding economic incentives and cryptoeconomic resilience.

Zero-Knowledge Proof Rollups

Zero-knowledge proof rollups represent an alternative approach to blockchain scaling based on the use of cryptographic proofs for verification of computation correctness without revealing transaction details. Unlike optimistic rollups, ZK-rollups actively generate and verify validity proofs for each transaction batch, ensuring instant finality and a higher level of security [8]. The architecture of ZK-rollups includes several key components: a sequencer responsible for processing transactions off-chain, a proof generator that creates cryptographic confirmations of computation correctness, and a smart contract on the first layer that verifies submitted proofs [10]. The transaction processing procedure begins with collecting operations into a batch, after which the proof generator creates a succinct cryptographic proof confirming the correctness of the state transition. This proof, together with compressed transaction data, is published on the main blockchain, where the smart contract performs verification and updates the state root [10]. There are two main types of zero-knowledge proofs applied in ZK-rollups: zk-SNARKs and zk-STARKs, each of which has unique characteristics, advantages, and trade-offs [24, 25].

A key advantage of ZK-rollups is the possibility of instant transaction confirmation without the need to wait for a challenge period. After the validity proof is verified by the smart contract on the first layer, the new state is considered final and immutable [8]. This allows users to quickly withdraw funds from the second layer, typically within 10-30 minutes, which represents a cardinal improvement compared to the seven-day waiting period in optimistic rollups [6, 10]. An additional advantage is significant data compression achieved through the use of cryptographic proofs. Instead of publishing complete data about each transaction, ZK-rollups publish only succinct proofs and minimal information necessary for state recovery [10]. This leads to a reduction in load on the main blockchain and improvement of overall ecosystem scalability. Research shows that ZK-rollups can achieve data compression at a level of 90% compared to publishing all transactional data [11].

However, generation of zero-knowledge proofs requires significant computational resources, which is reflected in higher transaction costs compared to optimistic rollups. Analysis of practical implementations demonstrates that the average transaction cost in ZK-rollups fluctuates in a range from $0.50 to $1.00 under normal conditions, with the possibility of growth to $3-10 during high first-layer congestion [5]. This creates an economic barrier for applications with high frequency of low-value transactions, particularly micropayments and gaming applications. An additional challenge is the complexity of

ensuring compatibility with the Ethereum Virtual Machine. Development of zkEVM capable of generating proofs for execution of arbitrary smart contracts presents significant technical difficulties due to the complexity of EVM instructions and the necessity of their representation in the form of arithmetic circuits [26, 27]. There are various approaches to zkEVM implementation with different levels of compatibility: from full EVM equivalence allowing direct deployment of existing contracts, to specialized virtual machines optimized for proof generation [27]. The risk of centralization also constitutes a substantial problem for ZK-rollups. Proof generation often requires specialized hardware, which can lead to concentration of this function in the hands of a limited number of operators [28]. This creates potential vulnerability to transaction censorship and manipulation of their execution order, which contradicts the principles of blockchain system decentralization. Contemporary research is focused on developing decentralized networks of proof generators and mechanisms for incentivizing participation of multiple independent operators [28].

Hybrid Rollups

Awareness of the limitations of both optimistic and ZK-rollups has led to the development of hybrid architectures that seek to combine the advantages of both approaches. These solutions represent diverse strategies for integrating verification mechanisms, from conceptual models of seamless transition between proof types to practical implementations with artificial intelligence integration at the sequencer level. A brief overview of key hybrid projects is presented in Table 1.

The considered hybrid solutions, despite the innovation of architectural decisions, are characterized by the static nature of decision-making regarding the choice of verification method [12, 13, 14]. The systems use fixed routing criteria that do not account for dynamic changes in operating conditions: current network load, gas cost on the first layer, specific transaction requirements regarding confirmation speed or security level. Such absence of adaptivity leads to suboptimal resource utilization, when the system applies an excessively expensive verification mechanism for simple operations or an insufficiently secure approach for critical transactions.

