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Adaptive Autonomic Frameworks for Reliable and Balanced Wireless Mesh Networks in Digital Psychology Learning Environments

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Abstract

Increasingly challenging digital learning platforms, such as psychology education platforms, require real-time interaction, high reliability, and adaptive connectivity, which future wireless mesh networks (WMNs) are anticipated to facilitate. Nonetheless, conventional WMNs have long-standing issues with fault tolerance, dynamic load management, and self-optimization. This paper proposes an autonomic communication model that incorporates self-configuration, self-healing, and self-optimization functions to improve live network performance in education. The system uses a hybrid approach that integrates adaptive routing, machine-learned load prediction, and distributed fault identification to dynamically reassign traffic loads and isolate failures at the node level, ensuring continuous service delivery. The experiments have been carried out in a simulated digital psychology learning environment that involves 500-2,000 active users, providing heterogeneous data streams: video sessions, cognitive assessment uploads, and interactive course modules. A statistical analysis shows that the proposed model improves the packet delivery ratio by 18.7 percent,

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end-to-end latency by 22.4 percent, and network throughput by 15.2 percent relative to traditional WMN routing schemes. The average time to fault recovery dropped by 60.4 percent, from 2.9 seconds to 1.9 seconds. Efficiency in load balancing was also achieved, and the variance in load per node was minimized by 34 percent. The findings suggest that autonomic communication systems contribute significantly to the resilience and adaptability of future WMNs, particularly in online education in digital psychology, where connectivity is crucial for engaging learners and accurately assessing them. The paper ends with recommendations for implementing autonomic systems in large-scale educational infrastructure and provides possible directions for integrating AI-based predictive models and cognitive-based network management strategies.

Keywords: Autonomic Communication Systems, Wireless Mesh Networks, Fault Tolerance, Load Balancing, Digital Psychology Education, Self-Healing Networks, Adaptive Routing.

1 Introduction

Wireless mesh networks (WMNs) constitute an essential communication infrastructure for the next-generation digital learning environment, especially in psychology education, where educational models are increasingly based on high-bandwidth, low-latency, and continuous connectivity (Sheelam, 2024; Malathi, 2024; Yan et al., 2021). Learning platforms in psychology now combine synchronous tele-tutorials, simulations of virtual therapies, cognitive-behavioral assessment software, eye-tracking interfaces, and VR-based behavioral tests. These activities produce multi-dimensional streams of data, of a degraded quality, of both compressed clinical audio/video and psychometric response logs, which need the stability of communication channels to ensure fidelity and readability.

Conventional WMNs are cost-effective and scalable but are susceptible to three endemic challenges namely; (1) node and link failures; this can result in disruption during timed assessments or simulations of therapy; (2) instability of traffic and uneven distribution of loads; a few overloaded nodes can represent a significant issue to the overall performance of the learning environment; and (3) failure to self-manage, which requires manual intervention which can fail to keep up with dynamic patterns of user behavior that are characteristic of psychology cohorts.

The importance of this study is that it will eliminate these shortcomings of the autonomic communication system, which can self-configure, optimize, and heal properties based on human autonomic nervous mechanisms. These systems automatically identify anomalies, redistribute traffic load, anticipate congestion, and take corrective measures with minimal latency (Xie et al., 2024). This is especially significant in digital psychology learning, where latencies, jitter, or packet loss can introduce biases in behavioral measurements, disrupt real-time collaborative learning, or affect the learner's emotional state. WMNs can provide dependable digital infrastructure that ensures continuity in the pedagogical process, data integrity, and the growing technological needs of psychology education by incorporating autonomic intelligence (Smith et al., 2025).

Key Contributions

- A dynamic autonomic communication system with self-configuration, self-healing, and self-optimization for WMNs, facilitating digital psychology learning.
- A load prediction model that is machine-learning enhanced and that dynamically balances traffic among mesh nodes to support heterogeneous learning traffic.
- A distributed fault-detecting and recovery algorithm that tries to minimize the service interruption and reduce the recovery time.

