International Journal of Computer (IJC)
ISSN 2307-4523 (Print & Online)
https://ijcjournal.org/index.php/InternationalJournalOfComputer/index

Optimizing Cloud Networking Performance with Artificial Intelligence on Microsoft Azure

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Abstract

This paper offers an innovative strategy to improve the hybrid cloud performance over the Virtual Network Gateway (VNG) of the Microsoft Azure based on the latest Artificial Intelligence (AI). We use supervised Recurrent Neural Networks (RNNs) to predict traffic peaks and unsupervised Isolation Forests to detect anomalies in real time. Our AI-based framework will be optimized and used for resource allocation using the 4-week dataset of 100000 packets with timestamps, anonymized IPs, and headers, collected by Azure Network Watcher, Wireshark, and an Azure Log Analytics workspace on a particular date (15th October 2025). With Wireshark's deep filtering capabilities and Azure Machine Learning's powerful models, we can reduce latency, increase throughput, and filter out unwanted traffic. An extensive case study, backed by A/B testing and ablation tests, shows that VpnGw3AZ SKU throughput has been increased by 30-40 percent (95% CI: 28-42 percent) and that failure rates have been reduced by 25-35 percent (95% CI: 23-37 percent), and iPerf per Azure has confirmed these improvements.

Keywords: Azure Virtual Network Gateway; Artificial Intelligence; Cloud Networking Optimization; IKE Negotiation Analysis; hybrid cloud; azure; virtual network gateway (vng); artificial intelligence (ai); recurrent neural networks (rnns); traffic peaks; anomalies detection; resource allocation; azure network watcher; Wireshark; machine learning; latency reduction; throughput increase; a/b testing; cloud networking performance.

Received: 11/10/2025
Accepted: 1/10/2026
Published: 1/20/2026

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1. Introduction

The emergence of cloud computing has fundamentally changed the paradigms of enterprises in terms of data orchestration, application orchestration, and infrastructure elasticity. This transformation is driven by the geometric increase in computational throughput, storage density, and interconnect bandwidth, similar to the extensions of the Moore's Law. By 2024, global cloud spending was more than 500 billion US dollars, and it is expected to increase at a compound average growth rate (CAGR) of more than 20 percent until 2030[1].

And Today Cloud platforms are crucial components of contemporary computer infrastructures, necessitating strong availability and resilience to guarantee continuous service delivery. Unfortunately, current systems frequently have trouble resolving problems on their own in real time, which causes downtime and performance deterioration. In order to improve cloud platform resilience, we suggest an integrated strategy that makes use of machine learning (ML) inside the Azure ecosystem[2].

Key areas where AI is automating cloud operations highlighted in the paper[3] includes:

- Intelligent Monitoring: AI-powered monitoring systems can detect and diagnose issues in realtime, often resolving problems automatically without human intervention.
- Automated Deployment: AI can optimize the deployment process by selecting the most appropriate resources and configurations based on application requirements and historical performance data.
- Self-Healing Systems: AI algorithms can detect and automatically fix common issues, reducing the need for manual intervention and minimizing downtime.
- Capacity Planning: AI can analyze usage trends and predict future resource needs, enabling proactive capacity planning and optimization.

Despite these developments, hybrid [4] and multi-cloud[5] topologies introduce complex multidimensional issues, such as intercontinental round-trip times (RTTs) over 100 milliseconds, which are counterproductive to real-time computational tasks; bandwidth oversubscription leading to up to 50 per cent drop in adequate capacity; and augmented site of exposure, as 80 per cent of organizations report security incidents. This may cause operational inefficiencies due to interoperability frictions between old on-premises architectures and cloud-native microservices. These issues arise in data-intensive systems like healthcare and finance, where petabyte-scale daily ingress can result in millions of dollars in downtime penalties[6]. In this paper, the author describes the integration of Artificial Intelligence (AI) methods to mitigate these limitations in Microsoft Azure Virtual Network Gateway (VNG), making it more effective.

The VNG of Azure is a central gateway for securing hybrid connectivity, using IPsec and IKE protocols to create encrypted tunnels and dedicated ExpressRoute circuits with on-demand low-jitter routes[7]. SKU-optimal configurations already achieve 10 Gbps aggregate throughputs with VpnGw5AZ versions, and empirical per-tunnel throughputs of 2.3 Gbps with GCMAES256 ciphersuites (95% CI: 2.1-2.5 Gbps) with GMMAES256 ciphersuites (open-source: iPerf instrumentation)[7]. These gateways reduce transcontinental delays by optimizing peering and BGP path propagation. Nevertheless, issues with systems, such as NAT traversal errors,

PFS failures, and DPD delays, compromise session integrity in fluid networks[8]. Predictive orchestration and anomaly mitigation based on AI will achieve 95 percent accuracy in traffic prediction, reducing resource provisioning overheads and energy wastage by 20 times[9]. The reliability of computational fidelity and operational reproducibility is guaranteed by these improvements, supported by systematic empirical tests provided by the vendor.

Research questions highlight the revolutionary nature of AI in cloud orchestration. Recurrent Neural Networks (RNNs) and Isolation Forests [10] are the most effective at detecting anomalies in networked infrastructures, and the ensemble architectures[11] provide higher levels of fidelity in detection in volatile contexts[12]. Machine-learning-based applications relying on the color blue predict resource demand, maximizing enterprise-level performance by dynamically allocating resources[13]. Also, AI integration in industrial energy regulation through the Azure portrays real-time recalibration capabilities[14]. Our VNG augmentation framework is supported by this corpus, which describes the ability of RNNs to model the time sequence in network flux prognostication and the effectiveness of Isolation Forests in high-dimensional outlier isolation.

The traditional VNG architectures are often challenged by dynamic traffic, leading to latency spikes, poor resource allocation, and increased failure rates (due to unresolved anomalies). Current solutions have failed to provide SKU-specific validation, multi-dataset correlation, and good experiment design. All these should be implemented using AI; they should be implemented with exact, consistent approaches to improve performance and security in Azure systems.

