

Highlights

AI-driven Orchestration at Scale: Estimating Service Metrics on National-Wide Testbeds

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- Forecasting behavior in production-ready network slicing architectures;
- Architectural study of embedded DNNs and basic ML for slicing SLA conformance;
- Evaluation of hyperparameter tuning for AI-native network slices on testbeds;
- Creation of a dataset workflow for realistic slicing application workloads;

AI-driven Orchestration at Scale: Estimating Service Metrics on National-Wide Testbeds

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Abstract

Network Slicing (NS) realization requires AI-native orchestration architectures to efficiently and intelligently handle heterogeneous user requirements. To achieve this, network slicing is evolving towards a more user-centric digital transformation, focusing on architectures that incorporate native intelligence to enable self-managed connectivity in an integrated and isolated manner. However, these initiatives face the challenge of validating their results in production environments, particularly those utilizing ML-enabled orchestration, as they are often tested in local networks or laboratory simulations. This paper proposes a large-scale validation method using a network slicing prediction model to forecast latency using Deep Neural Networks (DNNs) and basic ML algorithms embedded within an NS architecture evaluated in real large-scale production testbeds. It measures and compares the performance of different DNNs and ML algorithms, considering a distributed database application deployed as a network slice over two large-scale production testbeds. The investigation highlights how AI-based prediction models can enhance network slicing orchestration architectures and presents a seamless, production-ready validation method as an alternative to fully controlled simulations or laboratory setups.

Keywords: Network Slicing, Deep Neural Networks, Machine Learning, Service-Level Agreement, Distributed Database

1. Introduction

Modern applications require challenging behaviors from physical networks to satisfy stringent requirements such as ultra-reliability, low latency, and high throughput [1]. In addition to these quantifiable network requirements, it is necessary to incorporate seamless, intelligent, and pervasive network capabilities to satisfy user demands [2, 3]. Although network management, control planes, and data planes have evolved to address this issue, challenges remain and require further large-scale evaluation.

Many approaches, technologies, and methods have been developed to build user-oriented network architectures that provide connectivity in an isolated and personalized manner [4]. One key technological enabler of this vision is network slicing, which establishes network connectivity on top of physical infrastructure while ensuring isolation, end-to-end connectivity, and application-driven requirements, with dedicated control and data planes [5]. With this service-tailoring capability, Machine Learning (ML) effectively addresses various management and orchestration challenges, thereby enabling intelligent and real-time insights for service provider managers. A major

advantage of intelligent network orchestration is the ability of Artificial Intelligence (AI) to ensure and evaluate the service quality and user experience in network slicing [6].

AI techniques, such as reinforcement learning, supervised learning, and unsupervised learning, have been effectively integrated with network orchestrators to mitigate cybersecurity threats, enable intelligent resource allocation, and ensure Service-Level Agreement (SLA) assurance for network slicing [7, 8, 9, 10]. In network slicing SLA assurance and measurement, computational intelligence techniques have been progressively incorporated into the building blocks of orchestration architectures. However, these architectures are neither natively secure nor inherently intelligent, often leading to context-specific solutions [11]. Consequently, they remain dependent on third-party vendors, raising concerns regarding the security and privacy of network slicing services.

A key challenge in incorporating intelligence into network slicing architectures for the effective utilization of AI pipelines is ensuring data quality and granularity [12] while preserving user privacy and avoiding the exposure of network slicing application details. Our approach addresses this by leveraging generic infrastructure metrics appropriately combined to enable SLA fitting and forecasting across diverse network slicing applications. Although demonstrated through SLA prediction for Cassandra applications, the proposed methodology is designed with principles and techniques that can be generalized to various slicing applications. Evaluating the effectiveness of this intelligent orchestration mechanism requires analyzing net-

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work environments under conditions comparable to those of a production-ready network [13].

This paper investigated the performance of our intelligent native orchestration architecture in production-ready network scenarios under realistic conditions. Hence, we developed and enhanced an orchestration framework for network slicing [14]. We evaluated the capability of the newer Predictor Module within the “Slicing Future Internet Infrastructures (SFI2) AI Management” building block to forecast latency from a distributed database (Cassandra) deployed as a network slice, operating on nationwide testbeds FIBRE-NG [15] and Fabric [16]. Deep Neural Networks (DNNs) and basic ML algorithms were employed to predict Cassandra latency within our dataset generation framework.

This paper presents several key contributions: (1) an empirical analysis of DNNs and basic ML algorithms for network slicing latency forecasting on large-scale testbeds, (2) an in-depth investigation of hyperparameter tuning for DNNs, (3) the development of a realistic network application dataset with a comprehensive workload, and (4) a detailed deployment workflow for network slicing services on nationwide testbeds.

The structure of the remainder of this paper is as follows. In Section 2, we contextualize our work within a broader scope, highlighting the unique contributions of this research. The proposed method is presented in detail in Section 3, followed by a description of the experimental setup in Section 4. Section 5 discusses the results, and Section 6 presents the concluding remarks and future directions.

2. Related Work

In the literature, there are different uses of ML for predicting Quality of experience (QoE) or Quality of Service (QoS), both for applications in the context of mobile networks and generic applications on network slices [17]. Some approaches use machine learning algorithms pre-trained in simulation environments, validate how these algorithms behave, and compute performance metrics [18]. Other approaches have been proposed for network simulation environments, leaving aside the validation of these methods in real network testbeds [19].

Pasquini and Stadler [20] combined three metrics to estimate application QoE while running different applications in an OpenFlow network. They combined the operating system metrics, network flows in switch tables, and application metrics to train machine learning. The experiments considered two applications: Video on Demand (VoD) and Voldemort-distributed databases. They simulated two traffic behaviors to assess the suitability of QoE prediction by considering the observed metrics. Our approach further explores and validates whether ML behaves properly in a real network testbed.

In network slicing orchestration matter, Cui *et al.* [21] proposed reinforcement learning combined with the Long Short-Term Memory (LSTM) algorithm to guarantee QoS for vehicle-to-vehicle network slicing. The search space of Deep Reinforcement Learning (DRL) is a 5G antenna, where the action relies on the number of resource blocks. Our approach estimates QoE in a real network testbed.

Nougnanke *et al.* [22] proposed and evaluated an ML-based approach for modeling and predicting network traffic under different workloads. They can estimate latency under different network conditions using ML algorithms. They used a mininet and a simulated environment to validate their findings using three different datasets. Our approach involves creating a dataset to validate the estimation of some network metrics; however, our approach focuses on estimating the QoE in a real sliced network.

Ge *et al.* [23] proposed an Graph Neural Networks (GNN)-based end-to-end delay estimator for Software-Defined Networking (SDN) environments. They used a real dataset from the GEANT network to fit their model. In addition, as a proof of concept, they used the OMNet++ simulation environment to assess the prediction accuracy of the model for QoS assurance. A similar study using the same method as described above was differentiated using the Abline dataset [24].

Laiche *et al.* [25] introduced a multifactor influence in video QoE. They used machine learning to predict QoE assurance in an emulated network scenario. They used and compared the performance of the K-Nearest Neighbors (KNN), Random Forest (RF), and Decision Tree (DT) algorithms to predict user experience by considering popularity and user engagement on a well-known streaming web platform.

Abdelwahed *et al.* [26] proposed and evaluated an ML-based approach for estimating Web QoE using different context metrics. The metrics considered were network, browsing, and web user engagement. Using RF, DT, and KNN, they estimated Mean Opinion Score (MOS) by considering user-side metrics. Similarly, our approach aims to predict the application QoE by considering different metrics.

Regarding QoS estimation in network slicing using ML algorithms, Khan *et al.* [27] applied and evaluated Deep Neural Network (DNN) methods to select better network slicing according to connectivity services (mMTC, URLLC, and eMBB) requirements. Their experiments assessed how the ML algorithm handled accurate slice assignment, slice-load balancing, and slice-failure scenarios. Instead of using a simulated network, our approach evaluates the effectiveness of acML in a real network to predict the applications QoE.