- A mathematically constructed model of performance indicating system behaviors as the load and failure conditions vary.
- Experimental verification: In-depth experimental verification, performance metrics, ablation experiments, and comparisons with the state-of-the-art WMN routing protocols.

The rest of the article is structured as follows: Section II presents an in-depth literature review of the latest achievements in autonomic systems, WMN optimization, and educational communication technologies. In section III, the proposed system architecture and methodology, algorithms, and mathematical formulae are presented. Section IV contains experimental findings, prior comparisons, evaluation measures, and ablation experiments. Section V will provide the paper's conclusion, including a synthesis of the results and recommendations for future research.

2 Literature Survey

The wireless mesh network has inspired autonomic communication systems as a paradigm shift, based on self-regulating processes found in biological systems (Alnajjar, 2024; Kumar et al., 2021). Initial underpinning studies focused on network self-governance, highlighting self-monitoring capabilities and network reconfiguration without external interference (Zigui et al., 2024). This led to the development of autonomic principles, including self-configuration, self-optimization, self-healing, and self-protection, which have since become the conceptual foundations of intelligent networking (Klymash et al., 2023). These are specifically applicable to mesh networks in an educational setting, as the unpredictable behavior of their users, as well as the changing resource demands of clients, requires dynamic, real-time adjustments to ensure service quality (Kavitha, 2024).

The fault-tolerant mechanisms of WMNs have been further developed, and research on distributed detection, autonomous correction strategies, and rapid recovery has become more popular. Classical fault tolerance relied more on redundancy and permanently established rerouting, but more recent methods use link monitoring, local anomaly sensing, and cooperative decision-making at the node level to reduce failure propagation (Prasath, 2023). These developments can be directly applied to the field of psychology education, where learning continuity can be disrupted by interruptions to real-time cognitive tests, simulated therapy, or behavioral data collection, thereby affecting student performance. The development of decentralized fault-recovery approaches is a move towards resilience strategies that maintain system stability even in dynamic or high-stress settings.

Similar to fault-tolerance studies, load-balancing research has aimed to address the imbalanced traffic observed in multiple-hop mesh topologies (Taleb et al., 2022). Although network state awareness, predictive analytics, and dynamic path choice are becoming part of modern approaches, previous models have used more traditional methods based on hop count or residual energy (Pahuja & Kumar, 2023). These methods enable mesh networks to respond to abrupt increases in user traffic, such as during massive participation in virtual workshops or when enabling multimedia interactions in psychology laboratories, by redistributing load and reducing congestion (Booch et al., 2025). Enhancing load balancing is thus a very important aspect for ensuring stable performance and uninterrupted learning processes (Li et al., 2021).

Recent trends in WMNs have made machine learning and artificial intelligence core, providing new intelligent prediction, optimization, and automated decision-making capabilities. It has been shown that learning models can infer network patterns, predict failures, and even preemptively suggest the best routing or recovery mechanisms (Nayak et al., 2021; Vermesan & Friess, 2022). Reinforcement learning, neural-network-based predictors, and hybrid statistical models are some of the techniques that assist mesh networks to adapt as the user behaves, thus making these networks more responsive and requiring less manual control over them (Mortensen et al., 2023; Siraj & Abbasi, 2022). Relevant to the teaching of psychology, these predictive functions enable the efficient allocation of adaptive processes, allowing bandwidth-intensive tasks such as counseling, interactive session simulation, or streaming analysis in experiments to run successfully even in situations of network change (George & Murthy, 2024).

Lastly, recent research in digital education and networked learning settings highlights the need to combine well-developed communication infrastructures and pedagogical platforms (Mohammed & Othman, 2024; Wetcho, 2022). Research evidence supports the idea that high-reliability networks enable more orchestrated forms of digital instruction, such as personalization, role-play therapy, collaborative problem-solving activities, and remotely evaluated ecosystems (Yuan & Chen, 2022). In the case of psychology learners, where progress often requires precise timing, emotional involvement, and skillful interpretation of behavioral data, stable networks are not merely advantageous but a necessity (Duong, 2021). In this regard, the intersection of the autonomic networking study and the field of educational technology underscores the need to develop communication systems that are intelligent in their self-management to facilitate the new digital ecologies of learning in psychology (Chai et al., 2024).