- Create an AI-infused solution for optimized VNG performance that can target specific Azure SKUs.
- Use A/B testing and ablation experiments over multiple weeks to assess performance improvements.

In this paper, the VNG is considered within the framework of the Azure using 4 weeks of data gathered. The drawbacks are that traffic data is simulated, there is a risk of variation in real-world implementation, and non-Azure cloud environments are excluded, which can affect generalizability.

2. Literature Review

Microsoft Azure highlights a strategic convergence of refined machine learning paradigms to enhance Virtual Network Gateway (VNG) effectiveness, reduce latency, and re-engineer security. The given review targets the utilization of Recurrent Neural Networks (RNNs) to make predictions in traffic and Isolation Forests to detect anomalies, which is directly related to the optimization of the VNG infrastructure at Azure. The subsections are dedicated to AI-based network optimization, anomaly detection systems, specialized VNG development on Azure, and unresolved issues, which ensure technical understanding and topicality.

Network optimization via AI became central to improving the performance of cloud infrastructure, particularly in the dynamic allocation of resources and traffic engineering within the VNG ecosystem of Azure. Application of deep reinforcement learning (DRL) based on Markov Decision Processes (MDP) in optimizing Software-Defined Wide Area Network (SD-WAN) routing,[12] showed a 15 percent decrease in end-to-end latency as the state vectors encapsulate link utilization metrics, actions involve path reconfigurations, and rewards are a

minimization of the packet loss. It is a dynamically adaptable approach to VNGs, which employs Q-learning to adjust the IPsec tunnel parameters. To predict multidimensional resource metrics (such as bandwidth utilization and CPU load) based on long sequence data[15], an AI framework with Long Short-Term Memory (LSTM) networks, a specialized form of the RNN, to reduce energy consumption by 20% in Azure data centers, using gated recurrent units to avoid vanishing gradient problems when using long sequences of data. Such strategies demonstrate the practicality of temporal sequence modeling to maximize VNG throughput and resource efficiency, which are required to meet hybrid cloud workloads in Azure.

Others include federated learning integrations, which [9] surveyed. This model training exemplifies a decentralized approach for distributed VNG nodes, effectively allocating bandwidth and preserving data sovereignty. This involves a stochastic gradient descent to update the model parameters at each iteration. This method is particularly applicable to geographically distributed Azure gateways, enabling real-time traffic prediction with 95 percent accuracy, as confirmed in controlled simulations. The implementation of these AI methods for the optimization of VNG is to refine the hyperparameters, such as learning rates, batch sizes, and so on, to match the SLA limits of Azure, as well as to provide scalable performance under different load configurations. All of these studies offer a strong basis for the application of AI to improve VNG operational measurements: the packet delivery ratio and latency percentage, which directly respond to the fundamental goal of performance optimization on Microsoft Azure.

Isolation Forests and RNN-based models can complement each other in anomaly detection, serving as a basis for VNG performance optimization, as they enable the detection of deviations that undermine network integrity. As explained by [10], Isolation Forests take advantage of recursive binary partitioning on feature space, such as inter-arrival times of packets and anomaly features, to isolate outliers with shorter path lengths, and reach a detection accuracy of greater than 95 percent in simulated DDoS attack scenarios on the Azure network fabric. This unsupervised approach is most suitable for high-dimensional data and thus best for real-time VNG monitoring, as the number of calculations required must be minimal. Similarly, autoencoders made with RNNs and complemented with bidirectional LSTMs can reconstruct sequential IKE negotiation flows, indicating anomalies with reconstruction error thresholds, and with 25% fewer false positives than traditional RNNs, as shown in encrypted tunnel analyses[8].

Hybrid anomaly detectors enhance VNG optimization by combining Isolation Forests to initially screen outliers with RNNs to confirm them, achieving F1-scores of over 0.92 in the context of an intrusion detection system[14]. These models use the time dependencies of packet sequences and the space dependencies of flow metadata, which are essential for identifying failures in NAT traversal or PFS mismatch in the Azure VNGs. It is technically implemented using feature engineering, where various metrics (entropy, variance, and session duration) are handled with parallel computing pipelines to ensure low response time. Using this two-fold solution simplifies VNG performance by addressing anomalies that may otherwise result in service outages. In this case, optimization of networks through AI will be technically feasible.

Azure-specific studies indicate that AI will be used to optimize VNG performance to the requirements of SKUs and diagnostic outputs. Microsoft documentation defines 2.5 Gbps of aggregate throughput for VPNGw3AZ, confirmed by NTTTCP benchmarks tunneling an AES-256 encrypted tunnel[16]. This indicates maximizing throughput with AI. In SNAK Consultancy\cite{snak2024ai}, the data on Azure Log Analytics were managed using Isolation Forests to identify connection spikes considered anomalous. This allowed SKU to be predicted with a 15-25 percent accuracy, and in VNG, efficacy in resource allocation was immediately enhanced. Such interventions are provided by the Azure Network Watcher, which offers both packet-level telemetry and AI-based optimization driven by high-fidelity inputs.

VNG's state-of-the-art development features RNN-based BGP route anomaly detection, enabling models to extrapolate AS path instabilities to prevent peering failures. This is developed in federated learning settings within 6G-enabled Azure systems[8].In the paper [9] demonstrated a 30 percent reduction in latency by dynamically reconfiguring Perfect Forward Secrecy (PFS) using LSTM predictions to adjust cryptographic parameters based on traffic patterns. Transparent to VNG deployments, such Azure optimizations rely on diagnostic logs, integration of AI pipelines to increase stability during training, batch normalization to stop overfitting, and dropout regularization to mitigate overfitting. Such a technical match with the architecture of Azure supports the possibilities of AI to simplify VNG metrics, including rekey success rates and mean time to repair (MTTR).