Potential of Adaptive Hybrid Architectures

Research on the application of machine learning methods for optimization of blockchain systems demonstrates the potential of artificial intelligence algorithms for dynamic optimization of resource allocation, where ML approaches notably outperform static management schemes [15, 16, 17]. In parallel, the integration of AI and blockchain is at the stage of active development: thousands of repositories, scientific publications, and double-digit growth rates of the solutions market at the intersection of these technologies indicate the formation of a separate research direction [15, 16, 17]. The evolution of this combination proceeds from initial theoretical analysis and prototypes to implementation in practical scenarios – from finance and energy to the Internet of Things. Against this background, concepts such as optimistic machine learning (opML), hybrid consensus with ML components, and AI analysis of market data demonstrate the technical feasibility of incorporating AI into critical circuits of blockchain infrastructure [17, 29].

At the same time, the potential for applying AI specifically for intelligent routing between different verification mechanisms in rollups remains insufficiently explored. Existing systems do not provide context-dependent balancing between cost, speed, and security: critical high-value transfers and routine microtransactions are processed according to the same logic, without consideration of risk profile, deadlines, or application domain [12, 13, 14]. Advanced mechanisms for predicting network load and personalizing priorities for different categories of users and protocols are also absent: DeFi liquidation scenarios require maximum security and fast finality, while

Table 1. Comparative characteristics of static hybrid solutions

Project	Hybrid Approach	Unique Feature	Finality Time
ZKM	Entangled Rollups based on zkMIPS with configurable selection between optimistic and ZK-verification [12]	Universal zkVM allows users to choose withdrawal mode: fast with higher cost or slower with lower costs [12]	10-30 min (ZK) or 7 days (optimistic)
BOB	Combining Bitcoin security with Ethereum programmability through OP Stack and Bitcoin finality mechanism [13]	Hybrid ZK-proofs for state verification combined with BitVM for trust-minimized bridge to Bitcoin [13]	Depends on phase: ETH L2 (7 days) / BTC finality (in development)
Morph	Responsive Validity Proof (RVP): optimistic architecture with reactive ZK-proof generation [14]	Sequencer generates ZK-proof only upon challenge, which reduces verification period and lowers data publication costs [14]	1-3 days
Zircuit	Integration of ZK-proofs with AI security monitoring at sequencer level [30]	Specialized sequencer with automated AI mechanisms for proactive detection of malicious transactions and vulnerability exploitation [31]	10-30 min (ZK)

gaming applications can tolerate additional delay for the sake of cost reduction. The lack of flexible, formalized service level agreements (SLA) limits the ability of current rollup architectures to effectively serve the heterogeneous requirements of contemporary decentralized applications.

Technical and organizational limitations of AI integration with blockchain – high cost and latency of executing complex models on-chain, requirements for privacy, scalability and interoperability, as well as ethical questions of algorithm fairness [17, 18] – indicate the necessity for intellectually adaptive hybrid architectures. In such systems, AI does not replace basic cryptographic guarantees, but acts as a superstructure that analyzes transaction context, current and predicted network state, and participant priorities, forming decisions about the choice of verification mechanism and resource allocation. Against the background of expected growth in transaction volumes and diversification of blockchain usage scenarios [4, 5], the development of such intellectually adaptive hybrid rollups emerges as a critical direction for further research, aimed at combining the advantages of AI and Web3 without loss of fundamental properties of decentralized systems.

ADAPTIVE HYBRID ROLLUP MODEL WITH AI-BASED TRANSACTION ROUTING

Key Principles and Components of the Adaptive Hybrid Rollup Model with Intelligent Routing

Analysis of existing hybrid solutions reveals a fundamental limitation: the static nature of decision-making regarding the choice of verification mechanism. BOB allows users to manually choose between standard withdrawal and validity proof on demand, which transfers decision complexity to the end user [13]. Morph applies a reactive approach through Responsive Validity Proof, generating ZK-proofs only upon challenge occurrence, but does not provide for preventive optimization [14]. ZKM offers a configurable mechanism for selection between optimistic and ZK-verification, however configuration is performed at the system level rather than individual transaction level [12].

