PIQoS: A Programmable and Intelligent QoS Framework

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***Abstract*—Network management and Quality of Service (QoS) support are becoming more challenging with the increase in network traffic, size, and service requirements. To meet these challenges, we need a programmable and intelligent framework for automated QoS support; static or threshold-based approaches are not adequate. We propose a software-defined and machine-learning-based intelligent QoS framework called PIQoS. PIQoS enables software-defined networking (SDN) controllers to effectively, efficiently, and autonomously react, in a vendor agnostic way, to changes in network links by (1) placing link failure detection and recovery in the data plane and (2) applying supervised learning methods to the tasks of dynamically detecting link failures and congestion and appropriately reconfiguring the network so that it can continue to provide the required QoS as link properties change over time. To test the performance of a system based on PIQoS, we performed extensive simulation experiments in Mininet, using real network topologies. We also studied the comparative performance of several supervised learning methods applied to our specific detection and correction problems to determine which methods are most appropriate for this domain. Our simulation results highlight the potential efficacy of the PIQoS framework when applied in real networks.**

I. Introduction

Network monitoring and Quality of Service (QoS) support have become a challenge with an increase in network traffic, their dynamics, and service requirements [1]. Quality factors such as throughput, delay, and path length are important for service providers to maintain and provide a consistent user experience. However, network states change unpredictably, which demands dynamic policy management and configuration. Thus, it is not efficient to solve this problem using static policy management [2]–[4] or dynamic policy management with predefined thresholds [5]. Instead, QoS can be improved by automating the process of error detection and the root cause analysis. This automated QoS framework can be designed using a programmable and intelligent network.

Software-defined networking (SDN) [6], [7] allows network operators a programmatic and elegant way of dynamically implementing a wide-range of network policies and rapidly deploying new services. For instance, PolicyCop [5] configures network based on the dynamically changing policies. However, PolicyCop considers predefined policies and thresholds and consults a network manager in the case of existing policy violation. PolicyCop furthermore uses reactive link failure detection and recovery, i.e., upon detecting a link failure associated switch contacts the controller to recover from a failure. However, the reactive recovery introduces a delay that can impact the required QoS.

In this paper, we propose a programmable and intelligent framework called *PIQoS* for QoS automation. In PIQoS, we first push the link failure recovery at the data plane using proactive recovery scheme. In this scheme, a controller proactively installs alternative route between every source-destination pairs. We implement this recovery using the Fast Failover Group (FFG) of the OpenFlow protocol [8]. Note that the OpenFlow protocol enables communication between the data and control plane of an SDN architecture. The proactive recovery scheme improves both the delay and throughput by avoiding the communication delay between the data and control planes.

QoS requirements are different in different networking applications. Machine learning can improve the QoS by understanding the traffic patterns in a network and suggesting the network manager with better policy management in less time. Machine learning has been used in traffic classification and QoS improvement; however, there is no work on dynamic policy management in networks using machine learning. Thus, in PIQoS we use flow-level traffic to design two models using supervised machine learning algorithms. We consider supervised algorithms because of their prediction accuracy over unsupervised ones. The first model detects various errors in a network by analyzing the network state traffic and the second model predicts the root cause of the error to update the required policy for QoS provisioning. We consider both the link failure and network congestion to design and test the models, which are implemented in the controller to detect and react to link failures or congestion automatically.

We use real network topology like USNET [9] in Mininet [10] emulator to evaluate the performance of PIQoS. In Mininet, we use Ryu controller and Open Virtual Switch (OVS) [11]. The evaluation results reveal that PIQoS improves the link failure recovery time and network throughput compared to its counterpart. The results furthermore illustrate that the decision tree is the right supervised algorithm for the use cases considered in this paper. In a nutshell, we demonstrate that the learning based intelligent QoS provisioning is useful compared to static or threshold based QoS management.

The rest of the paper is organized as follows. We present necessary background to understand PIQoS in Section II and the related work on policy-based QoS management in Section III. Next, we describe the proposed PIQoS framework for QoS automation in Section IV. Section V provides the details of experimental setup. The following section presents the details of the data derived for the models. The experimental evaluation results in Section VII demonstrate the effectiveness of the proposed framework following some concluding remarks in Section VIII.