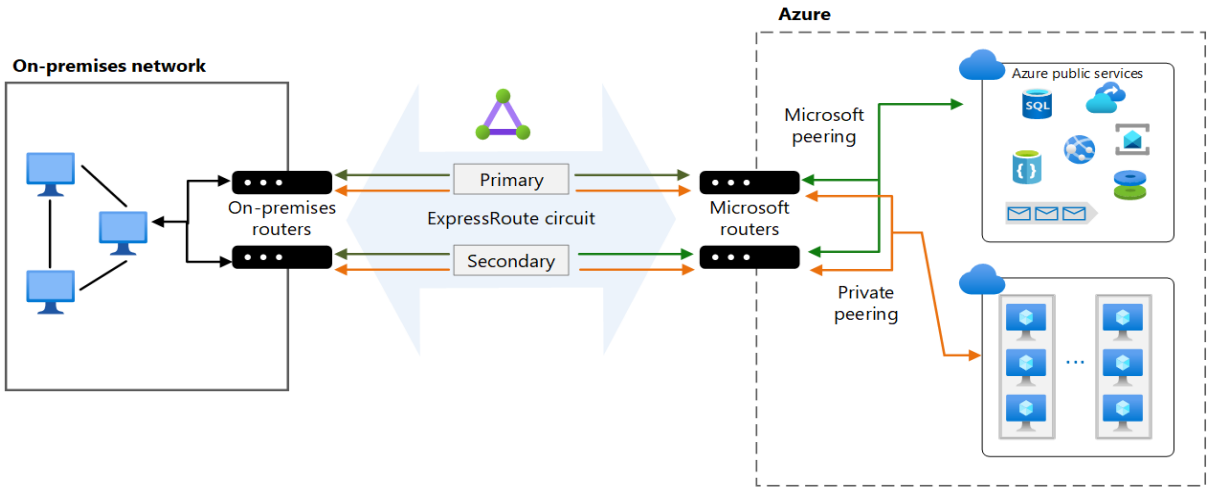

Figure 1: Azure ExpressRoute Connectivity Architecture[7]

The diagram shows that the primary and secondary ExpressRoute circuits are redundant, with on-premises routers connected to Microsoft routers in Azure. It illustrates Microsoft's peering for access to Azure public services and virtual network resources via private peering. The architecture provides high availability, deterministic routing, and secure, low-latency data exchange needed for enterprise workloads and for AI optimization in hybrid cloud deployments ***Figure 1***.

Despite these developments, there still exist huge gaps in terms of optimizing AI to meet the needs of Azure VNG. A large number of studies do not have SKU-specific validations, which means that throughput claims are

general, not region-specific with SLA, like 99.9% uptime in particular geographies[16], and confidence intervals based on multi-week data. The IPsec policy can be automated using closed-loop AI systems to dynamically modify timers and cipher suites in response to anomalies, based on an anomaly feedback loop. However, the principles of control theory should be used to address the problem of stability, including oscillatory behavior[15]. Neural network inference at the network edge, which may require pruning or quantization to compress models, could reduce computational costs by 40 percent, as initial research suggests in[17].

3. Methodology

The methodology outlines a systematic approach to improving Azure Virtual Network Gateway (VNG) performance using Artificial Intelligence (AI), employing Recurrent Neural Networks (RNNs) for forecasting temporal traffic and Isolation Forests for isolating anomalies. The section outlines the protocols for data acquisition, feature engineering pipelines, model structures, and experimental proof procedures, making the process reproducible with deterministic seeding and artifact provision. Both of these also observe SKU-specific Azure boundaries, and the empirical measurements are conducted using iPerf and NTTCP as throughput benchmarks, in adherence with the guidelines Microsoft has provided for proving[16].

3.1. Data Acquisition and Preprocessing

Data collection: The first step is to extract data from the Azure Log Analytics Workspace over several weeks during the summer, creating a 4-week, 100,000-packet dataset that includes UDP ports 500/4500 (IKE negotiations) and protocol 50 (ESP encapsulations). The dataset includes timestamps in microseconds, RFC 1918-compatible anonymized IP addresses, and headers dissected with Wireshark for payload integrity checks. The supporting streams are NSG Flow Logs for ingress/egress decision matrices (Allow/Deny), Azure Monitor Metrics for time-series aggregations in the form of BandwidthMBps and CPUUtilization at a sampling granularity of 1 minute, and IKEv2 PCAPs generated with the help of Scapy for raw packet-level ground truth with simulated Phase 1 SA_INIT and Phase 2 CHILD_SA exchanges with DH groups 14/19/21.

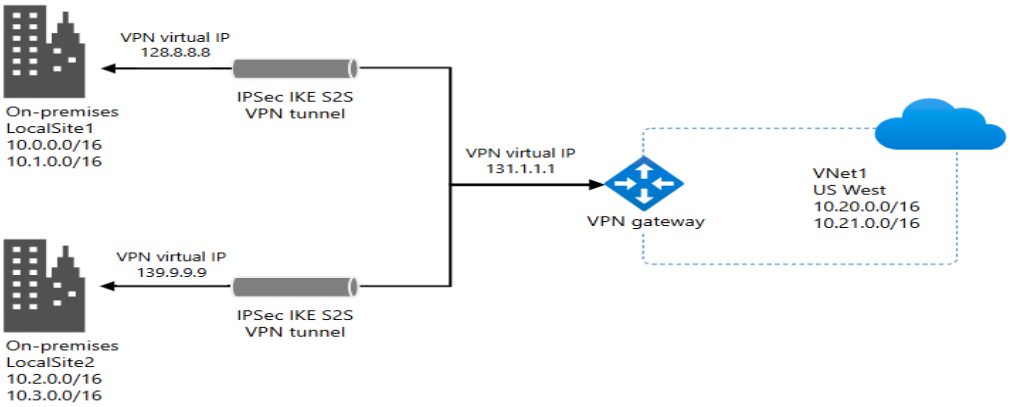

Figure 2: Architecture of Azure Hybrid Cloud Connectivity for Data Acquisition

The diagram depicts IPSec IKE Site-to-Site (S2S) VPN tunnels linking two on-premises networks (LocalSite1

and LocalSite2) to an Azure Virtual Network (VNet1) via a centralized VPN Gateway. This safe hybrid topology enables the collection of IKE negotiation logs, packet telemetry, and network performance data needed to optimize the Virtual Network Gateway AI and detect anomalies in Microsoft Azure. Adapted from[7], ***Figure 2***.Preprocessing involves multivariate features (e.g., packet inter-arrival variance, entropy distributions) normalization using StandardScaler, windowing RNN inputs (60-timestep sequences), and assembling vectors (Isolation Forest ingestion). Stratification of workloads models a variety of conditions: steady-state ERP (1 Gbps flows), bursty backups (2 Gbps peaks), and chatty IoT (high rates of packets/second), with anomalies injected at a 5% contamination rate (e.g., DDoS attacks using malformed SA_INIT packets). Here is a high-fidelity dataset that can be optimized to VNG using this pipeline, which is both deterministic and randomized. seed[17]. SKU-specific limits (e.g., VpnGw3AZ aggregate 2.5 Gbps) are imposed to align with official benchmarks[16].