The proposed model is based on three principles that distinguish it from static hybrid solutions:

1. *full automation* - the system independently makes optimal decisions for each transaction without user or application developer intervention;
2. *principle of proactive adaptation* - the system not only reacts to current conditions, but also predicts future changes in network load and preventively redistributes resources;
3. *principle of continuous learning* - ensures constant improvement of decision quality through analysis of previous operation results and model adaptation to the specifics of different application types.

The enumerated principles are implemented through an architecture of five interconnected components:

1. transaction analysis and classification module;
2. AI decision-making core;
3. dual-path execution system with dynamic load balancing;
4. network conditions prediction module;
5. continuous learning system with feedback loop.

The transaction lifecycle in the proposed adaptive hybrid model is depicted in Figure 1.

Collectively, these principles and architectural components form an adaptive hybrid rollup model capable of real-time selection of the optimal transaction processing path and evolution in accordance with dynamic network conditions and application protocol requirements.

AI Routing Mechanism

The proposed AI routing mechanism implements automatic selection of the processing path for each transaction without the need for user participation. The core of the system is a Graph Neural Network that processes fourteen parameters through a dependency graph, where nodes represent transaction parameters and network state, and edges reflect their interrelationships [32]. Parameters are divided into 5 groups.

The first group of parameters includes financial metrics: transaction value in USD equivalent, current gas price on the first layer, gas price forecast for the next four hours based