For 5G mobile network slicing, Thantharate and Beard [28] proposed and evaluated a transfer learning method for network slicing QoS. Their proposed rationale is based on training local models for different slice network requirements in the source domain. The model can predict the resources in the target domain to satisfy slicing quality agreement. Our approach further predicts the application of SLA conformance for an online network slice application in a real network testbed. Similarly, N. P. Tran *et al.* [29] proposed and evaluated an approach to estimate end-to-end throughput in 5G and B5G using LSTM.

Yu *et al.* [30] idealized a linear regression algorithm combined with Reinforcement Learning (RL) to predict slice mobility while ensuring QoS for the application, minimizing costs, and maximizing revenues and profits. They used different statistics, such as user demand for CPU, RAM, and slicing resources to train the ML algorithm offline. Our approach focuses on predicting application QoE through time-series regression, which

Table 1: Related works and their properties.

Paper	Experimental Environment	Evaluation Metrics	Dataset	Enabling Technologies	Applications
[21]	Simulated Network	Convergence Time and Mobility Velocity	Own	LSTM-DDPG	V2V Communication
[22]	Emulated Network	Normalized Mean Absolute Error (NMAE), and Prediction Time	Telecom Italia Big Data Challenge dataset [34]	SDN, P4, NS3, and ML Algorithms.	Network Connectivity
[23]	Emulated Network	Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Weighted Mean Absolute Percentage Error (WMAPE).	GEANT	GNN, MLR, XGBoost, and RF	Network Connectivity
[24]	Simulated Network	Packet Delay, Mean Squared Error (MSE), RMSE, MAE, and WMAPE.	Abilene Network	GNN, RF, and NN	Network Connectivity
[20]	Local Network	NMAE, and Training Time	Own	OpenFlow, and ML Algorithms	VoD, and KV
[25]	Simulated Network	RMSE, Correlation, and Outlier Ratio	Own	KNN, Decision Tree (DT)	VoD
[26]	Local Network	Accuracy, Correlation, and MOS rating.	Own	KNN, RF, and DT	Web
[27]	Simulated Network	Accuracy, Recall, Precision, and F-1 score	DeepSlice, and Secure5G	Convolutional Neural Network (CNN), LSTM and Python-based ML frameworks.	5G Verticals
[28]	Simulated Network	MSE, Correlation	Own	Matlab Deep Learning Toolbox.	5G Verticals
[30]	Simulated Network	RL-Convergence Time	Own	NetworkX	5G Verticals
[29]	Simulated Network	Mean Absolute Percentage Error (MAPE), packet loss, and delay	Own	LSTM, and Traditional ML Models	5G Verticals
[31]	Simulated Network	Accuracy	Own	Linear Regression methods	Virtual Reality
[32]	Simulated Network	Accuracy, Precision, Recall, and F1-Score	Unicauca IP Flow, and 5G Network Slicing	HHO, CNN, and LSTM	Network Slicing
[33]	Simulated Network	SLA Violations, End-to-End Delay, and Resource Utilization	Custom Simulated Data	SDN, Virtualization, and Edge Computing	Network Slicing, and Edge Computing Optimization
Our Approach	Production-ready Network	MAE, MAPE, and MSE	Own	DNNs, and Basic ML Models	Distributed Database on a Sliced Testbed

enables multi-step predictions over time.

Yang *et al.* [31] bring a method for predicting QoS for Virtual Reality applications in a network slicing using different machine learning algorithms. Their solutions can predict the latency, bandwidth, and different video codecs for different slicing models. Our approach aims to predict the Cassandra application SLA in a real network testbed by using ML algorithms.

Dangi and Lalwani [32] proposes a hybrid deep learning model for efficient network slicing in 5G networks. The model combines Harris Hawks Optimization (HHO) with Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to optimize hyperparameters and classify network slices. The methodology involves three phases: loading the dataset, optimizing it with HHO, and classifying slices using the hybrid model. The results demonstrate that the proposed model outperforms existing methods in predicting appropriate network slices and offers improved service quality and efficiency in 5G network slicing.

Baktir *et al.* [33] proposes a Mixed Integer Programming (MIP) model and a heuristic algorithm called NESECS to optimize network slicing for various service types with different performance requirements. The MIP model aims to provide optimal solutions for small network instances, whereas NESECS is designed to handle larger instances efficiently. This study evaluates the performance of these solutions through extensive experiments, demonstrating that the proposed methods can effectively manage network resources, reduce SLA violations, and improve the overall network performance by ensuring logical isolation and resource reservation for different service types.

Approaches in the literature close to this proposal are sum-

marized in Table 1. In this table, we have an “Experimental Environment” column related to which network environment the ML algorithm makes QoS or QoE predictions. Many approaches have used simulated environments or local networks. The “Evaluation Metrics” column aims to show which metrics (MAPE, MSE, RMSE, and others) the authors most often take into account to validate their proposals. The “Dataset” column indicates the dataset that each approach considers in the model training phase. Some approaches have created their own datasets, whereas others use datasets created by third parties. The “Enabling Technologies” column aims to identify which methods and technologies for both machine learning and simulating network environments are state-of-the-art. Many approaches still use classic ML approaches such as RF, DT, and KNN. Finally, the “Application” column reports the applications for which the prediction engines estimate QoS and QoE. Some approaches focus on 5G verticals, while others focus on specific applications.

3. Proposed Method

Deploying network slices across multiple domains still requires advanced management and orchestration technologies capable of influencing the underlying network, particularly when dealing with heterogeneous devices. Existing tools and techniques for implementing dynamic and elastic slices remain inadequately managed, presenting opportunities for improvement, especially with AI as a foundational enabler of such architectures. In this context, we previously proposed the Slicing Future Internet Infrastructures (SFI2) reference architecture to manage

and orchestrate AI-native network slices while integrating diverse testbeds [14].

3.1. SFI2 Slicing Architecture

The SFI2 architectural approach with native artificial intelligence embedded agents is illustrated in Fig. 1. AI-native embedded agents in the architecture target the preparation, commissioning, operation, and decommissioning phases of the network slicing life-cycle.

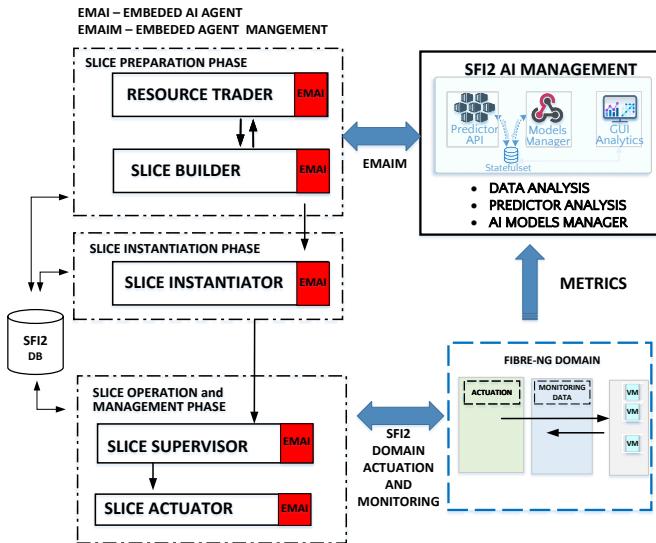


Figure 1: SFI2 Artificial Intelligence Agents Management within FIBRE-NG Domain Slices

Enhancements promoted by AI-embedded agents include predicting resource and performance parameters using distinct AI techniques, such as combinatorial optimization, reinforcement learning, and neural networks. Notably, a potential focus of AI-embedded agents is the orchestration process involving different steps and actions applied to instantiate and dynamically reconfigure slices according to user requirements.