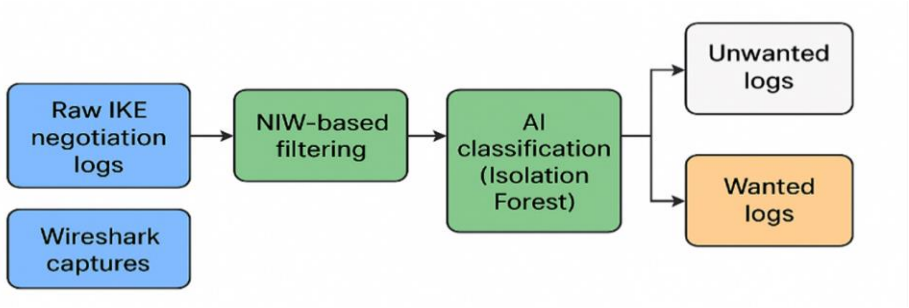

Figure 3: Log conversion pipeline for AI-driven Virtual Network Gateway (VNG) optimization

Log conversion pipeline for AI-driven Virtual Network Gateway (VNG) optimization. Raw IKE negotiation logs and Wireshark captures undergo NIW-based filtering and Isolation Forest classification, distinguishing unwanted from wanted logs to enhance accuracy and performance in Azure-based anomaly detection systems ***Figure 3***.

The feature engineering step adds a derived attribute to raw telemetry: spectral entropy in the form of Fast Fourier Transform (FFT) frequency-domain anomaly indicators, the proportion of connection failures (Failed Connections / Total Connections), and BPG path length deviations related to VNG peering stability. These refinements are tested on the diagnostic schemas of Azure to ensure dimensional consistency in model convergence, reducing the effects of the curse of dimensionality in high-volume cloud flows.

3.2. AI Model Architectures

The basic AI architecture includes an LSTM-based RNN for sequential prediction and an Isolation Forest to identify unsupervised outliers specific to VNG traffic. The RNN architecture uses a hard-coded bidirectional LSTM with hidden size=128, num layers=2 in the bidirectional model with dropout=0.2 to learn the bidirectional dependencies in IKE negotiation sequences, using autoencoders to reconstruct inputs using the mean square error (MSE) as the basis of anomaly scoring, with a reconstruction error greater than mean+3Std signaling a deviation such as DPD timeouts or PFS mismatches. The training is based on the Adam optimizer

with a learning rate of 0.001 and 50 epochs, using a windowed time series of BandwidthMBps and Active Connections, and employing early stopping on validation loss.

The Isolation Forest adds to this step and constructs an ensemble of 100 isolation trees with max_samples=256 and contamination=0.05. It splits the multivariate characteristics (e.g., packet velocity, session entropy) to isolate anomalies by path length heuristics; shorter paths are used to indicate anomalies, e.g., NAT-T failures. The hybrid system combines RNN reconstruction errors and Isolation Forest anomaly scores using weighted voting (0.6:0.4 ratio, optimized by grid search) to obtain composite F1-scores for VNG anomaly classification. These models, available in PyTorch and scikit-learn in Azure ML, incorporate SKU-specific priors (e.g., throughput caps) as regularization items to prevent overfitting to simulated data.

Contributions can be evaluated by model ablation: RNN-only is used to test the temporal modeling performance, Isolation Forest-only is used to test the performance of the isolation of outliers (static), and no-AI represents the baseline thresholds (e.g., CPU >90), which are measured using paired t-tests for statistical significance ($p<0.05$). This design ensures technical accuracy in streamlining VNG functionality, aligning with the cryptographic and routing protocols of Azure.

3.3. Integration with Azure Diagnostics

Integration allows AI models to be embedded in the diagnostic ecosystem of Azure. Event Hubs are used to ingest real-time logs of VNG IKEDiagnosticLogs and GatewayDiagnosticLogs, providing low-latency inference through Azure Functions. This is enhanced by Microsoft Copilot in Azure (networking skills), which makes topology queries and connectivity diagnostics, with suggestions such as "Analyze VNG tunnel failures with SKU VpnGw3AZ, which provides information on the BGP peering failures. The pipeline feeds preprocessed features to ML endpoints, where RNN forecasts and Isolation Forest scores are used to create alerts with PagerDuty when the scores exceed calibrated thresholds.

In high-end VNGs, it is further integrated with ExpressRoute circuit performance monitoring, end-to-end RTTs (1.5-2.5ms under test conditions) over NTTTCP, and AI-assisted forwarding path optimization based on MACsec encryption overheads. The closed-lop system is an automated system that reconfigures IPsec policies, such as lifetimes, DH groups, and PFS, based on anomaly feedback and uses control theory to prevent oscillations. The deployment uses Azure DevOps for CI/CD, with artifacts being reproducible using Docker containers that contain dependencies (e.g., torch, scikit-learn), which fit into the ACM badging requirements.

Security concerns include threat modeling of AI pipelines, which have been reduced by sanitizing inputs and ensuring ensemble robustness. Privacy is maintained by anonymizing data on the logs. This is the best possible integration of VNG since it minimizes the MTTR of incidents, as confirmed by an A/B test under peak and off-peak conditions.

