

Original Article

Intelligent Network Resource Optimization Using Predictive Analytics in Cloud-Connected Systems

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ABSTRACT

Cloud-connected systems enable a wide range of applications with the need for dependable connectivity, increasing computing power, and effective network resources usage. But dynamic workloads, varying traffic patterns, diverse devices and unpredictable service demands make traditional resource allocation schemes more complex. This paper proposes an intelligent network resource optimization framework using predictive analytics that predict traffic change and allocate network resources proactively. The suggested approach combines telemetry data collection, temporal feature engineering, workload forecasting, adaptive resource allocation and feedback-driven optimization. The bandwidth demand, congestion probability and resource utilization is estimated by predictive models; the allocation controller can therefore adjust the bandwidth, the routing preferences as well as the computing capacity based on the expected service requirements. A multi-objective optimization formulation is used that involves latency, throughput, packet loss, resource utilization and operational cost, while meeting QoS constraints. The evaluation approach involves comparing the two resource management strategies – predictive and threshold-based – using percentage-based performance metrics and workload traces. The evaluation approach is through the use of consistent workload traces and percentage-based performance metrics in comparing the two RM strategies – predictive and threshold-based. The framework focuses on the accuracy of the forecast, stability of allocation, scalability, and resilience of the network in different scenarios. Its design offers a systematic basis for optimizing the use of resources in cloud connected systems without compromising the reliability of services and enabling data-driven and adaptive network management.

KEYWORDS

Predictive Analytics, Cloud-Connected Systems, Intelligent Networking, Resource Optimization, Traffic Forecasting, Quality of Service, Machine Learning, Bandwidth Allocation, Congestion Prediction, Adaptive Resource Management.

1. INTRODUCTION

1.1. Background and Motivation

Cloud-based systems are now a vital part of modern digital infrastructure, powering enterprise applications, Internet of Things (IoT) devices, industrial automation, distributed analytics, and latency-critical services. These systems include end devices, communication networks, edge gateways and cloud platforms, which must all use bandwidth, routing paths and processing resources efficiently. As devices become more connected and applications more data dependent, traffic demands, workloads, and network congestion can be unpredictable. Traditional methods of resource management are mostly based on fixed thresholds and reactive scaling, leading to inefficient use of the resources, higher latency, and even degradation of services. Predictive analytics is a smart solution that uses past and current network data to forecast traffic trends and predict potential performance changes. Machine learning models like regression, decision trees, recurrent neural networks, and ensemble models can discover intricate patterns linking traffic volume, device usage, and network performance. This study combines traffic prediction, resource allocation, optimization, and continuous monitoring to facilitate proactive network management, enhance operational efficiency, and ensure the continuity and quality of network services.

1.2. Research Problem and Challenges in Intelligent Network Resource Allocation

Most of the conventional methods of resource allocation in cloud-based systems rely on the current values of traffic metrics, predefined set of rules and thresholds for fixed capacity. These approaches work well for more stable network environments, but may not be as effective when network traffic volumes fluctuate over time as a result of user activity, connectivity of devices and applications, and unexpected shifts in workload. These constraints can result in network congestion, poor bandwidth utilization, high transmission delays, packet loss, and needless investments in infrastructure. One of the key challenges is the ability to accurately forecast network demand based on historical data and real-time telemetry, especially in cases where network traffic doesn't follow a predictable pattern, such as having temporal dependencies, nonlinear relationships, sudden spikes, and unpredictable fluctuations. The other major challenge is to find a suitable resource allocation approach that minimizes the conflicting performance criteria, such as maximizing throughput, minimizing latency, minimizing packet loss, controlling energy consumption and maintaining operation cost efficiency. Moreover, if the network changes rapidly or if the training data used for the models do not match the emerging workloads, the prediction models can yield inaccurate predictions. However, if there is lack of coordination between prediction mechanisms and resource management controllers, there can be too much scaling, too many reconfiguration changes, too many resources unused, and too much network instability.

Thus, intelligent resource optimization demands an integrated framework that integrates predictive analytics, adaptive decision making, constrained optimization and continuous resource performance monitoring. The framework should measure relevant network metrics, predict future traffic volumes and make appropriate allocations of resources, without violating service level agreements or resource constraints. It should also include feedback mechanisms so that the results of

predicted conditions can be compared with the actual behavior of the network, and the decisions based on these comparisons can be independently modified. In addition, the framework should be scalable, efficient, robust and flexible to accommodate various forms of devices, applications and communication technologies in a heterogeneous environment connected to the cloud. The main research problem is therefore to find a resource optimization solution based on predictive analytics that can predict the demand of the network, adjust the available resources optimally, and reduce the performance degradation while avoiding any needless operational overhead. Solving this problem can lead to better network reliability, better quality of service, efficient use of infrastructure, and sustainable operation of increasingly complex cloud-connected systems.