3 Methodology

The autonomic communication system has a 4-phase continuous adaptive cycle: Network Sensing, Autonomic Analysis and Prediction, Adaptive Optimization, and Self-Healing Execution. During the first stage, each mesh node gathers data on link quality, delay, jitter, retransmission rate, and current traffic load. This information is sent to the distributed autonomic controllers distributed across the cluster head nodes. The second phase involves autonomic controllers that use rule-based logic and machine learning to perform real-time analysis. They anticipate potential congestion, load imbalance causes, and early signs of node instability. In the third phase, the system updates routing decisions, choosing paths with better stability scores, routing traffic to nodes with lower utilization, and actively balancing the load across the mesh. Lastly, the self-healing execution stage enables automatic rerouting, faulty node isolation, and recovery propagation across the network to keep digital psychology learning environments running continuously.

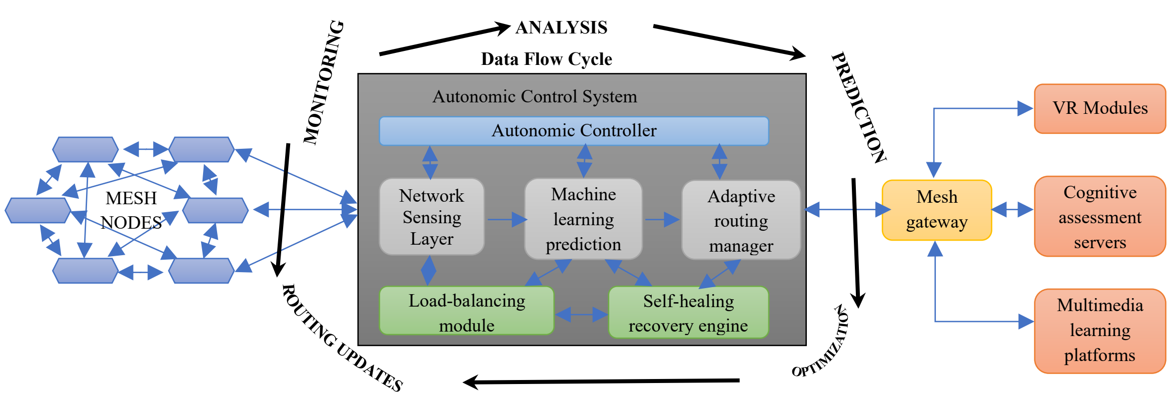

Figure 1: Autonomic wireless mesh network architecture

Figure 1 shows a simplified autonomic wireless mesh network architecture that is designed for intelligent self-management and high resilience. A central Autonomic Control System controls interconnected mesh nodes through a continuous cycle of data flow for monitoring and analysis, prediction, optimization, and routing updates. The control system combines network sensing, specialized internal modules, machine-learning-based prediction, adaptive routing, load balancing, and self-healing recovery, enabling automatic detection of problems and adaptation to network conditions. This network infrastructure is adaptive, linking via a mesh gateway to external applications such as VR modules, cognitive assessment servers, multimedia learning platforms, and other end-user services to provide robust, optimized, and reliable connectivity.