Furthermore, the SFI2 architecture aims to operate over heterogeneous infrastructure following the concept of Machine Learning as a Service (MLaaS). To achieve this, the SFI2 AI management module collects metrics from the target domains. It interacts with the embedded agents in the functional blocks to manage the learning model and the other required parameters. The SFI2 AI management module manages learning agents throughout all infrastructure components to support the training, prediction, or decision tasks.

3.2. Problem Setting and Method

This paper proposes the evaluation of network slicing latency forecasting in a sliced SFI2-conform large-scale production-ready testbed (FIBRE-NG and Fabric). The focus is on the SFI2 AI management functional block, which natively and intelligently orchestrates slices to estimate the SLA compliance of an application running on a network slice.

The proposed method is shown in Fig. 2, highlighting the functional block of the orchestrator architecture and its interaction with the network slice lifecycle.

Thus, adopting the premise that the slice is implemented by the SFI2 Orchestrator [14], the procedures for online forecasting of QoE begin by considering different metrics in different testbeds. The step ❶ of the method refers to the collection and aggregation procedure of different X metrics from the application, the network slice, and the underlying computational infrastructure. Application metrics $X_{application}$ refer to the statistics provided by applications at different execution stages. The $X_{cluster}$ infrastructure metrics refer to the computational resource consumption metrics demanded by the network slices from the underlying hardware. Network metrics $X_{network}$ refer to the network statistics of the network slice. These metrics are aggregated by data cleaning and standardization algorithms in the computational resource, resulting in a dataset $X = X_{application} \cup X_{cluster} \cup X_{network}$.

Cassandra, a distributed key-value database, is the application running on top of the network slicing used in this study. Using the cassandra-stress [35] tool, we generated logs of the reading and writing operations in this database to build a set of metrics $X_{application}$. cassandra-stress presents different performance metrics for reading and writing operations in the database, such as latency, operation rate, errors, and others.

The $X_{cluster}$ represents the statistics collected from the underlying infrastructure that supports the network slice execution. The metrics collected refer to the consumption of the Central Processing Unit (CPU), Random-Access Memory (RAM), and Input/Output (I/O) operations required by the network slice from the infrastructure. We also used the NetData monitoring framework to collect CPU, RAM, and I/O metrics, as well as other metrics related to computational resources.

The $X_{network}$ variable refers to the generic statistics collected from the network interfaces of each distributed entity comprising the network slice. We employ a native network metrics extractor (NetData) to gather statistics on the volume of transmitted, received, and lost data across the various interfaces that support the Cassandra service. These individual network interface statistics are then aggregated based on their respective timestamps.

The Y service-level metrics for the Cassandra application are defined by the mean latency of the Read (R) and Write (W) operations. This latency represents the time taken by the Cassandra application to complete R and W operations when induced by cassandra-stress. During the training phase of DNNs and basic ML algorithms, we extract features such as response time, errors, operations per second, and other relevant metrics from $X_{application}$ to construct the dataset. Conversely, in the Y testing phase, our objective is to estimate the mean latency of various operations in Cassandra by considering only the generic infrastructure metrics of the testbeds.

Step ❷ involves training using various algorithms based on ML for time-series regression. We employ basic ML and DNNs to leverage their potential in handling complex datasets that lack linear relaxations, exhibit high-dimensional characteristics, and seamlessly adapt to new scenarios, thereby facilitat-

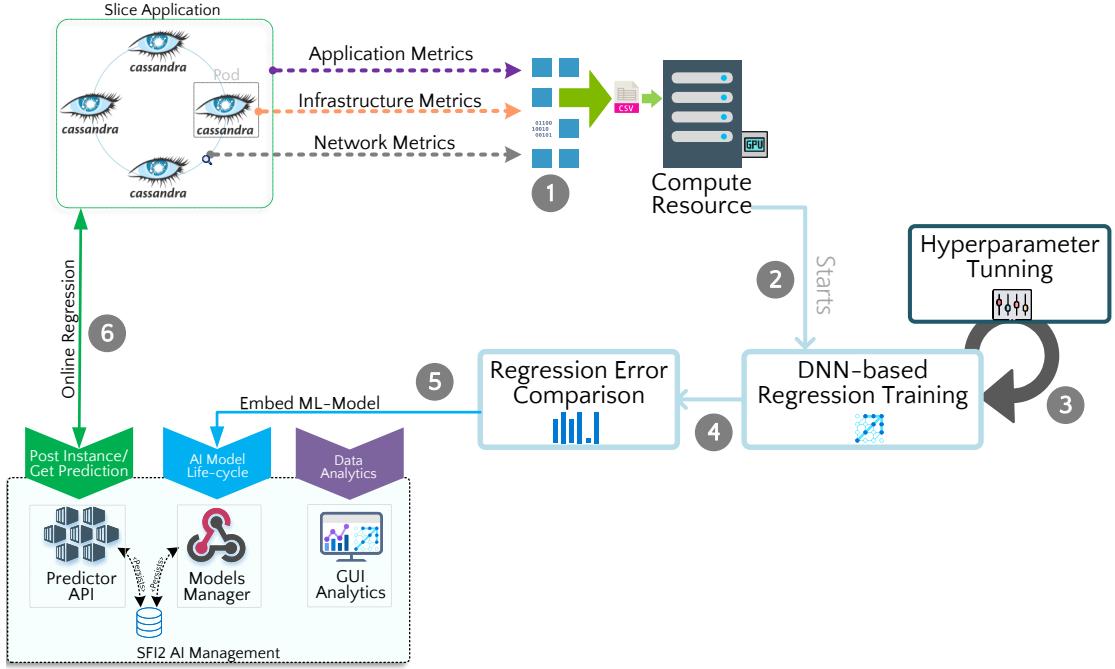


Figure 2: Proposed Method: Dataset Generation combined with DNNs training and test flow.

ing knowledge transfer.

Step ③ represents the search and adjustment of the hyperparameters for each DNN. At this stage, the hyperopt [36] tool uses Bayesian methods to find better parameters for training DNNs, such as learning rate, batch size, and epochs. At the end of this phase, the models are trained with the best hyperparameters and exported to enable inference through the SFI2 AI Management functional block.

The ④ step involves the empirical comparison of basic ML algorithms and DNNs using appropriate metrics for regression problems, such as MAE, MSE, and MAPE. MAE represents the average of the absolute differences between the predicted and actual values, while MSE is the mean of the squares of these differences, thereby emphasizing larger deviations in evaluating regression models. MAPE is a measure of relative error that expresses the difference between actual values and those predicted by a regression model as a percentage. MAPE is independent of the data scale, making it suitable for comparing the accuracy of regression models.

In step ⑤, we train the models and fine-tune the hyperparameters before integrating the trained models into SFI2 AI Management. The SFI2 architecture receives these models and makes them available for future SLA forecasting using the Predictor API.

In step ⑥, the Application Programming Interface (API) of the SFI2 AI Management block can handle some instances of $X_{application,cluster, network}$ and return a possible condition of the QoE Y in which the network slice is conditioned online, allowing us to evaluate whether the SLA is being honored.

3.3. Service Infrastructure Statistics and Service-Level Metrics

In this section, we detail the set of input features $X = X_{application} \cup X_{cluster} \cup X_{network}$ and denote the response variable Y . The $X_{application}$ statistics refer to the volume of operations performed on the database at a given timestamp, errors, and lines written per second for the Cassandra application. We extracted these metrics from the `cassandra-stress` utility, thus linking each record of these statistics to the corresponding timestamp. The $X_{cluster}$ statistics are metrics related to the consumption of the computational resources of each node that hosts the Cassandra application containers. These statistics are CPU consumption, RAM memory, and interrupts of the host machines collected through NetData.

The $X_{network}$ metric refers to the consumption of network resources by each computing node and container in the Cassandra application. Specifically, network statistics refer to the volume of data sent, errors received from the containers that run the Cassandra ring components, and computing nodes that host the application. These statistics were collected every second using NetData.