1.3. Research Objectives

The main goal of this work is to design and test a predictive analytics-based framework to optimize resource allocation in cloud-integrated systems by predictive forecasting, adaptive decision making and real time performance monitoring. The first goal is to create a telemetry-based forecasting mechanism that relies on the history of the network and various real-time performance indicators, such as traffic volume, bandwidth usage, packet delivery ratio, latency, and congestion levels, to determine the short-term demand of the network, and to detect possible congestion issues before performance becomes significantly degraded. The second goal is to incorporate predictive results in a multi-objective resource allocation mechanism that dynamically allocates available bandwidth, connection capacity and network processing resources based on predicted workload demands, service-level agreements and infrastructure constraints. This mechanism is designed to meet multiple goals, including high throughput, low latency and packet loss, high resource utilization, and low operating cost. The third goal is to develop a systematic comparative evaluation approach where the proposed predictive technique is compared against legacy reactive resource allocation approaches in various workload conditions, traffic intensities and network configurations.

The fourth goal is to explore the correlation between the accuracy of the predictions, the efficiency of the resources utilization, the latency of the services, the frequency of congestion and the stability of the operation of the network to see how the quality of the forecasts affects the overall performance of the network. It will take into account appropriate quantitative measures, controlled experimental conditions, and statistical analysis to facilitate reliable comparisons. The fifth goal of the project is to determine practical implementation needs for real-world, cloud-connected deployments, including scalability, telemetry collection, computation burden, monitoring frequency, controller reliability, and integration with current network management infrastructure. In addition, the study aims at evaluating the adaptiveness of predictive models to varying traffic patterns and how resource reallocations, based on feedback, can avoid unnecessary resource allocations and destabilizing control behavior. These goals provide a holistic framework for studying whether predictive analytics can enable better use-of-resources decision-making, better quality of service, better use of infrastructure, and better network reliability for the ever-changing workloads and growing complexity.

2. LITERATURE SURVEY

2.1. Cloud Networking and Resource Management

Cloud computing offers flexible provisioning of computational and networking resources based on the variability of application demands and workload. Buyya et al. [1] emphasized the need for efficient resource management and scheduling in a distributed cloud environment, while Armbrust et al. [2] pointed to scalability, availability, and cost issues with cloud computing. Bandwidth allocation, routing, queue management, and traffic prioritization are some of the functions of network resource management to ensure reliable service delivery. But traditional threshold-based approaches may only be triggered when congestion occurs, and there is a need for predictive resource management.

2.2. Predictive Analytics and Network Traffic Forecasting

Predictive analytics allows network administrators to predict future traffic demand, based on historical observations and real-time telemetry. Box et al. [3] set the framework for statistical time-series modeling, which can be used to analyse temporal dependence and repeat patterns in traffic. Long short-term memory networks (LSTM) introduced by Hochreiter and Schmidhuber [4] can be used to learn temporal relationships in sequences of data and for traffic forecasting. Liu et al. [5] explored the application of traffic prediction for cellular networks, showing its applications in proactive network planning; however, the accuracy of prediction is influenced by the quality of the data and the evolution of workload characteristics.

2.3. Software-Defined Networking and Intelligent Control

Software-defined networking (SDN) abstracts the network control plane away from the data plane and allows for programmatic network configuration and centralized management of resources. In the study of Reference [6] SDN architecture and potential benefits of its use for network flexibility, programmability and operational control was discussed. By combining predictive analytics with SDN, proactive routing adjustments, bandwidth allocation and traffic prioritization can be made based on the expected network conditions. However, overhead in the controller, communication delay, limitation of scalability and centralized failure risk have to be taken in designing reliable intelligent control mechanisms.

2.4. Research Gaps and Study Positioning

Though there are existing studies that provide important foundations for cloud resource management, traffic forecasting and software-defined network control, there are some practical challenges for integrating these. Traffic prediction isn't enough to ensure network performance improvements if its predictions are not translated into feasible resource allocation decisions. In addition, prediction inaccuracies, shifting traffic patterns, service level restrictions, and controller overhead can have an impact on the effectiveness of optimization. In this work, these gaps are overcome by bringing together forecasting, constrained resource allocation and continuous performance evaluation in a single framework to evaluate the efficiency, latency, resource utilization and stability of a network.