II. Background

In this section, we present the necessary background to understand the operation of PIQoS. Link failure can occur in data centers or enterprise networks. In SDN design, two types of link failure recovery approaches can be deployed: *restoration* and *protection* [12]. In the restoration scheme, a data plane switch contacts the controller upon detecting a link failure to receive alternative route configuration, which introduces communication delay. In the protection scheme, backup routes are configured before a failure occurs. Switches can locally detect a failure and redirect the affected traffic to alternative route without communicating the controller, which reduces the delay.

In SDN architecture, OpenFlow protocol supports Fast-Failover Group (FFG) to implement the failure recovery at the data plane. In particular, this switchover can be implemented using the Flow and Group tables of OpenFlow 1.3 [13] protocol. A switch maintains a group table with a number of active buckets. Each bucket is associated with a port from a route and only a single bucket is active at a time. The incoming packet flows through the port from an active bucket. In the case of a link failure, the next active port and bucket is chosen to redirect the affected traffic.

In general, machine learning algorithms fall into three categories: supervised, unsupervised, and reinforcement learning [14]. Supervised learning uses labeled data sets to create models, while unsupervised learning tries to discriminate patterns in unlabeled data. Reinforcement learning, on the other hand, considers rewards (or penalties) attributed to state-action pairs by the external world to decide which action to take. Each of these techniques is better suited for a particular type of application (e.g., classification, regression or clustering) and the method to be used depends on the way the problem is being formulated. Additionally, different learning algorithms (e.g., decision trees, neural networks or support vector machines (SVM)) can be used to solve the same problem, and the best choice depends on the requirements of each scenario (e.g., performance and accuracy constraints).

In this paper, we consider both the supervised and unsupervised algorithms as the former offers better accuracy, whereas the latter one avoids labeling training data set. Thus, we test both algorithms to find the suitable algorithm for the proposed learning models of PIQoS. In addition, we consider different algorithms from both the supervised and unsupervised algorithms to choose the suitable one.

III. Related Work

In this section, we present existing works that are closely related to the proposed PIQoS framework. Various policy enforcement frameworks have been proposed for QoS management [15]–[19]. Most of the existing works target inflexible QoS architectures, which lack a broader network picture, reconfigurability, and adaptability [20]. PolicyCop [5] implemented a QoS policy enforcement framework, which helped meeting SLAs by installing policies in a software-defined network. In the case of any violation of SLA, it takes action accordingly to the predefined policies. If there is no such configured policy, PolicyCop consults the network manager to install the newly required policy manually. Similar work is presented in [21] that mainly focuses on congestion control, whereas [22] improves the end-to-end delay. The proposed PIQoS, on the other hand, makes QoS provisioning automatic by implementing a network state learning module in the controller. This learning module predicts the reasons for failures and congestion to take quick recovery actions.

Machine learning algorithms have been used in networking for various state analysis [23]. A decision-tree-based model is used in [24], [25] to learn the QoS requirements of applications, and allocated resources accordingly. The major drawback of existing work in this area is the lack of adequate evaluation and no justification for the chosen algorithms. Hence, our understanding is, currently, incomplete. Additionally, the existing solutions did not consider link or node failures. PIQoS proposes two models and investigates different supervised and unsupervised algorithms to find the right algorithms for the proposed QoS automation framework.

IV. PIQoS Framework

In this section, we present the policy automation framework, PIQoS, which is presented in Figure 1. Existing policy management and QoS provisioning are static or threshold based that is mostly configured manually. For instance, PolicyCop deploys threshold based throughput and delay management approach. The static or threshold based is not adequate in dynamically changing network conditions. In addition, link failure recovery is proactive in PolicyCop that does not scale with increasing network size.