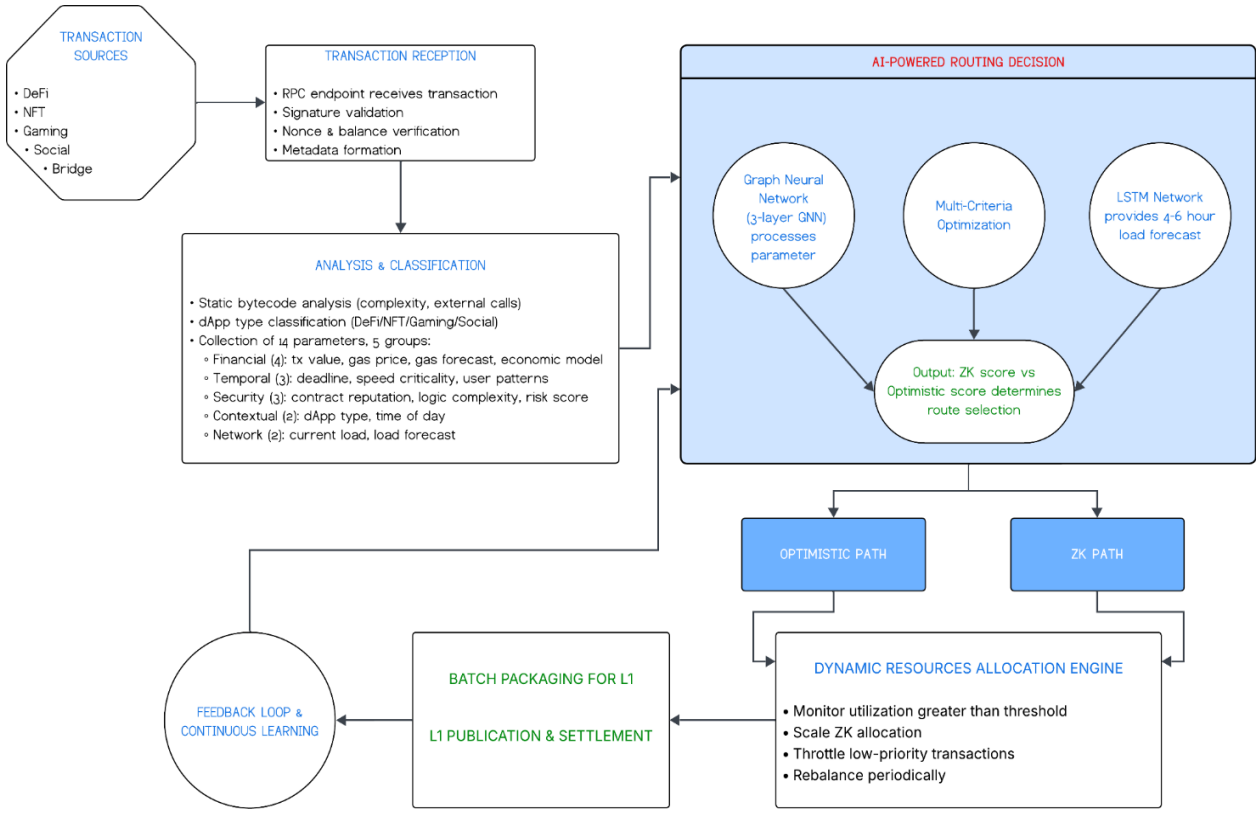


Fig. 1. Transaction flow in adaptive hybrid rollup architecture

on LSTM model, and economic model of the application. The second group encompasses temporal requirements: explicitly specified user deadline, speed criticality for application type (DeFi requires speed, gaming tolerates delays), and historical usage pattern of a specific user. The third group of parameters concerns security: smart contract reputation score based on audit history and incidents, transaction logic complexity determined through static bytecode analysis, and risk profile of sender address. The fourth group includes contextual data: application type (DeFi, NFT marketplace, gaming, social), time of day and day of week for detecting cyclical load patterns, and correlation with activity on other Layer 2 networks. The fifth group encompasses network conditions: current load of ZK and optimistic paths, transaction queue sizes, available throughput in both directions, and load forecast based on historical data of analogous periods [15, 16, 17].

In the proposed model, an important role is played by the Predictive Routing Algorithm, which transitions the system from a reactive to a proactive approach to transaction routing. The system uses an LSTM model with three layers to predict network load four to six hours ahead based on historical data from the previous six months [15, 16, 17]. The model accounts for cyclical patterns: daily activity peaks during opening of American and Asian markets, weekly patterns with higher activity in mid-week, and seasonal trends. If a period of high load is predicted, the system preventively redistributes non-critical transactions to the optimistic path 30-60 minutes before the expected peak, reserving ZK capacity for critical operations. The proposed strategy has the potential to significantly reduce the risk of ZK-path overload during peak load periods while simultaneously lowering average transaction costs compared to the reactive approach.

Dual-path System with Dynamic Balancing

Unlike static hybrid architectures with fixed or minimally adaptive resource allocation, the proposed dual-path system implements fully dynamic balancing of throughput between ZK and optimistic paths. The ZK-path uses zk-SNARK proofs for transactions requiring fast finality (10-30 minutes) and maximum security, with support for batch processing to amortize costs [10, 24]. The optimistic path applies the presumption of correctness with a dynamic challenge period from 24 hours to 7 days depending on transaction risk profile: operations with verified contracts and low value receive a shortened period, while suspicious or high-value operations are subject to the full seven-day period.

The presence of a Dynamic Resource Allocation mechanism ensures automatic scaling of available resources between paths in real time. The system monitors three key metrics: utilization coefficient of each path's throughput, average queue waiting time, and transaction processing cost. When the ZK-path reaches 80% load, the system automatically increases the share of proof generators allocated to this direction from the baseline level of 30% to a maximum of 70% within

5-10 minutes. In parallel, a throttling mechanism is activated for non-critical transactions: operations with a priority score below 0.3 are automatically redirected to the optimistic path or postponed until load normalization [17]. This approach ensures guaranteed service level for critical operations even during activity peaks, which is difficult or impossible to achieve with static systems.

Adaptive Multi-Criteria Optimization Framework

Traditional approaches to rollup system optimization use static weight coefficients for balancing between cost, speed, and security. The proposed Adaptive Multi-Criteria Optimization Framework introduces temporal dependence of weight coefficients that change in real time based on context. The optimization function is defined as Figure 2.