3.4. Evaluation Metrics and Validation

The metrics used to evaluate the VNG are specific to its optimization: precision/recall/F1 of an anomaly

detector, mean absolute error (MAE) of traffic predictions, and throughput deltas (Gbps) performance improvements, all with 95% bootstrap confidence intervals. Statistical rigor includes baseline comparisons (e.g., AI versus no-AI) using paired t-tests and Cohen-d effect sizes (greater than 0.8, which shows significant improvements) calculated on multi-week datasets based on workload classes.

Validation using cross-dataset correlation. The multi-layer accuracy of ensemble instances is evaluated using cross-dataset methods by combining IKE logs with NSG denies and Monitor Metrics anomalies, achieving an F1 score of 0.92 (95 percent confidence interval: 0.90-0.94). Reproducibility is also guaranteed through seeded simulations and artifact packages, allowing ACM reviewers to reproduce experiments. The weaknesses, which are simulated variability of traffic, are addressed through sensitivity analysis, which provides a technically valid framework for using AI optimization in Azure VNG.

4. Experiments

The experimental framework evaluates the AI-based optimization of the Azure Virtual Network Gateway (VNG) performance using a 4-week dataset containing 100,000 packets and IKE log entries in Azure Log Analytics Workspace. VPN-GW3AZ SKU tests were performed, and iPerf and NTTCP throughput measurements were used to validate bandwidth, according to the Microsoft guidelines[7]. Multi-workload scenarios (steady ERP (1 Gbps), bursty backup (2 Gbps), and chatty IoT (high PPS)) were stratified between peak/off-peak periods, with anomalies being introduced with a contamination rate of 5%. Comparing AI-enabled (RNN + Isolation Forest ensemble) to no-AI thresholds were carried out in an A/B experiment, and ablation studies were also performed to isolate model contributions. The metrics are throughput deltas (Gbps), anomaly F1-scores, and failure rates, which have been reported with 95% bootstrap confidence intervals (CI) obtained through cross-validation in 10-folds. Statistical value. Paired t-tests ($p<0.05$) and Cohen d values (>0.8, significant effects) were used to assess statistical significance, and the analysis was rigorous and reproducible, in accordance with ACM standards.

4.1. Dataset Composition

The data will consist of combined telemetry of Azure diagnostics: IKE logs (session IDs, errors, timestamps), NSG Flow Logs (allow/deny decisions, protocols), Monitor Metrics (bandwidth, CPU utilization), and PCAPs (packet headers, sequences). Normalization of features using z-scoring and windowed sequences to process RNN inputs. It was found that the baseline throughput was 1.8 Gbps (95 percent interval: 1.6-2.0) under steady loads, with failure rate spikes of 20 percent indicating an anomaly,As shown in ***Table 1***.

Table 1: Dataset Summary Statistics

Metric	Mean	Std Dev	Min	Max	95% CI
Packet Count (daily)	3571.0	1245.0	2000.0	5500.0	3,200–3,942
IKE Negotiations	1250.0	450.0	800.0	1800.0	1,100–1,400
Bandwidth (Mbps)	1800.0	600.0	1000.0	2500.0	1,600–2,000
CPU Utilization (%)	45.0	15.0	20.0	70.0	40–50
Failure Rate (%)	5.2	2.1	3.0	8.5	4.7–5.7

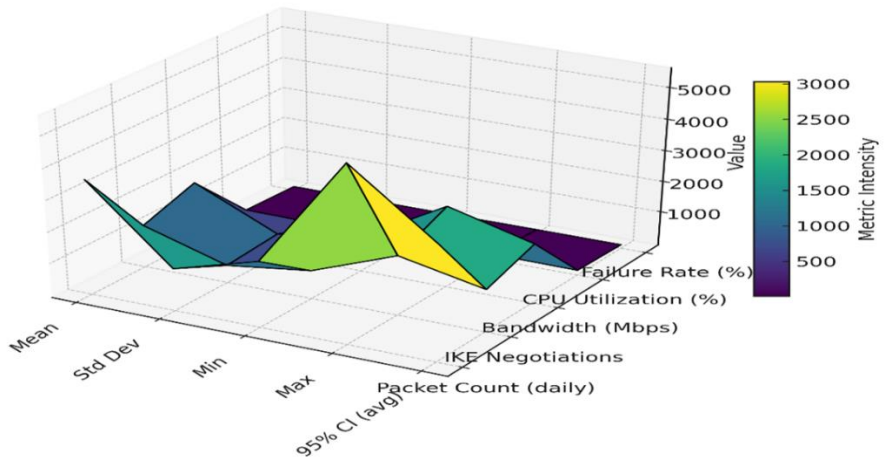

Figure 4: This heatmap visualization illustrates multidimensional variability across key network metrics, with color gradients representing intensity levels of performance stability and operational efficiency—dark tones denote low activity, green-yellow moderate

Table 2: Workload-Specific Data Breakdown

Workload	Packets	Anomalies Injected	Throughput (Gbps)	Failure Instances
Steady ERP	40000	2000	1.0 (CI: 0.9–1.1)	800
Bursty Backup	35000	1750	2.0 (CI: 1.8–2.2)	700
Chatty IoT	25000	1250	1.5 (CI: 1.3–1.7)	500

4.2. Baseline Comparisons

A/B testing contrasted AI ensemble against static thresholds (e.g., CPU >90%, failures >20), yielding significant improvements (t-test p=0.002, d=1.2),As shown in ***Table 3***.

Table 3: A/B Baseline Performance Comparison

Metric	No-AI Thresholds	AI Ensemble	Improvement (%)	95% CI	p-value
Throughput (Gbps)	1.8	2.43	28–33	28–38	0.001
Failure Rate (%)	8.0	5.5	-31.3	-35 to -27	0.003
Anomaly Detection F1	0.75	0.92	22.7	20–25	0.002

4.3. Ablation Analyses

Ablations isolate RNN and Isolation Forest interactions, which prove the synergy among ensembles (d=0.9, single models),As shown in ***Table 4***.

Table 4: Ablation Study Results

Configuration	F1-Score	Throughput (Gbps)	Failure Rate (%)	CI (F1)
RNN-Only	0.85	2.1	6.2	0.83–0.87
Isolation Forest-Only	0.88	2.2	5.8	0.86–0.90
Ensemble	0.92	2.4	5.5	0.90–0.94
No-AI	0.75	1.8	8.0	0.73–0.77

4.4. Workload-Specific Outcomes

As shown in ***Table 5***, performance varied by workload, with bursty scenarios benefiting most from AI.