The Y metric refers to the QoE experienced by a user when operating on a distributed database. This metric considers the average latency of write (W) and read (R) operations in Cassandra deployed on the testbed. The response variable metric Y was measured using the `Cassandra-stress` utility, and we linked each latency per second to a given timestamp. All write and read operations of our dataset generation framework in distributed testbeds did not take into account application caches in any of the replicas.

We model the collection of these metrics as X and Y time series so that our objective is to estimate the average of the W and R operations in the Cassandra application deployed by

the SFI2 Architecture over different testbeds using a regression problem in supervised learning [37]. Then, we estimate Y_t using machine learning algorithms that learn from the statistics $X_t = [X_{1t}, \dots, X_{dt}]$. Thus, we find a model $M : X_t \rightarrow \hat{Y}_t$, where \hat{Y}_t optimally approximates Y_t for a given X_t .

We used different ML models and DNNs model architectures to solve the regression problem. We used DT, RF, KNN, LSTM, CatBoost, and XGBoost. Among them we use DNNs such as: FCN [38], FCNPlus [39], ResNet [39], ResNetPlus [39], ResCNN [39], TCN [40], InceptionTime [41], InceptionTime-Plus [41], OmniScaleCNN [42], XCM [39], and XCMPlus [39] that are implemented in the framework Fastai and *tsai* [39, 43].

Table 2 provides an overview of the employed DNNs structure. The Trainable Parameters column indicates the number of parameters that can be adjusted during training, including the weights and biases. The total number of Layers refers to the overall number of layers in the model, encompassing convolutional, pooling, and fully connected layers. The kernel Sizes describe the dimensions of the filters used in the convolutional layers. Pooling highlights the presence of pooling layers, which help reduce data dimensionality. Mult-Adds (M) represents the computational cost measured in millions of multiplication and addition operations. Finally, the Estimated Size (MB) estimates the model's size in megabytes, reflecting the number of parameters and required storage.

Table 2: Detailed Structure of Employed DNN Models

Model	Trainable Parameters	Total Layers	Kernel Sizes	Mult-Adds (M)	Estimated Size (MB)
FCN	285,446	17	(7), (5), (3)	14.47	2.18
FCNPlus	285,446	18	(7), (5), (3)	14.47	2.18
ResNet	490,758	53	(7), (5), (3), (1) \times 3	24.86	3.74
ResNetPlus	490,758	56	(7), (5), (3), (1) \times 3	24.86	3.74
ResCNN	268,551	33	(7), (5), (3), (1) \times 3	13.58	2.05
TCN	71,406	95	(7) \times 2, (1), (7) \times 13	1.88	0.54
InceptionTime	460,038	90	(1), (39), (19), (9) \times 6	23.32	3.51
InceptionTimePlus	460,038	124	(1), (39), (19), (9) \times 6	23.32	3.51
OmniScaleCNN	5,239,596	68	(1), (2), (3), (5), (7), (11) \times 3, (1), (2)	266.26	39.97
XCM	328,584	29	(51), (1), (51)	24.64	2.51
XCMPlus	328,584	30	(51), (1), (51)	24.64	2.51

The choice of these neural networks aimed to fulfill our objective of empirically comparing the performance of DNNs in estimating the SLA compliance. We also used the Optuna [44] framework to optimize the hyperparameters of the DNNs for comparison and employed the Tree-Structured Parzen Estimator (TPE)-based algorithm [45]. Our optimizer sought to find the optimal parameters according to the search space, as shown in Table 3.

Table 3: Optuna Search Space for each Regression Model (DNNs).

Hiperparameter	Search Space
Batch Size	8, 16, 32
Learning Rate (LR)	0.1, 0.01, 0.001
Epochs	20, 50, 100
Patience	5, 10, 50
Optimizer	Adam, SGD
# of Layers	1, 2, 3, 4, 5
Hidden Size	50, 100, 200
Bidirectional	<i>True</i> , <i>False</i>

3.4. Dataset Generation

To understand how ML algorithms perform in real testbeds, we propose a dataset that generates workloads using a periodic-load pattern and a collection framework. Using *cassandra-stress*, we generated **Write** and **Read** requests for the application deployed on the Future Internet Brazilian Environment for Experimentation New Generation (FIBRE-NG) and Fabric testbeds. These requests follow a Poisson process where the request rate adheres to a sinusoidal function, starting with a level P_s and amplitude P_A until 500k lines are written or read from the Cassandra application. The initial Cassandra parameters were defined as follows: consistency level set to *quorum*, replica factor of 2, and 256 tokens.

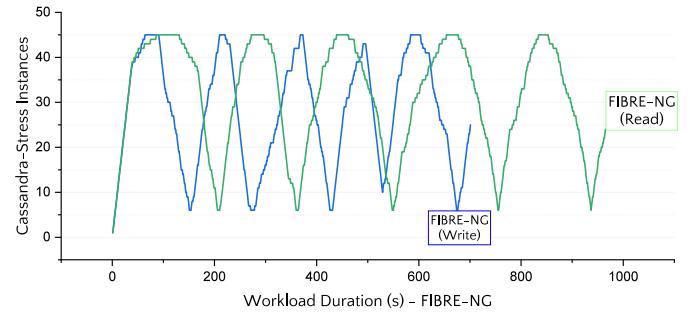


Figure 3: FIBRE-NG Testbed – Generating the traces.

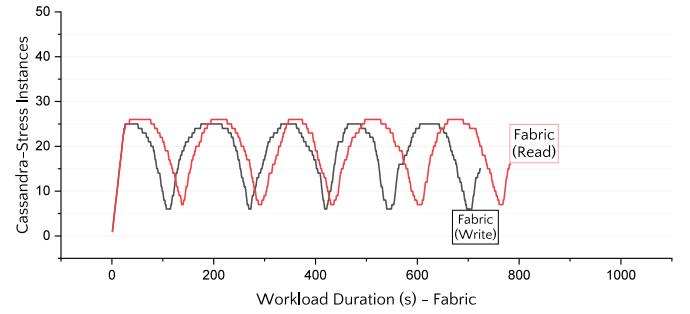


Figure 4: Fabric Testbed – Generating the traces.

In Fig. 3, and 4, the workload pattern represents the number of *cassandra-stress* processes created according to a sinusoidal function over simulation time. The traces in Fig. 3 and 4 refer to the instances of *cassandra-stress*, generating requests of different types, such as **Write** and **Read**, to create application metrics. Whenever a new *cassandra-stress* process is created, it triggers requests (W or R) to the Cassandra application running on the testbeds. We empirically define the parameters of the sinusoidal function as $f(t) = 22.5 + \frac{45}{2} \sin\left(\frac{2\pi t}{T}\right)$, where t represents time and T is the period of the function.

This function models a wave that oscillates between 0 and 45, with an amplitude (P_A) of $\frac{45}{2}$ units and an average value (P_s) of 22.5, providing an adequate representation for the desired variability in the generated processes. These values were defined empirically because of the restriction of computational resources for *cassandra-stress* (container), and high values of P_s and P_A imply high resource consumption and can lead to

container failure, thereby damaging the creation of the dataset. Both Write and Read operations were performed in Cassandra after the warm-up process.

Despite the Poisson model has limitations, particularly in representing peak load conditions, as it focuses on typical traffic rather than maximum loads. The dataset was generated in a live production environment using a synthetic workload application. The models were trained with realistic live production data, replicating actual network behaviors. This environment, with interconnected distributed nodes on a large-scale testbed, could experience unexpected traffic patterns and anomalies.

This method involves forecasting the next data point based on historical observations up to the current time and making continuous predictions as new data become available. The set of data generated from the Write and Read operations, as well as the training and testing splits, is shown in Figs. 5, 6, 7, and 8, where the operation latency is ms on the y-axis, and the timestamp of the experiment is on the x-axis.