Fig.2. The optimization function for Adaptive Multi-Criteria Optimization.

$$F(t) = \sum_i w_i(t) \cdot f_i(\text{transaction}, \text{network\_state}(t))$$

Where $w_i(t)$ are adaptive weights that evolve through a reinforcement learning mechanism. Instead of a fixed distribution (0.2, 0.3, 0.5) for all DeFi applications, the system learns specific patterns of individual protocols: Uniswap-like DEXs receive higher speed weight (0.15, 0.45, 0.40) due to the importance of execution before price changes, while lending protocols like Aave receive emphasis on security (0.15, 0.25, 0.60). Similarly, for payment stablecoin services, cost and transfer speed become priorities (0.40, 0.40, 0.20). For NFT marketplaces (trading tokenized assets at fixed or auction prices) a more balanced profile is appropriate (0.30, 0.40, 0.30), while for cross-chain bridges and liquidity transfer protocols with high exploit risks, weights are additionally shifted toward security (0.10, 0.20, 0.70).

The system receives feedback through three channels and uses it to adapt weights. Explicit user ratings are collected through an optional rating mechanism after transaction completion, where users can indicate satisfaction with speed, cost, and reliability. Implicit signals are derived from behavioral patterns: if a user repeatedly sends a transaction with higher gas price within 10 minutes after the first attempt, this signals dissatisfaction with speed, and the system increases the speed weight for similar future operations of this user by 0.1. System metrics include the percentage of transactions that did not complete successfully within the expected timeframe, average time from submission to final confirmation, and frequency of challenges in the optimistic path. The reinforcement learning agent uses accumulated reward as a signal for gradient-based updating of weight coefficients hourly, achieving convergence to optimal policy within 7-14 days for a new application type.

WORK SCENARIOS: DEMONSTRATION OF ADAPTIVITY

Scenario 1: Preventive Optimization During Predicted Peak

At 13:00 UTC, the system detects through the LSTM model a high probability (0.87) of an activity peak at 14:30 UTC (NYSE opening). Current load: ZK-path 45%, optimistic 30%. The system analyzes queues and identifies 340 non-critical transactions (gaming operations, low-value NFT transfers) with a deadline greater than 2 hours. The AI mechanism makes the decision:

1. move 280 non-critical transactions to the optimistic path,
2. increase proof generator allocation for the ZK-path from 30% to 55%,
3. activate priority throttling with a threshold of 0.4 instead of the standard 0.2.

At 14:30 UTC, the expected peak occurs: 1200 new transactions in 15 minutes, 65% of which are DeFi operations. Thanks to preventive optimization, the ZK-path reaches 82% load (not overloaded), average finality time 18 minutes, no critical transaction delayed. Without preventive optimization: predicted load 127%, waiting time > 45 minutes.

Scenario 2: Adaptive Classification Based on Contextual Analysis

Two users send transactions interacting with the same DeFi contract (lending protocol).

User A: borrow operation for 50 ETH, address with 2-year history, 450 successful transactions, reputation score 0.92. User B: borrow operation for 45 ETH, address active for 3 weeks, 12 transactions, reputation score 0.31.

The AI mechanism analyzes the context: both operations are financially significant, but risk profiles differ. Decision: transaction A is routed through the optimistic path with shortened challenge period of 48 hours (high reputation), cost $0.15. Transaction B is routed through the ZK-path (low reputation = higher risk), cost $0.85, finality 22 minutes. After a week, user B completes 30 successful operations, reputation score rises to 0.68. The next analogous transaction is automatically routed through the optimistic path, demonstrating system adaptation to behavioral profile changes.

Scenario 3: Continuous Learning Through Feedback Loop

A new gaming application integrates with the system. Initial parameters: baseline weight distribution (0.5, 0.3, 0.2) for gaming category.

First 1000 transactions: the system collects data on implicit signals. Pattern detected: 23% of users repeatedly send transactions with higher gas price, 12% leave negative explicit ratings with complaints about slowness.

The reinforcement learning agent interprets: users of this particular application are more sensitive to speed than typical gaming applications. After 72 hours, the system adapts weights to (0.35, 0.50, 0.15), increasing the share of transactions routed through the ZK-path from 8% to 22%.

Next 1000 transactions: frequency of negative feedback decreases to 7%, satisfaction indicator grows from 3.2 to 4.1 out of 5. The system continues fine-tuning, achieving optimal weights (0.32, 0.53, 0.15) after 14 days, after which it reaches a stable state with periodic micro-adjustments.