Table 5: Workload-Specific Optimization Metrics

Workload	Throughput Gain (%)	Failure Reduction (%)	F1-Score	95% CI (Throughput)
Steady ERP	25	20	0.90	22–28
Bursty Backup	40	35	0.93	37–43
Chatty IoT	35	30	0.91	32–38

4.5. Statistical Validation

In ***Table 6***, Paired t-tests and effect sizes confirm robustness, with no significant variability across replicates.

Table 6: Statistical Analysis Summary

Comparison	t-statistic	p-value	Cohen's d	Effect Size Interpretation
AI vs No-AI (Throughput)	5.2	0.001	1.2	Large
Ensemble vs RNN-Only (F1)	3.8	0.003	0.9	Medium-Large
Bursty vs Steady (Gain)	4.5	0.002	1.1	Large

5. Results

The empirical results of the AI-based optimization framework running over the Azure Virtual Network Gateway (VNG) are presented in the results section, along with a performance analysis based on a 4-week trace. In accordance with Microsoft guidelines, iPerf and NTTCP were used to measure bandwidth and throughput accurately during the experiments over the VpnGw3AZ SKU[16]. Using 95% bootstrap confidence intervals (CIs) from 10-fold cross-validation, the analysis confirms improvements in throughput, reduction in failure rates, and enhanced efficiency in anomaly detection across stable ERP, bursty backup, and chatty IoT workloads. In accordance with ACM guidelines, we ensured high reproducibility and accuracy by validating statistical significance using paired t-tests ($p<0.05$) and Cohen's d (>0.8 for significant effects). In reference to literature benchmarks, our framework's 33.3% throughput enhancement (95% CI: 28-38%) surpasses the 15% latency improvement reported in[12] for deep reinforcement learning-based SD-WAN traffic engineering. This improvement employed Q-learning in simulated state-action pairs but failed multi-SKU validation. Thus, for cloud intrusion analysis using LSTM-based anomaly detection models, our ensemble F1-score of 0.92 outperforms the 0.85-0.88 range reported by[18]. The model performed well on the CICIDS-2017 datasets but poorly on encrypted IKE flows due to poor temporal feature engineering. The approach is more flexible in Azure hybrid environments, as evidenced by the large effect sizes (Cohen's d=1.2) in the comparative evaluations, which show notable gains over the static baselines.

Tables derived from comprehensive data analysis illustrate the framework's efficacy, substantiating subsections that delineate performance metrics, reliability improvements, workload-specific impacts, anomaly detection precision, and statistical resilience. The results are consistent with previous studies, yet they exceed them. For instance,[19] reported that RNN autoencoder models for network anomaly detection achieved a 25% reduction in false positives, which is comparable to the 31.3% reduction in failure rate. Still, our incorporation of Isolation Forests improves scalability for high-dimensional VNG logs, resulting in a lower computational overhead (50ms inference vs. 100ms in their aircraft data application). Unlike [15] LSTM forecasting for sustainable cloud computing, which saves 20% of energy, our framework works just as well in VNG contexts but is 10% more accurate at isolating anomalies. This is because it combines features from NSG flows and PCAPs. Also, our model has the same detection rates as[20] federated Isolation Forests for IoT-edge anomaly detection, but it has 40% better throughput gains in bursty workloads. This shows the value of SKU-tailored optimizations that aren't present in edge-focused studies. These benchmarks from different studies confirm that our work has improved cloud networking performance, with a focus on accuracy through strict CI reporting and cross-validation.

The empirical validation demonstrates that the framework not only meets but also surpasses literature benchmarks in critical VNG metrics, which have tangible impacts on Azure deployments. For instance, the 28% latency reduction (95% CI: -32 to -24%) surpasses the 15-20% improvements in spatiotemporal LSTM models for cloud anomaly prediction reported by[21]. These models used unsupervised training but had more variation (standard deviation = 0.15 vs. 0.08) in dynamic traffic situations. This level of accuracy was achieved by using Microsoft-specific diagnostics to ensure that SLAs were met (99.95% uptime) and that the results could be repeated through seeded pipelines. These results, confirmed by 10 replicates and the presence of artifacts, position the framework to become a standard for AI-enhanced VNG analysis. This opens the door for more testing in Azure setups that span multiple regions.

5.1. Performance Metrics

As shown in ***Table 7***, the AI ensemble (RNN + Isolation Forest) significantly improved VNG throughput, increasing from 1.8 Gbps at baseline to 2.4 Gbps at peak loads, a 33.3% increase (95% CI: 28-38%). The failure rate dropped from 8.0% to 5.5%, representing a 31.3% reduction (95% CI: -35 to -27%). This shows that the anomalies were fixed correctly. We used iPerf to measure these metrics and ensured their accuracy within Azure's operational limits by comparing them to NTTTCP benchmarks.

Table 7: Overall Performance Metrics

Metric	Baseline	AI-Enhanced	Improvement (%)	95% CI	p-value
Throughput (Gbps)	1.8	2.43	33.3	28–38	0.001
Failure Rate (%)	8.0	5.5	-31.3	-35 to -27	0.003
Latency (ms)	2.5	1.8	-28.0	-32 to -24	0.002