PIQoS improved PolicyCop model by pushing the link failure detection and recovery at the data plane to improve the delay and throughput. The proposed recovery scheme also scale with a large network. In addition PIQoS framework has an learning-based policy automation module, which works as follows. We implement the proposed framework in the controller, which monitors network traffic to gather necessary state statistics. This network state traffic is sent to the *check policy* module, which checks for any policy violation based on corresponding predefined parameters at the initial stage of model development. In the case of any policy violation, *event classifier* classifies the event into one of the predefined cases. Depending on the classification a predefined action is taken; in the case of a missing action, the new policy is added to the system. We consider the above policy management of PIQoS

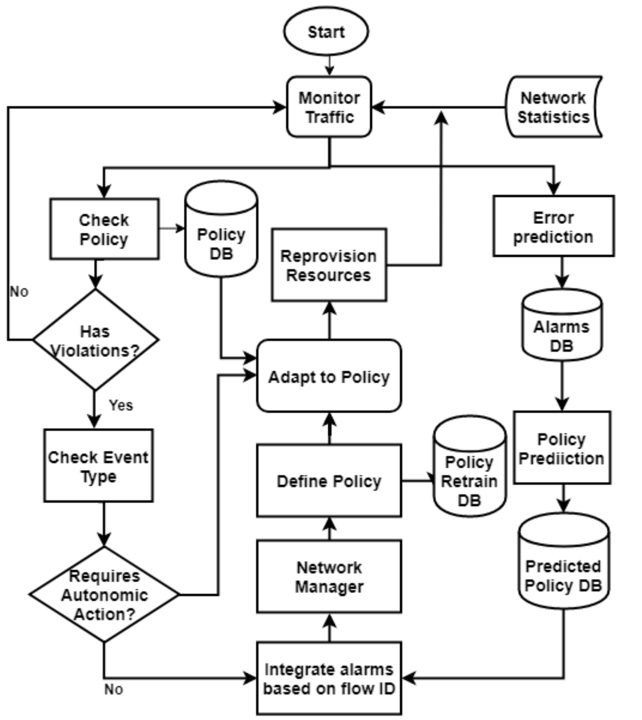

Fig. 1. The proposed PIQoS Framework.

as static, which mainly helps the adaptive ML-based model to adapt over time by proving additional classified traffic.

In addition, the monitored traffic is passed to train the *error prediction* model, which predicts any errors or unusual network states. These states are then sent to the *alarms database*. All alarms from different modules are integrated using flow IDs and then ranked according to their priority. The priority is assigned based on the error prediction model outcome of minor, major, or initial threshold. The alarms are then propagated to the *policy prediction* model, where the root cause of the errors and corresponding policy are predicted. The associated data are then forwarded to the *predicted policy database (PPDB)*. The network manager has access to the PPDB to observe the critical issues with predicted reasons and solutions. The network manager can define a new policy for the observed errors to accommodate any future events. The newly defined policies are accumulated in the policy database which can be used to retrain the models on a timely basis. As the model is trained over time, it becomes more accurate in predicting solutions. Thus, the learning models help the network manager resolve any unusual issues promptly, where prediction is based on past experiences.

V. Experimental Setup

In this section, we outline the experimental setup used to evaluate the performance of PIQoS. We evaluate the performance of the proposed framework in Mininet emulator using a Ryu controller. The controller controls the USNET topology (shown in Figure 2) formed out of a collection of software switches (OVS). We use iPerf to generate traffic and consider

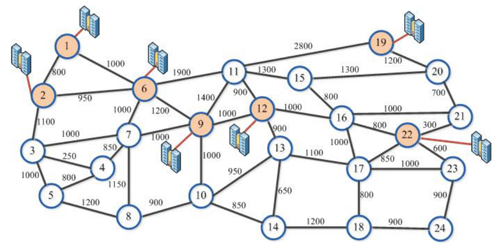

Fig. 2. The USNET Topology.

both TCP and UDP connections. The Ryu controller collects the statistics on network states at a regular interval, which are fed to the policy management module deployed in the controller. We use Scikit and Weka to implement the proposed learning models.

In order to evaluate the reliability performance of PIQoS, we consider a ten node mesh topology as well as the USNET topology, where each switch has an associated host. We measure the end-to-end delay and throughput to compare and contrast the reliability performance of PIQoS with PolicyCop. We define the delay as the total time a packet takes to travel from a source to a destination. Applications like VoIP and online games require a small delay to meet the QoS. The supervised machine learning models are trained and tested on the USNET topology, where link failure is tested with twenty-four switches each having one host, whereas congestion is checked with the same number of switches each having four hosts.