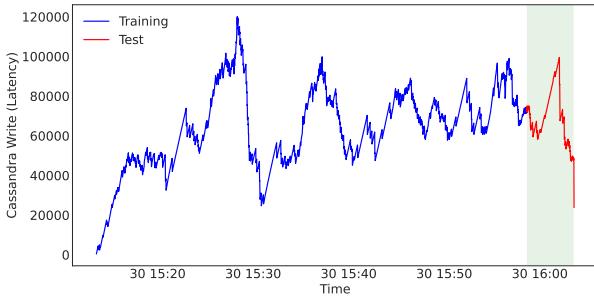


Figure 5: FIBRE-NG: Write Operation.

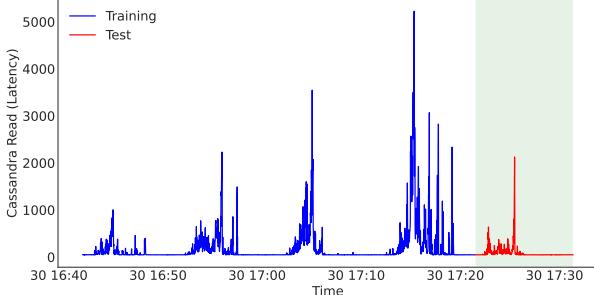


Figure 6: FIBRE-NG: Read Operation.

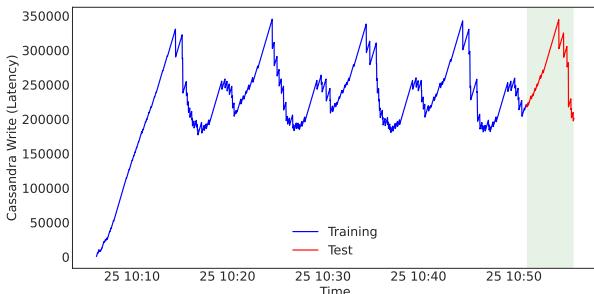


Figure 7: Fabric: Write Operation.

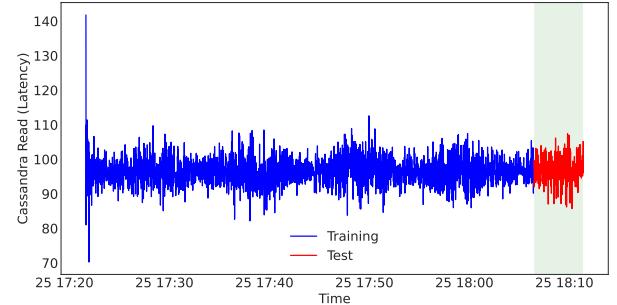


Figure 8: Fabric: Read Operation.

To adapt our structured numerical dataset for DNNs, specifically for Convolutional Neural Networks (CNNs), we applied a sliding window transformation using the Sliding Window method from the `tsai` library. Given a dataset with n variables (merged monitored metrics), where the last column represents the target variable (Cassandra latency), we constructed overlapping windows of length $w = 50$ with a stride of $s = 1$. Formally, let $\mathbf{X} \in \mathbb{R}^{m \times w \times (n-1)}$ be the input tensor and $\mathbf{y} \in \mathbb{R}^{m \times 1}$ be the corresponding target values, where m is the number of generated windows. Each window \mathbf{X}_i is defined as:

$$\mathbf{X}_i = [\mathbf{x}_i, \mathbf{x}_{i+1}, \dots, \mathbf{x}_{i+w-1}], \quad \mathbf{y}_i = x_{i+w}^{\text{target}} \quad (1)$$

where $\mathbf{x}_j \in \mathbb{R}^{n-1}$ represents the feature values at time step j . This transformation allows CNNs to extract spatial and temporal patterns effectively, treating each window as a structured input similar to an image. The sliding mechanism ensures that local dependencies are captured while enabling the model to generalize across different time segments. To evaluate model performance, we employed a time-based split using the Time Splitter function, reserving a predefined number of samples for testing.

4. Experiments and Model Computation

Our experiments sought to validate the behavior of DNNs in estimating SLA compliance in a nationwide network slice deployed through the SFI2 Orchestrator. Initially, we deployed the application to the testbeds and started the workload tests to generate datasets for different metrics. For each testbed, we seek to identify the Cassandra application's behavior and SLA and understand whether DNNs or basic ML algorithms can generalize predictions across geographically distributed testbeds that experience production-ready network conditions.

4.1. Testbeds

Fig. 9 shows the experimental setup used for our evaluation. What stands out is the Cassandra ring deployed on different computing nodes spread across each testbed FIBRE-NG [15] and Fabric [16]. We collected and processed the monitoring metrics, which are the features $X = X_{\text{application}} \cup X_{\text{cluster}} \cup X_{\text{network}}$, feeding the Predictor API that applies training with the different regression models.

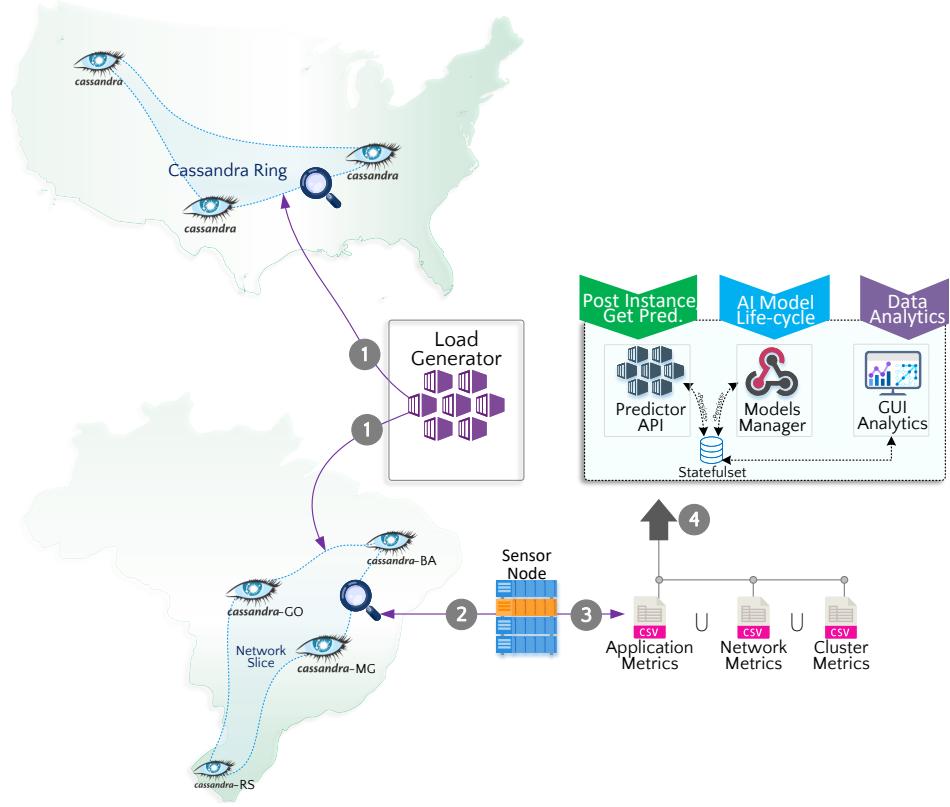


Figure 9: Deployment of Cassandra Application on nationwide testbeds.

To collect the application metrics, we employed a sensor and load-generating node. The load-generating pipeline shown in Fig. 9 executed read and write requests against the Cassandra ring (step ❶), whereas the sensor node generated flat requests simultaneously without altering the workload pattern (step ❷). Thus, we successfully gathered the necessary metrics of the application from the server side, which were subsequently compiled (step ❸) into a dataset. Finally, the dataset is uploaded to the SLA compliance training and validation framework (step ❹).

We deployed our network slice with the Cassandra application on two nationwide testbeds, FIBRE-NG and Fabric, considering the computational nodes in different geographic and intercontinental locations, such as the European Organization for Nuclear Research (CERN) node, presented in Table 4, which shows the rest of each testbed where we deployed the Cassandra application. This experimental setup aims to validate how DNNs deal with traces generated at nodes that transmit data in a production-ready network.