3. METHODOLOGY

3.1. System Architecture and Telemetry Collection

The design of the proposed system is divided into five main components: telemetry collection, feature processing, network demand prediction, resource optimization, and feedback monitoring, all of which contribute to intelligent resource management in cloud-connected systems. The telemetry collection component collects real-time and historical measurements from network switches, routers, virtual machines, container platforms, edge gateways and application endpoints to build a complete picture of the state of the network. These collected parameters comprise of the throughput, bandwidth utilization, round-trip latency, packet-loss ratio, queue occupancy, active connection counts, and workload characteristics. These measurements are grouped into discrete observation periods to provide a regular temporal view of network behaviour. A feature vector is then created for every observation time t : $\mathbf{x}_t = [u_t, d_t, l_t, p_t, q_t, c_t, s_t]^T$, where u_t is the bandwidth utilization, d_t represents observed traffic demand, l_t indicates network latency, p_t represents the packet-loss ratio, q_t denotes the queue occupancy, c_t represents the number of active connections, and s_t captures the temporal information or workload context. The feature processing component aligns time-stamps, removes duplicate measurements, fills missing values, normalizes measurements, and detects outliers from these measurements to create input for predictive models. Then the demand prediction part predicts the future network demands, namely $\hat{d}_{t+h}$ for the prediction horizon h . An appropriate horizon is vital since there should be enough time in advance of the predicted congestion for the resources to be scaled up, the bandwidth to be adjusted or traffic to be redirected. In the resource optimization feature, these forecasts help to identify viable allocation decisions based on capacity constraints, service-level needs, latency constraints, and costs. The feedback monitoring part is responsible for comparing the measured conditions of the network with the predicted conditions to assess the accuracy of the forecasts and the effectiveness of control. To avoid information leakage from future observations, observations are split by time into training, validation and testing sets. The integrated architecture can facilitate continuous learning, proactive resource allocation, and performance evaluation and guarantee scalability, operational reliability and efficient utilization of the network resources in heterogeneous cloud-connected environment.

3.2. Forecast generation based on predictive modelling

The forecasting part uses historical measurements, real-time telemetry and context based workload characteristics to predict future traffic requirements on the network. Some of the candidate algorithms include long short term memory (LSTM) networks, gradient boosted trees, random forests and linear regression. Validation results measuring prediction accuracy, inference latency, computational overhead and scalability to traffic changes are used to determine the best model. If forecasts are accurate, the resource allocation controller can predict congestion and proactively manage the resource allocation before network performance suffers.

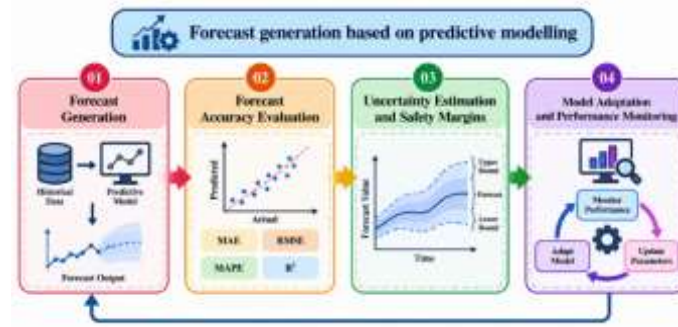


Fig 1 - Forecast Generation Based on Predictive Modelling

3.2.1. Forecast Generation

The future traffic demand is estimated by a learned function in the supervised forecasting model:

$$\hat{d}_{t+h} = f_{\theta}(\mathbf{x}_{t-w+1:t})$$

In this, f_{θ} stands for the trained prediction model, θ for the parameters of this model, h for the prediction horizon and w for the length of the historical observation window. The model uses recent network measurements to predict future network needs, which will help with proactive bandwidth provisioning, traffic rerouting and resource scaling. The prediction horizon needs to be chosen based on the response time and operational constraints of the target infrastructure.

3.2.2. Forecast Accuracy Evaluation

The performance of the forecasting is assessed by mean absolute error (MAE) and root mean squared error (RMSE) for the traffic demand difference between the actual and predicted values. The advantage of MAE is that it represents the average absolute prediction error, while RMSE puts more emphasis on large deviations, and is therefore suitable for detecting large forecasting errors. Both measures give complementary information and need to be reported together when comparing predictive models. The smaller the error values, the more accurate the predictions, but the operational value of the error should also be evaluated by network performance measurements.