VI. Model Evaluation Data

A machine learning model can be trained and tested using either offline or online data. The former option allows gathering a large amount of data for model training and testing, whereas online or real-time network steaming can be used as feedback or input to the model [14]. The streaming data is mostly used in the production network to detect and analyze error conditions on-the-fly. In this paper, we consider offline data to demonstrate the effectiveness of the proposed PIQoS framework; however, it can be deployed in a production network. We configure the Ryu controller to collect statistics at a regular interval to capture a wide range of features like throughput, delay, number of packets and bytes, port speed and capacity, and flow ID to evaluate our model. The captured data has associated timestamp to help the network manager to track incidents.

In the case of error prediction model, we use parameters like Flow ID and associated source-destination hosts, ports, the corresponding number of bytes and packets, and timestamp. We also gather information about throughput and delay. Data collection considered a different level of granularity like a switch, port, or flow. The sample data for the prediction model is presented in Table I. We consider a total of 1500 instances for the error prediction model and 800 instances for the policy prediction model. We consider link failure and congestion to predict unusual conditions in the network, which

TABLE I
SAMPLE DATA FOR POLICY PREDICTION MODEL

Time stamp	Flow ID	Source Node	Dest. Node	Source Out-port	Dest in Port	Packets	Bytes	Link speed	Source Outport Capacity	Dest inport Capac-ity	Source port Speed	Dest port Speed	Delay (ms)	Classification
2018-11-1116:23:27	32	17	8	5	8	2	2132	0	10	10	0	0	7	Link Failure
2018-11-1116:23:28	32	8	6	3	5	2	2132	0	10	10	0	0	7	Link Failure
2018-11-1116:28:28	112	8	11	2	7	439	658340	22.8	10	10	22.1	25.3	2.371	Congestion

can be extended to cover other use cases. Note that due to the space limitation we are not presenting sample data from error prediction model, which is similar to that of policy prediction model.

TABLE II
THE LIST OF FEATURES USED IN PIQOS.

Feature	Explanation
Time stamp	Time at which the the link in a flow is generated
Flow ID	ID of a flow or path
Source Node	Source node of the link in a flow
Destination Node	Destination node of the link in a flow
Source Outport	Port from which source nodes sends the packets
Destination Inport	Port from which destination nodes receive the packets
Packets	Total number of packets sent in that link
Bytes	No of bytes of information sent in that link
Linkspeed (B/Sec)	Speed of a link
Source Outport Capacity	Maximum capacity of a source outport at that time
Destination Inport Capac-ity	Maximum capacity of a destination inport at that time
Sourceport Speed (B/s)	Speed at which source outport sends packets
Destination port Speed (B/s)	Speed at which destination inport receives packets
Delay (ms)	Time taken for packet to be transferred from source to destination in a flow
Error Prediction Classifi-cation	A flow has an issue or not (error/no error)
Policy Prediction Classifi-cation	Classification of an issue type (link fail-ure/congestion)

TABLE III
THE NUMBER OF FLOWS AND LINKS USED FOR TRAINING AND TESTING MODELS.

ML Models	Total Flows	Total Links	Training Flows	Training Links	Testing Flows	Testing Links
Error Pre-diction	318	1020	225	714	93	306
Policy Prediction	151	465	106	326	45	139

We use the set of features shown in Table II for the proposed error and policy prediction models. There are fifteen features, which are chosen based on the standard parameters and metrics used in real networks for policy management and QoS provisioning. We plan to explore other features in our future research. The total number of flows and links used for training and testing our models is shown in Table III.

We use K fold cross-validation (K=5) to test the proposed models to avoid over-fitting and selection bias problems. The cross-validation also gives an insight on how a model can be generalized to an independent data set. In the k-fold cross-validation, we partition the training data set into k=5 bins. At each of the k iterations, one bin is used for testing and rest of the k-1 bins are used to train the model.

VII. DISCUSSION ON THE EVALUATION RESULTS

A. *Reliablility of PIQoS*

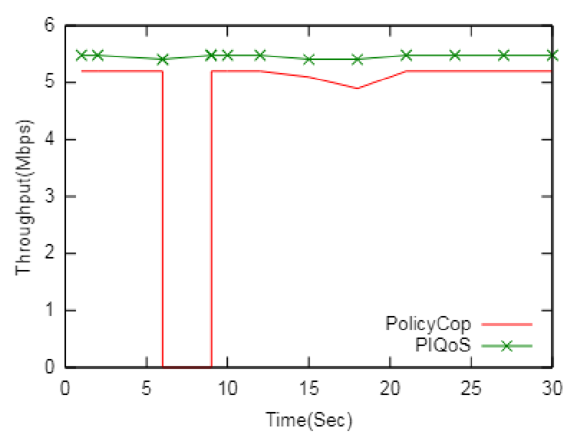

Fig. 3. The average throughput with local link failure recovery.