4.2. Model Training

In the experimental training and validation phase of the basic ML algorithms and DNNs, we used RTX 4060ti 16 Gb GPU hardware with an CPU Intel(R) Core(TM) i5-4430 CPU @ 3.00GHz with 32 GB of RAM. Furthermore, we used the PyTorch framework together with *FastAi* [43] and *tsai* [39] tools to build the DNNs training setup. All models were trained and validated with no seed locks and with tuned hyperparameters,

Table 4: Testbeds Compute nodes hosting Cassandra services (containers) in a distributed manner.

Testbed	Pod Name	Node Name	Location
FIBRE-NG	cassandra-0	WHX-SC	Santa Catarina
	cassandra-1	WHX-RS	Rio Grande do Sul
	cassandra-2	WHX-PB	Paráiba
	loadgen	WHX-RN	Rio Grande do Norte
Fabric	cassandra-0	Great Plains Network (GPN)	
	cassandra-1	CERN	
	cassandra-2	The University of Utah	
	loadgen	Rutgers University	

and we collected ten (10) samples of training time and performance metrics. The choice of DNNs and basic ML models aims to represent different model architectures for generalization and in-depth analysis.

Our training and test pipeline involves data ingestion, timestamping, and indexing, followed by splitting into training and testing subsets. Data transformation includes resampling, interpolation, and normalization, with feature selection and separate scaling of the target variable. The Sliding Window method generates input-output pairs for time series forecasting, while TSDatasets and TSDataLoaders apply further transformations. Hyperopt optimizes hyperparameters like batch size and learning rate. The model is trained using Learner with early stopping to prevent overfitting, and performance metrics are recorded for evaluation, ensuring robust data preparation and optimization.

5. Evaluating Results

To validate our contribution, we initially analyze the impact of different network factors on our case study network slicing application response time. We also discuss aspects of Model Tuning for our employed neural network. Later, we evaluate different ML approaches on a production-ready network and assess the feasibility of our dataset generation method, which expresses real network conditions and enables fitting and training models to forecast SLA violations on network slicing architectures.

5.1. Impact Analysis in a Large-Scale Network

To assess the impact of realistic and production-ready network metrics on our experimental deployment, we used a chaos engineering tool to simulate latency with jitter and packet loss [46]. We systematically applied jitter ranging from 1 ms to 10 ms, following a uniform distribution, and introduced a packet loss between 1% and 10% in our experimental sliced application. For token management, we implemented two distinct slices containing our distributed database application by varying the number of tokens from 32 to 256.

We employed three-way Analysis of Variance (ANOVA) to evaluate the effects of three independent factors and their interactions on a dependent variable. The factors are: (1) Fixed Latency with Jitter induction with levels 1ms and 10ms, (2) Network Packet Loss with levels 1% and 10%, and (3) Cassandra Tokens with levels 32 and 256. The response variable analyzed is the Cassandra Write and Read Latency. This method tests the main effects of each factor, the two-way interactions between factors, and the three-way interaction, using the F-statistic and corresponding p-value. A p-value of $p < 0.05$ indicates that the effect or interaction is statistically significant.

Table 5: Experimental Factors influence on Write Operations.

Source of Variation	F Value	P Value
Network Delay	7.58245	0.00612
Network Loss	580.45267	< 0.0001
Cassandra Tokens	0.25329	0.615
Network Delay \times Network Loss	4.32445	0.03811
Network Delay \times Cassandra Tokens	0.45758	0.49909
Network Loss \times Cassandra Tokens	1.24777	0.26455
Network Delay \times Network Loss \times Cassandra Tokens	1.77435	0.18349

The three-way ANOVA results as Table 5 show that for Write operations, Network Delay (Jitter) ($F(1, 472) = 7.58$, $p = 0.00612$) and Network Packet Loss ($F(1, 472) = 580.45$, $p < 0.0001$) have significant effects on latency, while Cassandra Tokens ($F(1, 472) = 0.25$, $p = 0.615$) do not. The interaction between Network Delay and Network Packet Loss is also significant ($F(1, 472) = 4.32$, $p = 0.03811$), suggesting non-additive effects. However, interactions involving Cassandra Tokens and the three-way interaction are not significant ($p > 0.05$). These results emphasize that network-related factors are the primary contributors to latency during Write operations.

The results in Figure 10 suggest that high network latency (10ms) combined with high packet loss (0.1) significantly degrades performance, as seen in the red line dropping from 9000 to 8000.

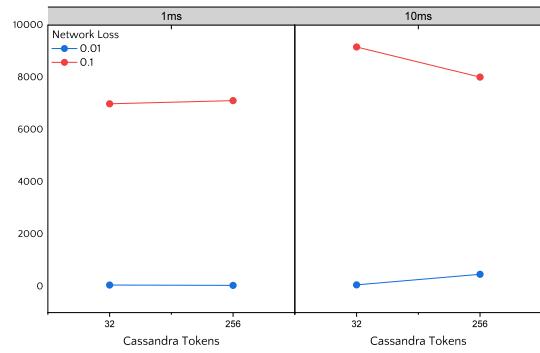


Figure 10: Impact of Network Latency, Cassandra Tokens and Packet Loss on Cassandra Write Operations.

In contrast, low latency (1ms) with high packet loss starts at around 7000, with a slight increase. Configurations with low packet loss (0.01) maintain stable performance despite increased latency. ANOVA confirms these findings, with network delay and loss showing high statistical significance ($P < 0.0001$). These results highlight the importance of optimizing network conditions for enhancing the efficiency and reliability of distributed database systems like Cassandra.

The three-way ANOVA results for Read operations as Table 6 indicate that both Network Delay ($F(1, 473) = 4.19$, $p = 0.04124$) and Network Packet Loss ($F(1, 473) = 172.78$, $p < 0.0001$) significantly affect latency. Additionally, Cassandra Tokens shows a marginally significant effect ($F(1, 473) = 3.81$, $p = 0.0515$), suggesting a potential influence on latency that may be worth further exploration. The interaction between Network Delay and Network Packet Loss is also nearly significant ($F(1, 473) = 3.58$, $p = 0.05896$), while the interaction between Network Delay and Cassandra Tokens is not significant ($F(1, 473) = 0.48$, $p = 0.491$). Furthermore, the interaction between Network Loss and Cassandra Tokens is significant ($F(1, 473) = 5.79$, $p = 0.01648$), suggesting that these two factors jointly influence latency. The three-way interaction between Network Delay, Network Loss, and Cassandra Tokens is not significant ($F(1, 473) = 2.69$, $p = 0.10178$). These findings highlight the dominant influence of network-related factors on latency during Read operations, with Cassandra Tokens potentially having a marginal effect and interactions between network factors playing a role.

Table 6: Experimental Factors influence on Read Operations.

Source of Variation	F Value	p Value
Network Delay	4.19	0.04124
Network Packet Loss	172.78	< 0.0001
Cassandra Tokens	3.81	0.0515
Network Delay \times Network Packet Loss	3.58	0.05896
Network Delay \times Cassandra Tokens	0.48	0.491
Network Loss \times Cassandra Tokens	5.79	0.01648
Network Delay \times Network Loss \times Cassandra Tokens	2.69	0.10178

In Figure 11 suggests that high network latency (10ms) combined with high packet loss (0.1) significantly degrades performance, with a notable decline observed in the graph. Conversely, lower latency (1ms) with high packet loss exhibits a

slight performance increase. Moreover, configurations with low packet loss (0.01) demonstrate minimal impact from increased latency, indicating stability in performance. These trends are corroborated by ANOVA results, highlighting the statistical significance of network delay ($P = 0.00612$) and network loss ($P < 0.0001$), as well as their interaction ($P = 0.03811$). These findings underscore the importance of optimizing both latency and packet loss to enhance the efficiency and reliability of distributed database systems like Cassandra.