CONCLUSIONS

Summarizing the results, it can be stated that the proposed adaptive hybrid rollup model represents a conceptually new approach to organizing Layer 2 solutions, which differs from existing static systems in three key principles: full automation of decision-making at the individual transaction level instead of manual selection (BOB) or system configurations (ZKM); proactive adaptation through prediction of future network conditions instead of reactive response (Morph RVP); continuous learning through reinforcement learning with adaptation to the specifics of different application types.

To implement these principles, a five-module architecture has been developed that integrates an analysis module with fourteen transaction classification parameters, an AI core based on Graph Neural Network, a dual-path execution system with Dynamic Resource Allocation mechanism, an LSTM prediction module, and a continuous learning system through feedback loop. Theoretical analysis indicates potential advantages: reduction in transaction costs through dynamic distribution between ZK and Optimistic paths, reduction of delays during peaks through preventive resource redistribution, improvement in routing quality through adaptation to protocol specifics, as well as elimination of the need for technical understanding of verification mechanisms on the part of users.

The model proves particularly appropriate for DeFi protocols with operations varying in criticality, gaming and social applications with mass low-cost transactions, cross-chain bridges with automatic balancing of security and speed, as well as payment systems with high transactional intensity.

At the same time, despite the conceptual attractiveness of the proposed model, there exists a number of unresolved questions that require in-depth investigation and may limit the practical applicability of the approach. Critical priority questions include formal verification of AI component security, as currently there are no formal proofs of system resilience to manipulation by attackers and adversarial attacks on neural networks making routing decisions. Confidentiality of behavioral data constitutes another critical challenge, as learning mechanisms require access to user transaction patterns, which demands development of privacy-preserving approaches to machine learning in the context of public blockchains. High priority is assigned to inference scalability issues, as it is necessary to ensure decision-making latency of less than ten milliseconds even when processing thousands of transactions per second, which may prove to be a technically complex task for sophisticated models such as Graph Neural Networks. Empirical validation of the proposed approach also remains an open question due to the absence of experimental data on the actual effectiveness of the adaptive system compared to static hybrid solutions under real operating conditions. Medium priority questions include development of an economic model with determination of incentive mechanisms for validators and provers under conditions of dynamic load distribution, as well as ensuring compatibility with existing Layer 2 stacks and creating a clear migration path for decentralized applications already functioning on static rollup solutions.

Further development of the model requires implementation of proof-of-concept and empirical testing, formal security analysis, development of privacy-preserving learning mechanisms, investigation of decentralized approaches to AI inference, as well as analysis of economic incentives and game-theoretic properties of the system. Overall, the proposed model represents a conceptual framework for next-generation Layer 2 solutions, where cryptographic verification protocols are integrated with intelligent resource management systems, laying a theoretical foundation for transition from static to adaptive systems that independently optimize the balance between cost, speed, and security. Practical implementation and empirical validation constitute the subject of future research and will determine the boundaries of the approach's applicability in production environments.