In this section, we present the performance of PIQoS regarding reliability and efficiency. We compare the results with PolicyCop. The evaluation results are shown in Figure 3 and Figure 4. The policy management module of the controller gathered the network statistics every three seconds. Thus, PolicyCop can learn any link failure event once a new set of statistics is gathered. Then, Policycop reactively installs an alternative route to redirect the affected traffic. In PIQoS, we pushed that recovery at the data plane using proactive scheme, i.e., the controller installs alternative route at each switch to recover from the failure. Thus, upon detecting a link failure, a switch uses FFG of OpenFlow protocol to locally redirect the traffic to alternative route without controller's intervention.

The average throughput of PolicyCop and PIQoS are shown in Figure 3. The result illustrates that the performance of PolicyCop drops in between two following statistics gathering events as the controller needs to learn a failure event to reconstruct a new route. PIQoS, on the other hand, locally recovers from a link failure, which immediately improves the throughput. Local recovery scheme furthermore reduces control packet propagation between the data and control plane to scale with a large network.

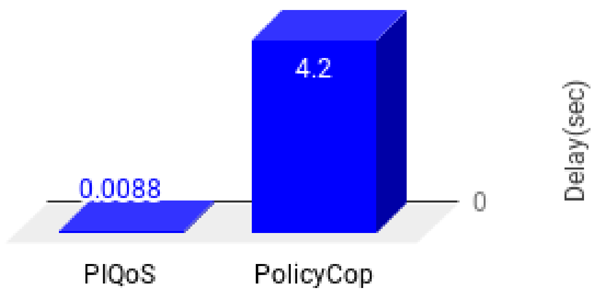

Fig. 4. The average delay with local link failure recovery.

The average delay experienced by PolicyCop and PIQoS is presented in Figure4. The link failure recovery time of PolicyCop is on the order of seconds, whereas it is on the order milliseconds in PIQoS. It is because PolicyCop reactively restores the route, which involves communications between data and control plane. Thus, we conclude that proactive link failure recovery at the data plane is useful to improve both the delay and throughput to achieve better QoS.

B. Intelligence of PIQoS

PIQoS proposes dynamic policy management using machine learning. The PIQoS framework can significantly improve network error detection and recovery and avoid time-consuming and error-prone network diagnosis and policy management. We propose two machine learning models to dynamically detect error conditions and update policy accordingly.

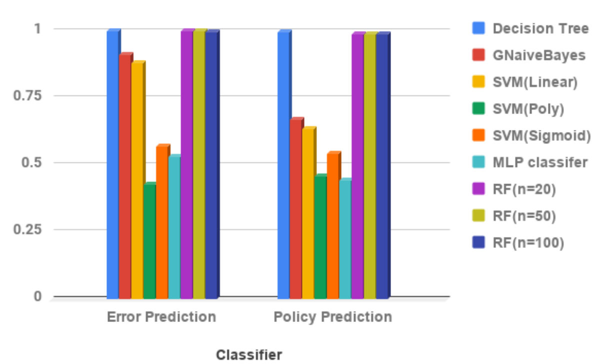

Fig. 5. The accuracy of different supervised algorithms for error and policy prediction models.

The error prediction model predicts errors using a pre-defined thresholds at the beginning and then gradually sets thresholds automatically once the model is smart enough. The error data is then sent to the policy prediction model for root cause analysis and policy updates. The errors and corresponding predictions are also sent to the network administrator as an alarm. This helps the administrator to identify any unusual error rates and the root cause behind that errors.

We have chosen supervised learning to design both of our models because of their accuracy. At first we have evaluated different supervised machine learning algorithms to find the best algorithm.

In order to choose an appropriate supervised algorithms, we have done an initial investigation on Naive Bayes, Support Vector Machine (SVM), Random forests (RF) and decision trees. The results are illustrated in Figure 5.