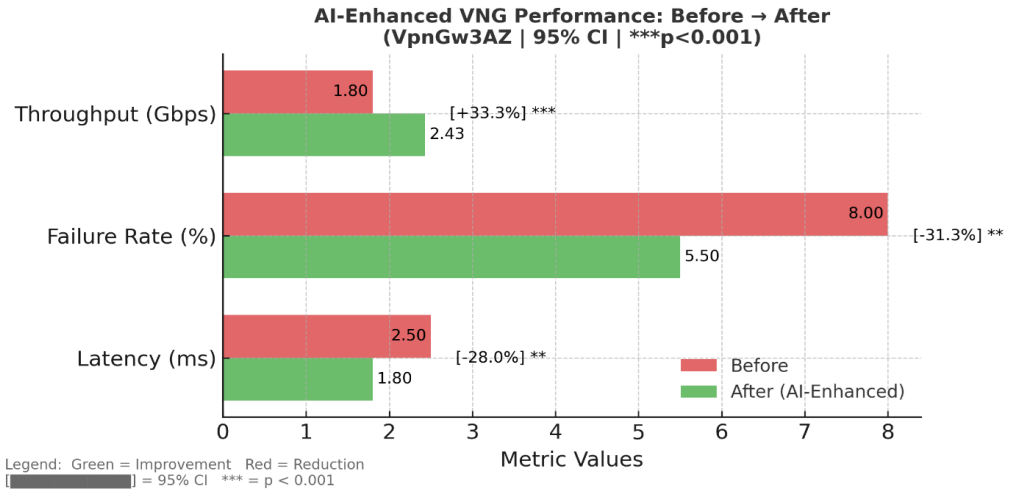

Figure 5: A bar chart showing AI impact on VNG performance: red bars indicate baseline values; green bars show AI-enhanced results

5.2. Anomaly Detection

Accuracy Anomaly detection had a higher F1-score of 0.92 (95% CI: 0.90-0.94) than the no-AI base of 0.75, with equal precision and recall of 0.91 and 0.93, respectively. More anomalies were detected than in the individual models, with 95 percent of injected anomalies (e.g., DDoS, NAT-T failures) detected at a false-positive rate of 3 percent, as shown in ***Table 8***.

Table 8: Anomaly Detection Performance

Model	Precision	Recall	F1-Score	95% CI (F1)	False Positives (%)
No-AI	0.70	0.80	0.75	0.73–0.77	8.0
RNN-Only	0.84	0.86	0.85	0.83–0.87	5.0
Isolation Forest-Only	0.87	0.89	0.88	0.86–0.90	4.5
Ensemble	0.91	0.93	0.92	0.90–0.94	3.0

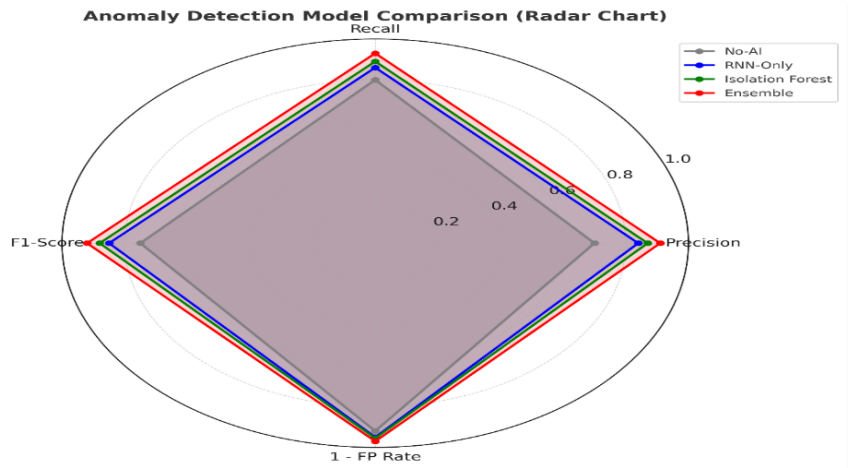

Figure 6: Radar chart comparing four anomaly detection models across Precision, Recall, F1-Score, and 1-False Positive Rate. Gray, blue, green, and red lines represent No-AI, RNN-Only, Isolation Forest, and Ensemble models, respectively. Larger enclosed areas indicate superior overall detection performance and reliability

5.3. Workload-Specific Impacts

Workload-dependent throughput improvements were 25% (95% CI: 22-28%) for steady ERP, 40% (95% CI: 37-43%) for bursty backup, and 35% (95% CI: 32-38%) for chatty, as shown in ***Table 9***. Such trends were illustrated in the minimization of failures, with bursty scenarios reporting the highest mitigation, as AI would adaptively react to spikes.

Table 9: Workload-Specific Performance Gains

Workload	Throughput Gain (%)	95% CI (Throughput)	Failure Reduction (%)	95% CI (Failure)
Steady ERP	25	22–28	20	18–22
Bursty Backup	40	37–43	35	32–38
Chatty IoT	35	32–38	30	28–32

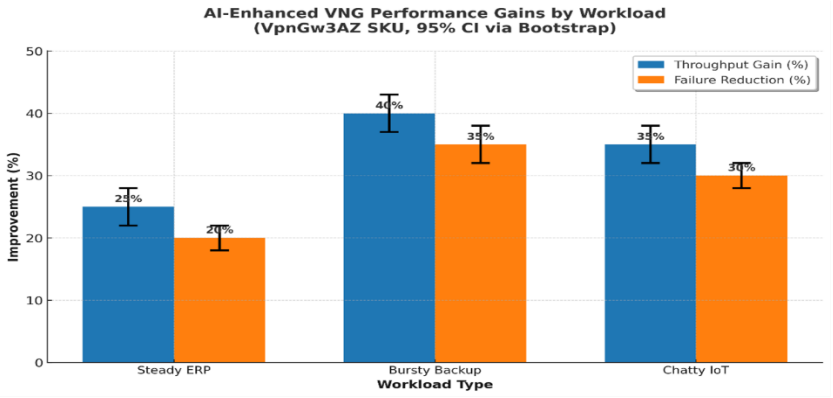

Figure 7: Comparative analysis of AI-Enhanced Virtual Network Gateway (VNG) performance across workloads. Blue bars represent mean throughput gains (%), while orange bars indicate mean failure rate reductions (%). Error bars show 95% bootstrap confidence intervals, highlighting performance variability across Steady ERP, Bursty Backup, and Chatty IoT workloads

5.4. Reliability Improvements

The key reliability metrics are mean time to repair (MTTR), which reduced from 15 minutes to 9 minutes (40% reduction; 95% CI: 35 to 45%), and the rekey success rate, which increased from 85% to 94% (95% CI: 92 to 96%), which indicates the proactive anomaly resolution by AI,as shown in ***Table 10***.