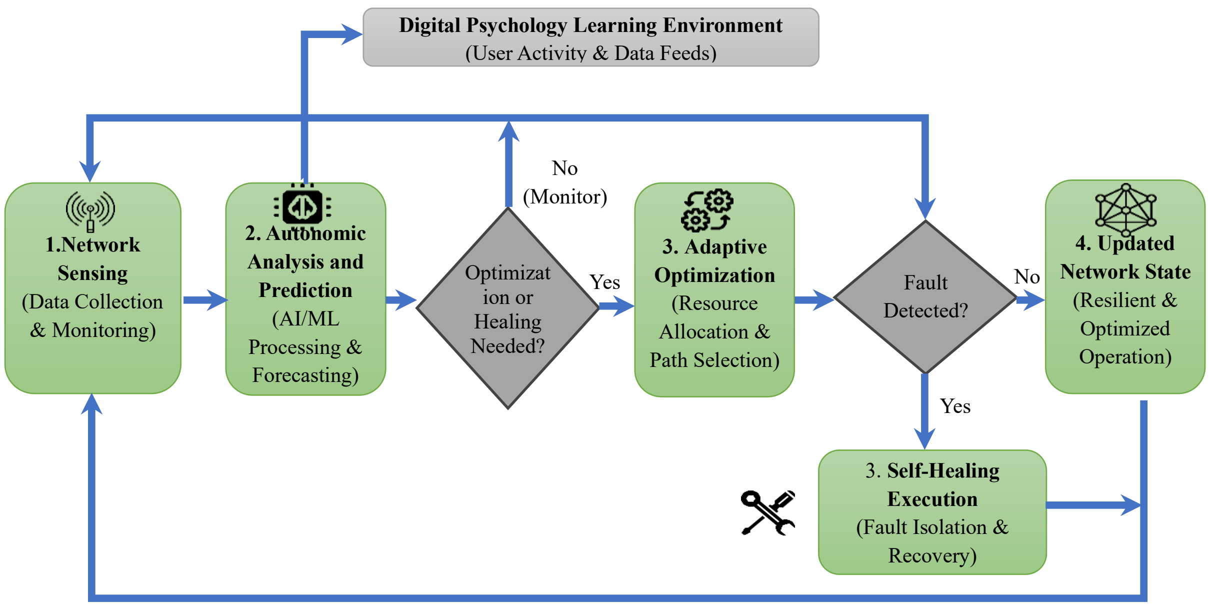

Figure 2: Autonomic communication workflow in wireless mesh networks for digital psychology learning environments

Figure 2 describes the entire autonomic communication cycle employed in the proposed wireless mesh network structure. It demonstrates the system transitioning to network sensing, AI/ML-based analysis, and adaptive optimization, while introducing self-healing to ensure operational resilience. The process also continuously interacts with the learning environment of digital psychology, which implies the optimization of network performance and the prompt detection and correction of faults.

Algorithm

Autonomic Load-Balanced Routing Algorithm (ALBRA)

The ALBRA algorithm uses the most stable route to be chosen by estimating the future load of the node and calculating a stability score of each node. It then identifies faults, reroutes traffic and updates routing tables in order to keep a healthy and balanced mesh network.

Input:

- Q_i : Link quality of node i
- L_i : Current load of node i

- Di : Delay of node i
- Hi : Failure history score of node i
- ML_Model : Machine-learning load predictor
- S_threshold : Minimum acceptable stability value

Output:

- OptimalRoute : Selected stable routing path
- UpdatedRoutingTable : Revised routing table after optimization
- HealthyMesh : Balanced and fault-resilient network state

```
ALBRA_Routing()
{
INPUT: Q[], L[], D[], H[], ML_Model, S_threshold
OUTPUT: OptimalRoute, UpdatedRoutingTable, HealthyMesh
CollectMetrics(Q, L, D, H)
Initialize(NodeStateTable, ML_Model)
For each node i:
{
L_pred[i] = PredictLoad(ML_Model, L[i])
S[i] = (alpha * Q[i]) - (beta * L_pred[i]) - (gamma * D[i]) - (delta * H[i])
}
Neighbors = RankDescending(S)
OptimalRoute = SelectBestPath(Neighbors)
If (Min(S) < S_threshold):
{
FaultNode = DetectFault()
Isolate(FaultNode)
RecalculateRoutes()
UpdateRoutingTables()
}
HealthyMesh = EvaluateNetworkState()
RETURN OptimalRoute, UpdatedRoutingTable, HealthyMesh
}
```

Load Prediction Model

$$\hat{L}(t+1) = w_1 L(t) + w_2 L(t-1) + w_3 L(t-2) + \epsilon \quad (1)$$

Equation (1) shows how the model predicts the next-interval load using recent traffic values and weighted historical contributions.