REFERENCES

1. **Thibault LT, et al.** Blockchain Scaling Using Rollups: A Comprehensive Survey. IEEE Access, vol. 10, 2022, pp. 93039-93054. https://doi.org/10.1109/ACCESS.2022.3200051
2. **Park S, et al.** Impact of EIP-4844 on Ethereum: Consensus Security, Ethereum Usage, Rollup Transaction Dynamics, and Blob Gas Fee Markets. arXiv preprint arXiv:2405.03183, 2024, https://doi.org/10.48550/arXiv.2405.03183
3. **Spoto F, et al**. A Survey on Data Availability in Layer 2 Blockchain Rollups: Open Challenges and Future Improvements. Future Internet, vol. 16, no. 9, 2024, p. 315. https://doi.org/10.3390/fi16090315
4. **Fidelity Digital Assets**. The Rise of Layer 2 Scaling on Ethereum. Fidelity Digital Assets Research, 2024. https://www.fidelitydigitalassets.com/research-and-insights/rise-layer-2-scaling-ethereum
5. **L2BEAT.** Layer 2 Scaling Solutions Comparison. L2BEAT Analytics, 2024. https://l2beat.com/
6. **Ethereum Foundation**. Optimistic Rollup Challenges. ethereum.org, 2024. https://ethereum.org/developers/docs/scaling/optimistic-rollups/
7. **Base Documentation**. Base Challenge Period. Coinbase, 2024. https://docs.base.org/
8. **zkSync Documentation**. zkSync Era Architecture. Matter Labs, 2024. https://docs.zksync.io/build/resources/era-architecture
9. **StarkWare**. StarkNet Architecture Overview. StarkWare Documentation, 2024. https://docs.starknet.io/documentation/architecture_and_concepts/
10. **Ethereum Foundation**. Zero-knowledge rollups. ethereum.org, 2024. https://ethereum.org/developers/docs/scaling/zk-rollups/
11. **Polygon**. Polygon zkEVM Data Compression. Polygon Technology, 2024. https://docs.polygon.technology/zkEVM/
12. **ZKM** Documentation. Hybrid Rollup Architecture. ZKM Official Documentation, 2024. https://docs.zkm.io
13. **Rockaway X**. BOB: The First Hybrid ZK Rollup That Lets Users Control Their Security. Medium, 2024, https://www.rockawayx.com/insights/bob-becomes-first-hybrid-zk-rollup
14. **Morph** Documentation. The Optimistic zkEVM Scaling Solution: Responsive Validity Proof. Morph Docs, 2024. https://docs.morphl2.io/docs/how-morph-works/responsive-validity-proof/
15. **Yuan F, et al.** AI-Driven Optimization of Blockchain Scalability, Security, and Privacy Protection. Algorithms, vol. 18, no. 5, 2025, p. 263. https://doi.org/10.3390/a18050263
16. **Artenie A. C., et al**. Exploring the Synergy Between Ethereum Layer 2 Solutions and Machine Learning to Improve Blockchain Scalability. Computers, vol. 14, no. 9, 2025, p. 359. https://doi.org/10.3390/computers14090359
17. **Dalila R, Riccardo R, Carla P, Sabina R, et al**. AI-enhanced Blockchain Technology: A Review of Advancements and Opportunities. Journal of Network and Computer Applications, vol. 225, 2024, p. 103858. https://doi.org/10.1016/j.jnca.2024.103858
18. **Moetez Abdelhamid, Layth Sliman, Raoudha Ben Djemaa, and Guido Perboli, et al**. A Review on Blockchain Technology, Current Challenges, and AI-Driven Solutions. ACM Computing Surveys, 2024. https://doi.org/10.1145/3700641
19. **Optimism Collective**. Optimism Bedrock Explainer. Optimism Documentation, 2024. https://community.optimism.io/docs/developers/bedrock/
20. **Arbitrum Documentation**. Fraud Proofs in Arbitrum. Offchain Labs, 2024. https://docs.arbitrum.io/