3.2.3. Uncertainty Estimation and Safety Margins

The predictive part can provide an estimate of the uncertainty or upper quantiles of traffic demand in order to cover for unforeseen load growth. These estimates can be used by the resource allocation controller to set a proper safety margin and avoid having to skim resources during peak periods. But, too generous margins could consume resources and costs. Thus, the uncertainty-aware allocation needs to be designed to protect against congestion while ensuring efficient utilization of the available network capacity.

3.2.4. Model Adaptation and Performance Monitoring

The forecasting part continuously assesses the difference between the forecasted and actual traffic demand to detect how the forecasting accuracy is changing. If there is a gradual rise in the

forecasting error, it can be a sign of concept drift that could be due to the evolution of application behaviour, changing device activity and/or new traffic patterns. Under these conditions, the system can adaptively re-calibrate itself, re-train itself, and/or update parameters based on recent observations. The continuous monitoring allows one to keep prediction reliability high and prevents computational overheads and disruption of resource allocation operations when updating the model.

3.3. Multi-Objective Resource Allocation

The multi-objective resource allocation mechanism converts the predicted network demand into optimized resource allocation decisions by ensuring the stability of the infrastructure, the efficiency of the system and the level of service. The optimization controller takes account of the bandwidth needs, routing configuration, expected latency, probability of packet loss, resource availability and operational expenditure to make appropriate resource assignments for various services. The bandwidth that can be used for service i is denoted by b_i , traffic demand for service i is denoted by d_i , and the expected latency for service i is denoted by L_i . The controller optimizes a objective function which takes into account latency, packet loss, resource cost and load imbalance, and is expressed as $J = \alpha J_{\text{latency}} + \beta J_{\text{loss}} + \gamma J_{\text{cost}} + \delta J_{\text{imbalance}}$, where the non-negative parameters α , β , γ and δ are used to weight the importance of each objective. The weights can be modified based on the priority of the application and the service-level agreements. The optimization process takes into account the capacity constraints because it does not want the overall capacity of the allocated bandwidth to exceed the available network capacity, that is, $\sum_{i=1}^M b_i \leq B_{\text{available}}$, where M is the number of services. Other constraints impose lower bounds for bandwidth and upper bounds for the acceptable latency for critical applications.

If this is not possible at the same time, the controller follows an admission control policy to prioritize critical services, or to permit service degradation as per pre-defined policy through negotiation. Moreover, the level of predictive uncertainty can be used to adjust allocation decisions to include the necessary resources to prepare for unforeseen growth whilst not over-provisioning. Elastic workloads can be shifted to less congested paths while latency-sensitive applications are given priority to stay responsive. To avoid too many changes in the configuration and non-stable control behaviour, the controller restricts allocation changes from one observation interval to the next and calculates the effects of the proposed changes before they are actually carried out. Linear programming and quadratic programming can be used for optimization problems where the mathematical formulation is tractable; heuristic or metaheuristic techniques can be used for larger environments, where the constraints are complex. The monitoring component runs after every allocation cycle, and compares the actual performance of the network against predicted conditions and optimization targets. Based on this feedback, the decisions made in the next step should include what was observed, so as to become more adaptable, efficient in the use of resources, more stable in operation, and more reliable in service delivery, while facing the dynamically changing network workload.

4. RESULT AND DISCUSSION

4.1. Evaluation Design and Performance Metrics

The proposed predictive resource allocation framework should be tested by conducting a well-designed experiment to assess its effectiveness compared with an existing reactive threshold-based allocation algorithm with the same network workload. Both must be run on the same workload traces, in the same order, for a fair comparison and to avoid experimental bias. Stable traffic demand, recurring traffic peaks, traffic bursts and different numbers of services to be operated should be included in the workload scenarios to ensure that the following ranges of operating conditions are covered in cloud-connected environments. Whenever possible, experiments should be repeated with different random seeds and/or different trace segments to increase the reliability and reproducibility of the results. The key operational performance metrics should consist of the bandwidth utilization, average network latency, packet-loss ratio, provisioning cost, useful throughput, and number of violations of service-level objectives. The indicators offer complementary information about the efficiency of the network, quality of the services and operational costs. Performance of forecasting should be evaluated independently with the use of mean absolute error (MAE) and root mean squared error (RMSE), so that the analysis can distinguish between the accuracy of the forecasts and the actual benefits of the optimization of the resources. In addition, the execution time of the controller, overhead for collecting the telemetry, latency of the prediction, and computational resources usage should be calculated to ensure that the proposed framework can fit within practical requirements of the control-loop timing. To measure the relative improvements, such as latency, packet loss and provisioning cost, for metrics where lower is better, the relative improvement can be computed as:

$$(I_{\%}) = \frac{P_{\text{baseline}} - P_{\text{predictive}}}{P_{\text{baseline}}} \times 100\%$$

$$P_{\text{predictive}} \{ P_{\text{baseline}} \} \times 100\%$$

Where (P_{baseline}) and $(P_{\text{predictive}})$ are the values measured for the reactive and predictive approaches, respectively. On the other hand, if the higher the better such as useful throughput under equivalent workloads, then the improvement is computed as:

$$(I_{\%}) = \frac{P_{\text{predictive}} - P_{\text{baseline}}}{P_{\text{baseline}}} \times 100\%$$

$(P_{\text{baseline}}) \{ P_{\text{baseline}} \} \times 100\%$. If the base level number is zero, alternative absolute differences should be used as a measure of improvement due to no indicator of percentage improvement. Descriptive statistics, variability estimates and significance tests (where applicable) should be used to summarize results. This approach to evaluation allows a fair comparison of different allocations of predictive resources in terms of the performance gain, computational cost, operational reliability and practicality of implementing them, while not assuming that there will be an improvement in all workload scenarios.

4.2. Illustrative Percentage-Based Comparison

Table 1 provides a hypothetical comparison format for the evaluation of the performance of predictive resource allocation compared to the conventional reactive approach. The percentage changes show how improvements and decreases in key network performance indicators can be reported in the final manuscript. The values presented here are simply typical and should be measured in the experiment to form conclusions for research purposes.

Table 1: Illustrative Percentage-Based Comparison

Performance indicator	Illustrative change	Desired direction
Network resource utilization efficiency	12%	Increase
Average end-to-end latency	-18%	Decrease
Packet-loss ratio	-15%	Decrease
Resource provisioning cost	-10%	Decrease
Quality-of-service violations	-22%	Decrease
Peak-demand handling capacity	14%	Increase

4.2.1. Network Resource Utilization Efficiency

The 12% illustrative efficiency increase in resource use means that resources are used more efficiently to meet the demands of applications. Predictive allocation can optimize resource utilization by dynamically modifying bandwidth allocations based on workload trends and mitigating over or under allocation. Real improvements should be confirmed with controlled experiments with the same workload.

4.2.2. Average End-to-End Latency

A representative decrease of 18% in the average end-to-end latency equates to quicker data transport from application end points. By providing adequate bandwidth ahead of traffic, predictive resource management can help prevent congestion. These improvements should be evaluated experimentally to prove they are consistent with various traffic volumes and service priorities.

4.2.3. Packet-Loss Ratio

A display of a drop of 15% in packet-loss ratio indicates better reliability in network data delivery. The controller can predict traffic surges and control the queue's occupancy, which can help minimize packet drops due to congestion and capacity constraints. To determine the effectiveness of the proposed allocation strategy the actual packet-loss measurements are needed.

4.2.4. Resource Provisioning Cost

A typical reduction in the amount of resources provided of 10% suggests that capacity can be used more effectively in the network, which is good for the bottom line. During lean times, predictive forecasting can be used to prevent over-reservations of resources, and during busy times, it can be used to scale up when needed. Cost should be considered in terms of infrastructure usage, scaling operations and resources needed to run predictive models.

4.2.5. *Quality-of-Service Violations*

Illustrative reduction of 22% in the number of quality-of-service (QoS) violations shows that application requirements are met with greater consistency. By using proactive allocation, you can help ensure that critical services are delivered with a desired latency, throughput, and packet-loss target. The evaluation should include actual frequency of violation over similar observation periods to assess the meaningfulness of the predictive control.

4.2.6. *Peak-Demand Handling Capacity*

The illustrative growth in the handling capacity of the peak demand of 14% implies that the network has the capacity to serve higher traffic loads while still meeting service levels. Forecast-driven scaling and congestion-aware routing might make the controller better able to handle sudden surges in workload. This should be verified by conducting burst-load tests to determine throughput, latency, and packet loss and resource saturation.