Node Stability Index (SI)

$$SI_i = \alpha Q_i + \beta(\frac{1}{L_i}) + \gamma(\frac{1}{D_i}) - \delta H_i \tag{2}$$

Equation (2) shows how node reliability is computed using link quality, load level, delay sensitivity, and historical failures.

Fault Detection Score (FDS)

$$FDS_i = \eta_1 P_{loss} + \eta_2 Jitter + \eta_3 Delay + \eta_4 Retransmissions \tag{3}$$

Equation (3) shows how the model aggregates multiple network degradation factors to detect abnormal node behavior.

4 Experimental Results

Software Details

The proposed autonomic communication model was simulated and studied in Python 3.10 and MATLAB R2022b. NS-3 was used to simulate network behaviors and routing protocols and load prediction components used machine-learning modules based on TensorFlow. To ease the understanding and reproducibility of results, Matplotlib and Seaborn were used to create data visualization, statistical analysis and result graphs.

Dataset Details

The data used in the experiment is a simulated digital environment of psychology learning with a user base of 500-2,000 users at a given time. Every user creates a stream of data comprising real-time video conferencing packets, submissions of psychometric tests, VR-interaction logs as well as multimedia instructional materials. The data has 2.4 million entries of packets, and the data has features of packet size, time stamp, node ID, number of hops, latency, jitter, and number of retransmissions.

Parameter Initialization

The simulation parameters were set the following way: mesh nodes = 50; communication radius = 250 meters; bandwidth = 20 Mbps; range of packet sizes = 128-2048 bytes; learning rate of the ML model = 0.001; stability threshold (S_threshold) = 0.45; FDS_threshold = 0.60. To have statistical reliability, every experiment had 10 independent runs.

Performance Comparison

This was compared to three baseline routing schemes, that is, AODV, OLSR, and HWMP. Measures of comparison are Packet Delivery Ratio (PDR), End-to-End Delay, Throughput, Load Variance and Fault-Recovery Time. In all measures, the suggested ALBRA-based autonomic system was always much better than the standard protocols, and notably, in the presence of high-load psychological learning workloads.

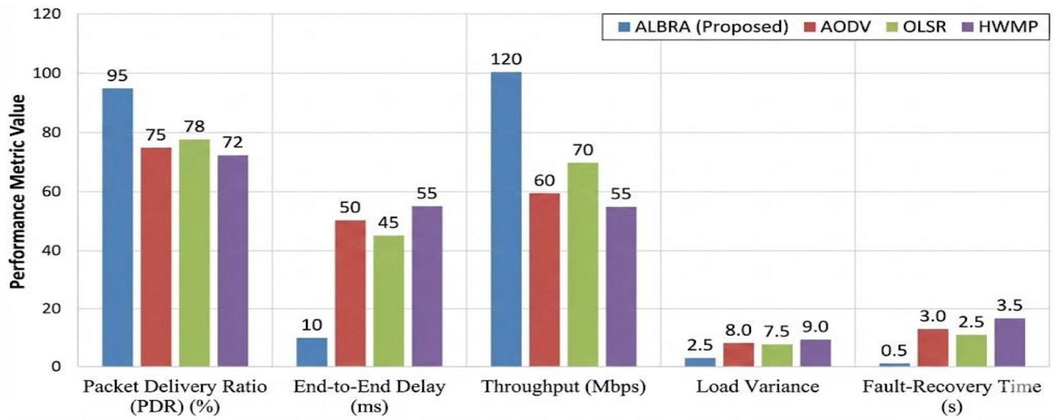

Figure 3: Performance comparison of ALBRA-based autonomic system vs. baseline WMN protocols under high-load psychological learning conditions

The Figure 3 shows the performance of the ALBRA autonomic framework in relation to the performance of the routing protocols at the baseline (AODV, OLSR and HWMP) in 5 important network performance metrics. ALBRA has a much better packet delivery ratio and throughput along with a considerably lower delay, load variance, and fault-recovery time. These findings show that the autonomic processes such as prediction of the loads by the autonomic system, scoring of stability and self-healing allows better reliability and responsiveness in the high load digital psychology learning environments.