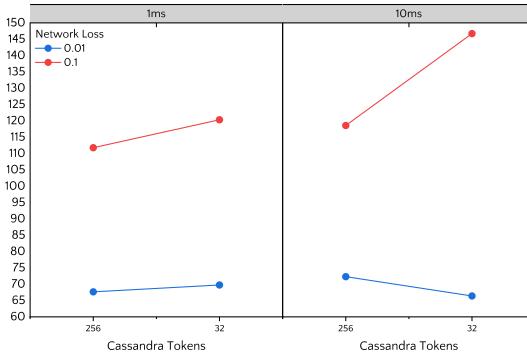


Figure 11: Impact of Network Latency, Cassandra Tokens and Packet Loss on Cassandra Read Operations.

5.2. Model Tuning

In this section, we present the results of the hyperparameter optimization of DNNs and the performance in estimating SLA for each model for the different operations (W and R) and testbeds (FIBRE-NG and Fabric). Therefore, we conducted hyperparameter optimization for the four constructed datasets ‘fibre-read.csv’, ‘fibre-write.csv’, ‘fabric-read.csv’, and ‘fabric-write.csv’.

We summarize the hyperparameters found by Optuna for the FIBRE-NG testbed in Table 7, and 8. Furthermore, we tuned the hyperparameters of the same models for the dataset generated from the Fabric testbed, as shown in Table 9, 10. With these adjusted values, we proceeded with an empirical evaluation of the performance of these models for predicting the SLA in each testbed.

Table 7: Write Dataset: Hyperparameter tuning values for the FIBRE-NG Testbed.

Model	Batch Size	Learning Rate	Epochs	Patience	Optimizer	Layers	Hidden Size	Bidirectional
FCN	8	0.1	20	10	Adam	2	100	False
FCNPlus	16	0.1	20	50	Adam	4	200	False
InceptionTime	16	0.1	100	50	Adam	4	100	False
InceptionTimePlus	16	0.1	100	50	Adam	1	50	True
OmniScaleCNN	32	0.1	20	50	Adam	2	100	True
ResCNN	32	0.1	20	10	Adam	5	100	False
ResNet	32	0.1	50	50	Adam	2	100	True
ResNetPlus	32	0.1	20	5	Adam	5	200	False
TCN	32	0.01	100	50	Adam	2	100	True
XCM	16	0.01	50	50	Adam	1	50	True
XCMPlus	8	0.1	100	50	Adam	3	200	True

Table 8: Read Dataset: Hyperparameter tuning values for the FIBRE-NG Testbed.

Model	Batch Size	Learning Rate	Epochs	Patience	Optimizer	Layers	Hidden Size	Bidirectional
FCN	16	0.1	20	10	Adam	3	200	True
FCNPlus	16	0.1	20	50	Adam	4	50	False
InceptionTime	8	0.01	20	10	Adam	5	100	True
InceptionTimePlus	16	0.1	20	50	Adam	2	200	False
OmniScaleCNN	8	0.1	50	50	Adam	2	50	True
ResCNN	16	0.1	20	10	Adam	3	100	False
ResNet	16	0.1	20	10	Adam	1	200	True
ResNetPlus	8	0.1	20	50	Adam	2	50	False
TCN	32	0.01	50	50	Adam	4	50	False
XCM	8	0.01	20	10	Adam	3	200	False
XCMPlus	16	0.01	50	50	Adam	3	50	True

Table 9: Write Dataset: Hyperparameter tuning values for the Fabric Testbed.

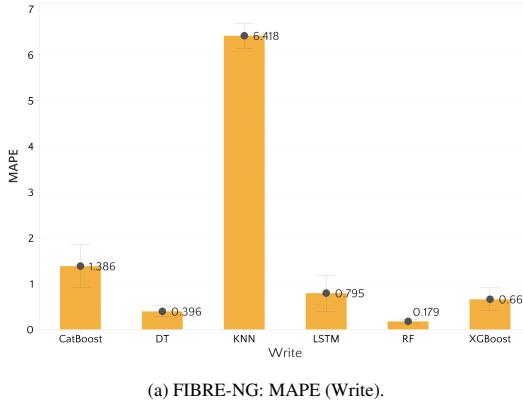
Model	Batch Size	Learning Rate (LR)	Epochs	Patience	Optimizer	# of Layers	Hidden Size	Bidirectional
FCN	32	0.01	20	10	Adam	3	50	True
FCNPlus	32	0.1	100	50	Adam	5	100	True
InceptionTime	32	0.1	50	50	Adam	2	200	False
InceptionTimePlus	16	0.1	100	50	Adam	4	50	True
OmniScaleCNN	16	0.01	50	10	Adam	4	100	True
ResCNN	32	0.01	50	50	Adam	5	100	False
ResNet	32	0.01	50	50	Adam	4	50	True
ResNetPlus	16	0.1	20	10	Adam	3	200	True
TCN	8	0.001	100	50	Adam	2	50	False
XCM	16	0.1	50	50	Adam	3	50	False
XCMPlus	16	0.1	100	50	Adam	1	50	True

Table 10: Read Dataset: Hyperparameter tuning values for the Fabric Testbed.

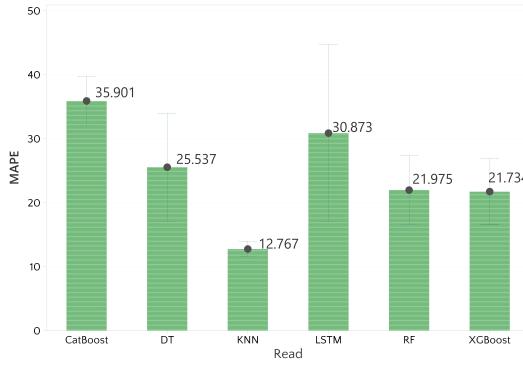
Model	Batch Size	LR	Epochs	Patience	Optimizer	# Layers	Hidden Size	Bidirectional
FCN	32	0.1	20	10	Adam	3	100	False
TCNPlus	8	0.1	20	10	Adam	3	200	True
InceptionTime	32	0.1	100	10	Adam	5	50	True
InceptionTimePlus	16	0.1	100	50	Adam	2	50	False
OmniScaleCNN	8	0.001	20	50	SGD	4	100	False
ResCNN	32	0.1	20	10	SGD	2	100	True
ResNet	32	0.1	20	50	Adam	4	100	True
ResNetPlus	8	0.1	20	5	Adam	4	200	False
TCN	32	0.01	20	10	Adam	2	100	True
XCM	8	0.1	100	10	SGD	3	50	True
XCMPlus	8	0.1	100	10	SGD	5	200	True

5.3. Basic Model Performance

Through our dataset construction framework on sliced testbeds, we aggregate the metrics $X = X_{application} \cup X_{cluster} \cup X_{network} \rightarrow Y$ and configure the datasets generated to submit it to the training and assessment process. Thus, we empirically use the division 80% for training and 20% for testing and build the regression model aiming at the one-step-ahead prediction method that, given a statistic i of X_i , the model can estimate the operation latency (W or R) in the next step.



(a) FIBRE-NG: MAPE (Write).



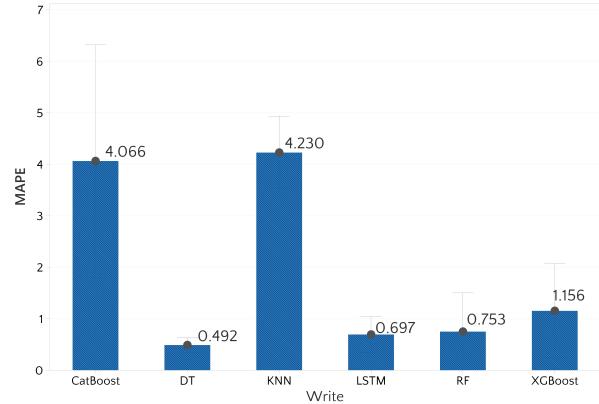
(b) FIBRE-NG: MAPE (Read).