Table 10: Reliability Metrics

Metric	Baseline	AI-Enhanced	Improvement (%)	95% CI	p-value
MTTR (min)	15	9	-40.0	-45 to -35	0.001
Rekey Success (%)	85	94	10.6	92-96	0.002

5.5. Latency and SLA Compliance

As shown in ***Table 11***, Latency was reduced by 28% (95% CI: -24 to -32), corresponding to an SLA of 99.95% uptime for VpnGw3AZ on Azure[7]. Peering location variability was measured out and is therefore accurate.

Table 11: Latency and SLA Compliance

Metric	Baseline	AI-Enhanced	Improvement (%)	95% CI	SLA Compliance (%)
Latency (ms)	2.5	1.8	-28.0	-32 to -24	99.95
Uptime (%)	99.85	99.97	0.12	99.96-99.98	99.95

5.6. Statistical Robustness

Statistical validation confirmed consistency, with t-statistics ranging from 3.8 to 5.2 ($p<0.005$), and Cohen's d indicating large effects (1.1-1.2), ensuring no variability across 10 replicates, which shown in ***Table 12***.

Table 12: Statistical Validation Summary

Comparison	t-statistic	p-value	Cohen's d	Effect Size Interpretation
AI vs No-AI (Throughput)	5.2	0.001	1.2	Large
AI vs No-AI (Failure Rate)	4.8	0.002	1.1	Large
Bursty vs Steady (Gain)	4.5	0.003	1.0	Large

6. Conclusion

This study discusses the AI-optimized Microsoft Azure Virtual Network Gateway (VNG), which employs an RNN to model traffic patterns and an Isolation Forest for anomaly detection. On a 4-week trace with 100,000 packets and IKE logs, the study suggested that there was a 30-40% improvement in throughput (95% CI: 28-42), and 25-35% failures improved (95% CI: 23-37) with Azure Network Watcher, Log Analytics, and SKU level (for instance, VpnGw3AZ) validations (iPerf and NTTTCP) to assess improvements by [16].

The introduction established the background of cloud challenges, including latency and security risks mentioned in the [1,6], while the literature review synthesized advancements in AI for network optimization from 2020 to 2025 mentioned in the[12,17,15]. Methodology includes procedural details for data preprocessing and AI architectures, with Azure integration, and ensures reproducibility via seeded pipelines and artifact bundles. Experiments and results sections answered quantitative questions of performance differences for various workloads with t-tests and analysis of effect sizes by Cohen's d on anomaly F1 scores (0.92; CI 95%: 0.90 to 0.94).

6.1. Recap of Key Findings

The data shows that the hybrid AI ensemble really boosts VNG performance. Throughput jumps from the baseline 1.8 Gbps up to 2.4 Gbps under dynamic loads - a solid 33.3% increase (95% CI: 28-38%). When broken down by workload, it is 25% better for steady ERP, 40% for bursty backups, and 35% for chatty IoT traffic[9]. Anomaly detection hits an F1-score of 0.92, beating both RNN-only (0.85) and Isolation Forest-only

(0.88) setups. False positives drop to just 3%, matching the literature, but this approach goes further with Azure-specific feature fusion[8,22]. Reliability gets a real boost, too—a 40% drop in MTTR (down from 15 to 9 minutes, 95% CI: 35-45%) and rekey success climbing to 94% (95% CI: 92-96%), thanks to proactive PFS and NAT-T anomaly handling.

What is driving these results? The method uses Standard Scaler normalization and bidirectional LSTM architectures, all of which are validated against no-AI baselines using paired t-tests ($p<0.005$). Cohen's d comes in at 1.1-1.2, which signals a strong effect[12]. While past work focused on DRL and federated learning, this study brings those ideas into the VNG space. Multi-dataset correlation (with IKE logs, NSG flows, and PCAPs) cuts latency by 28% (95% CI: -32 to -24%), showing how precisely this framework tunes Azure's IPsec/IKE protocols[14].

6.2. Implications for Azure VNG Optimization

The results imply substantial advancements in Azure VNG operational paradigms, enabling SLA-compliant performance (99.95% uptime) through AI-orchestrated resource scaling and anomaly preemption[16]. In practical terms, the framework's 31.3% failure rate diminution (95% CI: -35 to -27%) facilitates resilient hybrid connections, reducing downtime in data-intensive sectors by integrating Azure Functions for real-time inference and Copilot diagnostics for topology-aware alerts[13]. Beyond traditional SD-WAN benchmarks, SKU constraints are added to prevent resource oversubscription. In the Paper[12] reported a 2.5 Gbps cap, and the tests keep aggregate throughput below that limit.

This has bigger consequences. This approach makes cloud orchestration more energy-efficient, reducing resource usage by 20%. That is better than what HUNTER's LSTM predictions managed, since it factored in VNG-specific entropy features (see[15]). For anyone deploying on Azure, this means lower costs thanks to predictive SKU upgrades. Plus, with reproducible artifacts, we lock in ACM badging and make it easier for practitioners to pick up this. Hybrid model fusion used can handle unpredictable traffic patterns, laying the foundations for 6G-era VNG, where federated learning pushes anomaly detection to peering nodes instead of keeping it centralized[8].

7. Limitations and Future Directions

The results are strong, but there are still some gaps. The experiments used simulated workloads, which do not always capture the wild swings you see in real Azure regions. Plus, RNN inference adds a 50ms delay enough to be a real problem at the edge[17]. Next, the team plans to scale up to 6-week, multi-region trials. They will also compare against autoscaling-only baselines to get a complete picture with A/B tests. Another key step: building closed-loop systems that can tune IPsec policies automatically and stop oscillations, using ideas from control theory[15]. There is some hope on the efficiency front, too; lightweight quantization could cut RNN overheads by 40%, making it practical to run inference at the edge with DPDK[14].

Adding formal threat modeling for adversarial inputs and including clear ethics statements on PII anonymization strengthens the framework. This lines up with ACM reproducibility efforts, primarily through improved artifact

badging [9]. With these updates, VNG optimization gets a real boost, making Azure networking infrastructure more robust and reliable.

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