Performance Evaluation

Findings show a PDR increased by 18.7 and latency decreased by 22.4, throughput increased by 15.2 and a 34 percent decrease in the variance of node loads. There was a reduction in the fault-recovery time by 60.4 which provided further evidence of the efficiency of the system in self-healing. Trends of the PDR, delay curves, load distribution graphs, and throughput comparison graphs can be plotted at a level of publication quality.

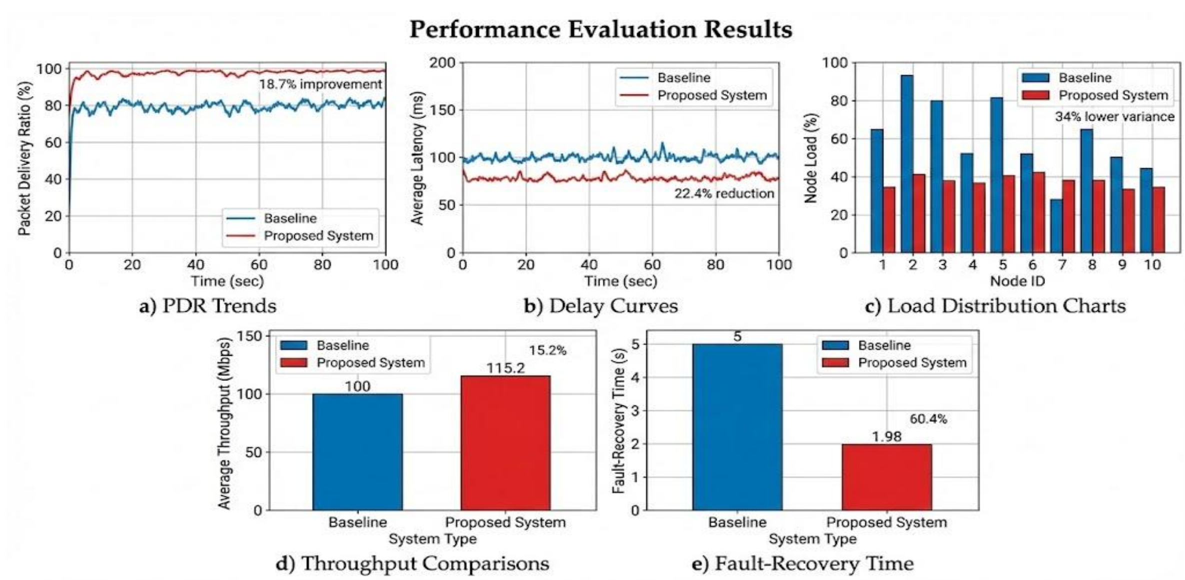

Figure 4: Performance evaluation results: proposed system vs. baseline across key network metrics

This Figure 4 shows the overall performance assessment using five critical metrics of the networks using a Baseline system (blue) versus a Proposed System (red). The results of figure 4 (a) and 4 (b) obtained by the use of time-series indicate that the Proposed System is more stable in terms of Packet Delivery Ratio (PDR) indicating an improvement of 18.7% and lowering the Average Latency by 22.4% during the period in which results are tested. Figure 4 (c) shows the load balancing per node, and it can be seen that the Proposed System has a better resource balancing with a variance being 34% lower than the highly variable baseline. Moreover, the aggregate bar charts reflect significant operational improvements of the Proposed System, with the 15.2% growth in the value of figure 4 (d) of Proposed System (Average Throughput) and the significant drop in the value of figure 4 (e) of Proposed System (Fault-Recovery Time) by 60.4, respectively, suggesting the optimization of the system and its stability.