RF consists of several decision trees and offers good prediction accuracy. However, this accuracy cannot be generalized similar to decision trees. The accuracy of Naive Bayes and SVM is similar; however, they tend to under-fit our models. Among all the algorithms decision tree offers best accuracy for both the models. Furthermore, decision trees can analyze a large volume of data using standard computing resources in a reasonable time and are not sensitive to imbalanced data.

TABLE IV
THE ACCURACY OF DECISION TREE AND RANDOM FOREST

Classifier	Error Prediction	Policy Prediction
Decision Trees	0.9986013986	0.9967741935
RF(n=20)	0.9985915493	0.9870967742
RF(n=50)	0.9985915493	0.9903225806
RF(n=100)	0.9971929479	0.9903225806

Thus, we have chosen decision trees, in particular, the ID3 algorithm in our models. We have used other decision tree algorithms like C4.5, where the chosen algorithm offers the best results. Also, it is simple, accurate, and computationally efficient. The results in Table IV furthermore illustrate that both of our proposed models offer high accuracy.

C. Comparison with Unsupervised Learning

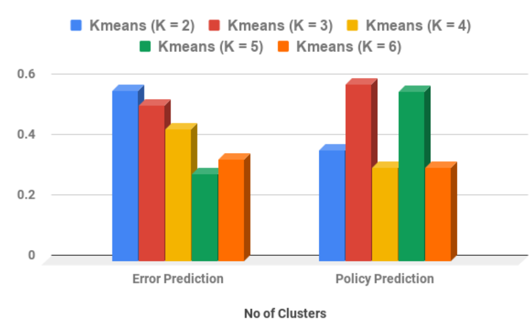

Fig. 6. The accuracy of k-means clustering algorithm for error and policy prediction models.

We have observed that the accuracy of our models using decision tree is quite impressive. However, supervised learning algorithms require labeling training data, which may not be feasible for large networks. Thus, we design a prediction model using unsupervised machine learning algorithm. We have first analyzed the performance of k-means and DBSCAN algorithms to choose the best unsupervised algorithm. The results in Figure 6 and Figure 7 illustrate that k-means offer better accuracy compared to DBSCAN. In particular, the DBSCAN algorithm is not suitable for high dimensional data because of the curse of dimensionality problem. We have not tested local outlier factor and auto-encoders, which is part of our future work.

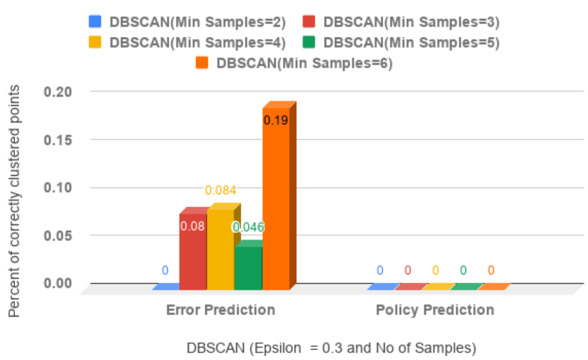

Fig. 7. The accuracy of DBSCAN algorithm for error and policy prediction models.

In Figure 6, we observe that both of our models offer their best accuracy for k=2 clusters. The cluster members are nicely fit in their respective group when there are two clusters, and the corresponding accuracy is around 50%. Thus, supervised decision tree algorithm offers significantly higher accuracy compared to the unsupervised algorithms. We conclude that there is a tradeoff between the prediction accuracy and computation complexity of the learning models if we consider supervised vs. unsupervised algorithms. In our future work, we plan to explore semi-supervised algorithms to balance between the accuracy and complexity.

VIII. Conclusions

At present, companies spend a significant amount of time to diagnosis their network to detect and recover from various error conditions that violate QoS and SLA. In this paper, we have shown that using intelligent models in network monitoring and management helps better QoS provisioning and SLA. In particular, we have designed a programmable and smart QoS framework called PIQoS. It first pushes link failure recovery at the data plane to improve the delay and throughput. Furthermore, the proposed framework offers two supervised machine learning models for efficient network state diagnosis and selecting corresponding management policies. We implement and evaluate the proposed framework in a realistic simulation environment and demonstrate that proposed models can accurately predict link failure or network congestion and let the system update management policy accordingly.

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