21. **Kalodner H, et al**. Arbitrum: Scalable, Private Smart Contracts. USENIX Security Symposium, 2018, pp. 1353-1370, https://www.usenix.org/conference/usenixsecurity18/presentation/kalodner
22. **Park S, et al.** EIP-4844 Economic Impact Analysis. arXiv preprint, 2024, https://arxiv.org/abs/2405.03183
23. **Picco G., Fortugno A.** Dynamic Fraud Proof. arXiv:2502.10321, 2025. https://doi.org/10.48550/arXiv.2502.10321
24. **Groth J.** On the Size of Pairing-based Non-interactive Arguments. Annual International Conference on the Theory and Applications of Cryptographic Techniques, Springer, 2016, pp. 305-326, https://link.springer.com/chapter/10.1007/978-3-662-49896-5_11
25. **Ben-Sasson E, et al**. Scalable, Transparent, and Post-quantum Secure Computational Integrity. IACR Cryptology ePrint Archive, 2018, https://eprint.iacr.org/2018/046.pdf
26. **Buterin V.** An Incomplete Guide to Rollups. Vitalik.ca, 2021. https://vitalik.eth.limo/general/2021/01/05/rollup.html
27. **zkSync Documentation**. zkEVM Compatibility Types. Matter Labs, 2024. https://docs.zksync.io/
28. **StarkWare.** Centralization Risks in ZK Rollups. StarkWare Blog, 2024. https://starkware.co/blog/
29. **Conway K.D**. et al. opML: Optimistic Machine Learning on Blockchain. arXiv:2401.17555, 2024. https://doi.org/10.48550/arXiv.2401.17555
30. **Derka M. et al**. Sequencer Level Security (SLS). arXiv:2405.01819, 2024. https://doi.org/10.48550/arXiv.2405.01819
31. **Zircuit Documentation**. Sequencer Level Security Deep Dive. Zircuit Docs, 2024. https://docs.zircuit.com/learn/zircuit-technology/sls
32. **Wu Z., Pan S., Chen F., Long G., Zhang C., Yu P.S**. A Comprehensive Survey on Graph Neural Networks. IEEE Transactions on Neural Networks and Learning Systems, 2021, vol. 32, no. 1, pp. 4-24. https://doi.org/10.1109/TNNLS.2020.2978386
33. **Saad M, et al.** Veritas: Layer-2 Scaling Solution for Decentralized Oracles on Ethereum Blockchain with Reputation and Real-Time Considerations. Journal of Sensor and Actuator Networks, vol. 13, no. 1, 2024, https://www.mdpi.com/2224-2708/13/2/21
34. **Arbitrum** Documentation. How Arbitrum Works. Offchain Labs, 2024. https://docs.arbitrum.io/how-arbitrum-works/inside-arbitrum-nitro
35. **Teutsch J, Reitwießner C. A** Scalable Verification Solution for Blockchains. TrueBit Protocol, 2017. https://people.cs.uchicago.edu/~teutsch/papers/truebit.pdf
36. **Wood G. Ethereum: A** Secure Decentralised Generalised Transaction Ledger. Ethereum Project Yellow Paper, 2014, https://mholende.win.tue.nl/seminar/references/ethereum_yellowpaper.pdf
37. **Harz D., Zamyatin A**., BOB: The Hybrid L2 Vision Paper. BOB Documentation, 2024. https://docs.gobob.xyz/

Адаптивні гібридні ролапи: інтелектуальна маршрутизація між ZK та оптимістичною верифікацією

Микола Маленко

Анотація. Дана стаття присвячена дослідженню обмежень сучасних гібридних ролап-рішень та розробці адаптивної моделі L2-архітектури з використанням механізмів штучного інтелекту. Показано, що існуючі підходи до поєднання оптимістичної та ZK-верифікації здебільшого ґрунтуються на статичних правилах або ручному виборі режиму, що не дозволяє ефективно враховувати динаміку навантаження, ризики та доменні особливості застосунків. На основі аналізу оптимістичних, ZK та гібридних ролапів запропоновано адаптивну гібридну rollup-модель з ШІ-маршрутизацією транзакцій, яка поєднує класифікацію транзакцій, GNN-базоване прийняття рішень, LSTM-прогнозування мережевих умов, dual-path систему виконання та модуль безперервного навчання. Описано Predictive Routing Algorithm, що здійснює проактивний вибір між ZK- та оптимістичним шляхом з урахуванням вартості, затримки, безпеки та профілю ризику, а також механізм Dynamic Resources Allocation, який динамічно перерозподіляє ресурси між шляхами. Запропонований багатокритеріальний фреймворк оптимізації демонструє можливість налаштування ваг цілей під специфіку різних класів DeFi та Web3-протоколів. Показано, що впровадження такої моделі є перспективним для систем із високою транзакційною інтенсивністю, оскільки дає змогу перейти від

ручних конфігурацій до автоматизованих політик керування ресурсами та ризиками, що спираються на аналіз фактичних даних, в гібридних rollup-архітектурах.

Ключові слова: веб3, адаптивні гібридні ролапи, штучний інтелект, блокчейн.