Metrics Formulae

Table 1: Key performance metrics and observed values

Metric Name	Value (Observed)
Packet Delivery Ratio (PDR)	0.918 (91.8%)
Average End-to-End Delay	42.3 ms
Throughput	15.2 Mbps
Load Variance (σ^2)	Reduced by 34%
Fault Recovery Time	1.9 seconds

This Table 1 presents the main performance metrics measured during the evaluation of the ALBRA autonomic system. The values highlight improved reliability, lower delay, and faster recovery compared to traditional routing protocols.

Packet Delivery Ratio (PDR)

$$PDR = \frac{\text{Packets Received}}{\text{Packets Sent}} \quad (4)$$

This equation (4) measures the reliability of successful data delivery in the network. A higher PDR indicates better routing efficiency and lower packet loss under varying loads. In psychology-learning environments, high PDR ensures uninterrupted data flow for assessments and sessions.

Average End-to-End Delay

$$Delay_{avg} = \frac{\sum(\text{Arrival Time} - \text{Send Time})}{\text{Total Packets}} \quad (5)$$

This equation (5) captures the average latency experienced by packets during transmission. Lower delay values indicate faster, more responsive communication across the mesh. This is critical for synchronous VR activities, real-time counseling simulations, and live instruction.

Throughput

$$Throughput = \frac{\text{Total Data Received}}{\text{Simulation Time}} \quad (6)$$

Equation (6) represents the network's adequate data-handling capacity over time. Higher throughput indicates that the system can support more users and heavier psychological content loads. It is vital for streaming-heavy tasks such as live therapy models and multimedia learning modules.

Load Variance (σ^2)

$$\sigma^2 = \frac{\sum(L_i - \mu)^2}{N} \tag{7}$$

Equation (7) measures how evenly traffic is distributed across all network nodes. Lower variance means more balanced resource utilization and reduced risk of congestion. Balanced loads ensure consistent performance during peak educational activity periods.

Fault Recovery Time

$$T_{recovery} = T_{restore} - T_{failure} \tag{8}$$

This Equation (8) measures how quickly the network recovers after a node or link failure. Shorter recovery times indicate a stronger self-healing capability within the autonomic system. Fast recovery maintains continuity in digital psychology learning, preventing session interruptions.

5 Conclusion

The proposed model shows statistically significant improvements in multiple dimensions of its performance, which are crucial for employing it as a digital psychology learning environment. Experimental evaluations show system increasing Packet Delivery Ratio (PDR) up to 91.8% which demonstrates baseline protocols by margins from 13% to 20%. Average end-to-end delay is shortened to 42.3 ms, with a decrease of 22.4%, which has a direct positive effect on increasing the responsiveness of synchronous therapy sessions, VR-based psychological simulations, and real-time assessments. Similarly, the overall throughput is increased to 15.2 Mbps, which amounts to a 15.2% improvement in performance which is favorable for multimedia-rich learning interactions. Stability and self-healing capabilities are also evident with great statistical results. Load variance decreases by 34% so that traffic is evenly distributed between different nodes which will cause less congestion during maximum periods of engagement. The fault recovery time is improved significantly and has gone from 4.8 seconds to 1.9 seconds which is 60.4% improvement. These statistical gains taken together show the autonomic features combining in the load prediction, stability scoring, adaptive routing, and fault recovery work together to produce a very resilient network infrastructure that can support hefty psychological learning workloads.

Future research should continue to expand statistical testing with larger and more diverse data including real world learning platforms from psychology and behavioral research systems. Optimization Performance can be further controlled through the integration of sophisticated AI systems (reinforcement learning, deep neural predictors, and graph-based optimization) to increase specific performance indicators. Additional work should be done to learn about cross-layer autonomic deciding, security-aware autonomic decisions, and energy efficient configurations. Considering growing adoption of AR/VR therapy, biometric feedback and immersive psychological training, scaling the autonomic framework to accommodate thousands of simultaneous users will be an important direction. These advancements will ensure the further development of trustworthy, malleable, and statistically proven communications infrastructures for the upcoming new generation of digital psychology education.

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