4.3. **Interpretation, Limitations, and Practical Implications**

The effectiveness of predictive resource allocation in cloud-connected systems should be assessed based on its effect on network efficiency, service quality, operational cost and control stability during various workload scenarios. If experimental results indicate that resources, such as network resources and/or bandwidth, are being used more efficiently and latency reduced as a result of the forecasting of future traffic demand, these results would suggest that the controller would be able to allocate bandwidth and adjust network resources prior to the onset of severe congestion. Likewise, if reduced packet loss and service-level objective violations are observed, then predictive management can enhance the reliability of services if the traffic pattern is predictable, and/or the necessary resource changes can be performed within the time horizon for which more accurate predictions can be made. However, predictive resource allocation is never going to be better in all cases of operation. Bursts of traffic, changes in application behaviour, missing telemetry and incorrect forecasts can lead to under provisioning or excessive reservation of resources, which can lead to loss of efficiency and increase operational expenditure. Moreover, machine learning inference, telemetry processing, and optimization computations add extra overhead, which could be bigger than the benefits provided by machine learning in small scale systems and/or very short control intervals.

The success and efficacy of the framework thus relies on the accuracy of prediction, the response time of infrastructure, the nature of the workload and the computational resources used to make decisions. To draw reliable conclusions, the evaluation should include repeated experimental trials, confidence intervals, appropriate statistical significance tests, and a comprehensive analysis and reporting of forecast errors. The effects of predictive forecasting, uncertainty-aware safety margins and optimization mechanisms need to be studied separately in ablation studies to identify the largest contributing factors for any observed change in performance. Comparisons should also account for equal resource limits, network configurations, and workloads between predictive and reactive controllers, and not include future information on the baseline that isn't available during normal operation. Also, sensitivity analyses should be performed for varying prediction horizons,

varying sampling intervals for the telemetry, varying weights for optimization, and varying workload intensities. From a practical point of view, this means that a monitoring infrastructure is required that is reliable and can be used to gather telemetry, as well as a robust controller that will operate even if a failure occurs, and recovery mechanisms that ensure that service quality is not affected should predictions prove to be inaccurate. The conclusions obtained are valid for the specific network topology, load distribution, forecasting models and orchestration setup tested. A balanced assessment can help determine the circumstances when predictive resource management provides measurable benefits and help inform the decision making process for implementing scalable, efficient, and reliable network optimization solutions.

5. CONCLUSION

This paper described a new intelligent network resource optimization framework for cloud connected systems that combines traffic forecasting, constrained resource allocation and feedback-driven control to enhance the network efficiency and service reliability. Unlike current reactive resource management, the proposed approach make use of historical and real time network telemetry to predict future traffic demands and proactively adjust resources to avoid congestion before it has a significant impact on performance. It integrates the collection of telemetry data, feature engineering, predictive modelling, multi-objective optimization, policy execution, and continuous performance monitoring in a streamlined management process. The methodology includes network workload forecasting models to predict the future network workloads and an optimization mechanism which takes into account latency, packet loss, provisioning cost, and allocation imbalance while meeting bandwidth capacity and service-level requirements. Policy adjustments and fall-back mechanisms further contribute to operational stability and mitigate risks of inaccurate predictions. A key advantage of the framework is that it is separated from forecasting accuracy and actual network performance; the latter must show improved impacts on resource usage, latency, reliability, and operational efficiency.

In real-world cloud-connected scenarios, predictive resource management can enable proactive bandwidth allocation, early congestion management, and better alignment of cloud resource configuration and orchestration systems, especially when cloud traffic characteristics are learnable and resource configuration can be performed within the available prediction window. But, careful management of model drift, prediction uncertainty, telemetry reliability, computational overhead, cyber security risks, and competing quality-of-service requirements are required for successful deployment. So, production implementations should include controlled deployment process, auditable allocation process, ongoing monitoring, and reliable fallback controllers to ensure service continuity. The framework should be tested in the future using reproducible network traces, simulation environments, and network emulation and real-world test beds. Comparative studies of statistical models, tree-based algorithms and sequence-learning architectures might help determine appropriate compromises between forecasting accuracy, inference latency, and computational expense. Future work should consider uncertainty-aware optimization, online learning, distributed control, multi-agent coordination, energy efficiency, carbon-aware allocation and fairness among

competing tenants. Concept drift, telemetry loss, unexpected traffic bursts, adversarial conditions and controller failures are also important factors to test the robustness of the system. Finally, the utility of predictive analytics needs to be proven through transparent experiments that can be statistically validated for consistent operational improvement for different workloads, network configurations, deployments, etc.

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