G.H. Raisoni College of Engineering

Department of Electronics & Telecommunication Engineering

Subject : Wireless Sensor Network

TAE 2 : IEEE Paper Review

TOPIC – QoS Framework

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Paper Title -

PIQoS: A Programmable and Intelligent QoS Framework
(Published in IEEE INFOCOM WKSHPS: NI 2019)

Paper Link :- https://ieeexplore.ieee.org/document/8845158

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1. Objective of the Paper

The paper addresses the challenges of providing **Quality of Service (QoS)** in modern, dynamic, and large-scale networks. Traditional static or threshold-based policy management techniques are inadequate due to:

- Increasing traffic load
- Rapidly changing network states
- Diverse service requirements

The authors propose **PIQoS**, a **software-defined networking (SDN) and machine learning (ML)-based QoS framework** that aims to:

- Automate error detection and root cause analysis
- Improve recovery from link failures and congestion
- Provide adaptive, intelligent, and vendor-agnostic QoS provisioning

2. Key Contributions

1. **Programmable QoS Automation**:
   - Integrates **SDN controllers** with ML-based decision-making.
   - Automates detection and reconfiguration instead of relying on human operators or static rules.
2. **Fast Failure Recovery**:
   - Pushes recovery mechanisms into the data plane using Fast Failover Groups (FFG) in OpenFlow.
   - Enables *protection-based* recovery (pre-installed backup routes) rather than *restoration-based* recovery (controller intervention after failure).
   - Reduces recovery time from **seconds to milliseconds**.
3. **Machine Learning for QoS Management**:
   - Uses supervised learning (Decision Trees, Random Forests, SVM, Naïve Bayes) for error prediction and policy prediction.

   - Shows Decision Trees (ID3) achieve the best accuracy (>99%).
   - Compares supervised with unsupervised (K-means, DBSCAN) and shows unsupervised methods perform poorly (~50% accuracy).
4. **Evaluation on Real Topologies**:
   - Tested on USNET topology in Mininet using Ryu controller + OVS switches.
   - Demonstrates improved throughput and reduced delay compared to PolicyCop (a prior SDN-based QoS tool).

3. Framework Workflow (PIQoS)

- **Static Module**:
  - Uses initial thresholds and predefined actions for policy violations.
  - Helps build a baseline dataset for ML models.
- **Adaptive Module**:
  - Collects flow-level statistics (throughput, delay, port speeds, etc.).
  - Trains error prediction models to detect link failures or congestion.
  - Predicts the root cause → maps to the right policy.
  - Stores results in a Predicted Policy Database (PPDB) for future reference and retraining.

4. Experimental Results

- **Throughput**: PIQoS maintains higher throughput after link failures because recovery happens locally.
- **Delay**: Reduced from seconds (PolicyCop) to milliseconds (PIQoS).
- **ML Model Accuracy**:
  - **Decision Tree (ID3):** ~99.8% (best performer).
  - **Random Forest:** ~99% (slightly lower).
  - **Unsupervised (K-means, DBSCAN):** ~50% (much weaker).
- **Scalability**: By pushing recovery to data plane and reducing controller communication, PIQoS scales better to large networks.

5. Strengths of the Paper

- Novel combination of SDN + ML for QoS automation.
- Strong experimental validation using realistic topologies.
- Demonstrates practical performance improvements (delay, throughput).
- Identifies Decision Trees as the most effective ML algorithm in this domain.

6. Limitations / Open Issues

- **Supervised Learning Dependency**: Requires labeled datasets for training, which may be hard to generate in real networks.
- **Limited Error Conditions**: Only tested for link failure and congestion. Other QoS issues (e.g., jitter, packet loss patterns, security attacks) are not covered.
- **Offline Training**: Models were trained using offline data, not continuously updated in real-time production networks.
- **Scalability of ML Models**: Large-scale, high-dimensional networks may require more advanced/semi-supervised methods.

7. Future Research Directions (Suggested by Authors & Reviewer Insight)

- Explore semi-supervised ML to reduce dependency on labeled datasets.
- Extend PIQoS to handle more diverse QoS violations (jitter, loss, security breaches).
- Incorporate real-time online learning for continuous adaptation.
- Study energy efficiency and computational overhead of ML integration.
- Evaluate on larger-scale topologies and real-world testbeds beyond emulation.

8. Conclusion of the Review

This paper makes a significant contribution by proposing PIQoS, an intelligent, SDN-enabled, ML-driven QoS management framework. It convincingly demonstrates improved resiliency, adaptability, and efficiency over existing solutions like PolicyCop. The work is timely and relevant as networks become more dynamic and complex.

While promising, PIQoS still requires further validation in real deployments and more robust learning approaches. Overall, it is a strong step towards autonomous QoS management in next-generation networks.