Figure 12: MAPE results for Write and Read operations on FIBRE-NG.

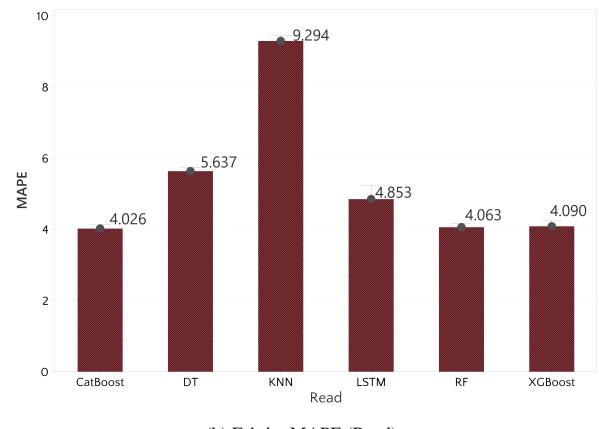
As Fig. 12-a, the Write operation on the FIBRE-NG testbed, and RF presented the lowest mean MAPE (0.17), indicating the best predictive accuracy, followed by DT (0.39). The KNN had the worst performance, with an average MAPE of 6.41, which is significantly higher than that of the others. Models such as CatBoost, LSTM, and XGBoost have intermediate performance but are still superior to KNN. In addition, RF demonstrated greater stability, with the lowest standard deviation (0.064).

In the Read operation, as shown in Fig. 12-b on the FIBRE-NG testbed, KNN obtained the lowest mean MAPE (12.77), indicating the best predictive accuracy. In contrast, CatBoost (35.90) and LSTM (30.87) presented the highest errors with high variability, as evidenced by the high standard deviation of LSTM (19.34). RF and XGBoost had intermediate performances, with mean MAPEs of 21.98 and 21.73, respectively. Meanwhile, DT showed a mean error of 25.54, with high dispersion.

During the writing operation, as shown in Fig. 13-a, on the testbed Fabric, the DT presented the lowest mean MAPE (0.49), indicating the best predictive accuracy, followed by LSTM (0.69) and RF (0.75). XGBoost had a slightly higher error (1.16) but was still lower than CatBoost (4.07) and KNN (4.23), which had the worst performance. In addition, DT showed the lowest standard deviation (0.19), suggesting greater stability.



(a) Fabric: MAPE (Write).



(b) Fabric: MAPE (Read).

Figure 13: MAPE results for Write and Read operations on Fabric.

In the Read operation, as Fig. 13-b, on the testbed Fabric, RF presented the lowest mean MAPE (4.06), closely followed by XGBoost (4.09) and CatBoost (4.03), indicating very similar performances. DT had a higher error (5.64), while KNN obtained the worst result (9.29), with the highest standard deviation (0.22), demonstrating low precision. LSTM showed an intermediate MAPE (4.85), but with greater variability (0.53). Thus, RF, XGBoost, and CatBoost stand out as the most effective approaches for predicting the latency in the Read operation of the distributed Cassandra on the testbed Fabric.

These experiments with basic ML algorithms for forecasting highlight the contribution of our study, which discusses the suitability of laboratory-trained algorithms in real-world scenarios and production networks with geographically distributed nodes. In the four analyzed scenarios, RF and DT demonstrated the lowest mean MAPE, indicating higher predictive accuracy. In the Write operation on the Fabric testbed, DT had the best performance (0.49), while in the Read operation on the same testbed, RF stood out (4.06). On FIBRE-NG, RF and KNN were more accurate in the Read operation (21.98 and 12.77, respectively), whereas DT had the lowest error in the Write operation (0.40). In contrast, KNN and CatBoost exhibited the worst performances in various scenarios. These results suggest that tree-based models, especially RF and DT, are more effective for forecasting in sliced testbeds.

5.4. DNN-based Model Performance

We computed the DNNs training time demands for Write and Read operations on the FIBRE-NG and Fabric testbeds and compared the results in Fig. 14. Therefore, it is possible to infer that with a confidence level of 95%, the read datasets generated in different testbeds require the same training time. In contrast, we noticed a difference in the training time between the Read and Write operations owing to the size of the generated dataset and the variations in network conditions experienced by each test workload.

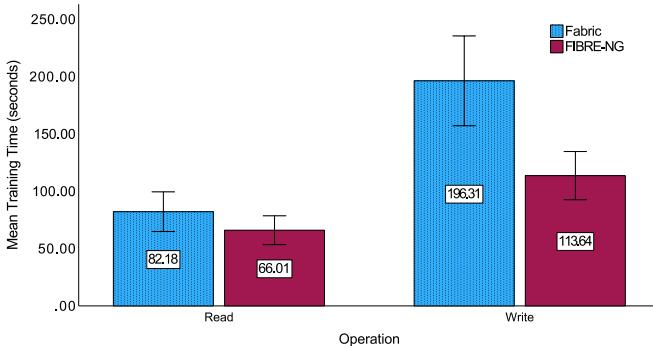


Figure 14: Training Time for different Operations (W and R) on Testbeds.

We deepened our analysis by observing the generalization capacity of the DNNs used to predict the Write and Read operations latency in Cassandra deployed on the FIBRE-NG and Fabric Testbeds. We present in Fig. 14 the training and validation behaviors of only the best DNNs for the two operations (W and R) and testbeds considering the MAE metric and the measured values in Table 11 and Table 12.

Table 11: Summarizing the DNNs performance for FABRIC using MAE.

Neural Network	Read Mean	Read StDev	Write Mean	Write StDev
FCN	0.040	0.000	0.016	0.005
FCNPlus	0.042	0.004	0.012	0.004
InceptionTime	0.041	0.003	0.020	0.008
InceptionTimePlus	0.040	0.000	0.030	0.017
OmniScaleCNN	0.046	0.005	0.027	0.018
ResCNN	0.043	0.005	0.021	0.007
ResNet	0.040	0.000	0.059	0.033
ResNetPlus	0.048	0.006	0.024	0.007
TCN	0.040	0.000	0.012	0.004
XCM	0.054	0.014	0.027	0.018

Table 12: Summarizing the DNNs performance for FIBRE-NG using MAE.

Neural Network	Read Mean	Read StDev	Write Mean	Write StDev
FCN	0.017	0.008	0.021	0.007
FCNPlus	0.013	0.005	0.014	0.005
InceptionTime	0.013	0.005	0.024	0.027
InceptionTimePlus	0.011	0.003	0.016	0.007
OmniScaleCNN	0.020	0.009	0.035	0.025
ResCNN	0.021	0.019	0.026	0.013
ResNet	0.010	0.000	0.012	0.004
ResNetPlus	0.014	0.005	0.017	0.005
TCN	0.019	0.007	0.015	0.005
XCM	0.025	0.007	0.035	0.012

We choose to employ the MAE metric rather than RMSE or MSE for regression on the Read and Write latency owing

to its robustness to outlier handling and ease of interpretation. Additionally, MAE shares the same unit of measurement as the dependent variable, facilitating a more intuitive comprehension of its meaning and magnitude.

Table 13: Summarizing the DNNs performance for FABRIC using RMSE.

Neural Network	Read Mean	Read StDev	Write Mean	Write StDev
FCN	0.050	0.000	0.020	0.000
FCNPlus	0.052	0.004	0.019	0.003
InceptionTime	0.055	0.005	0.025	0.010
InceptionTimePlus	0.053	0.005	0.034	0.016
OmniScaleCNN	0.059	0.003	0.033	0.021
ResCNN	0.054	0.005	0.024	0.007
ResNet	0.051	0.003	0.066	0.038
ResNetPlus	0.061	0.010	0.030	0.012
TCN	0.050	0.000	0.021	0.003
XCM	0.065	0.014	0.020	0.005
XCMPlus	0.065	0.009	0.026	0.005

For the read and write datasets from the FIBRE-NG testbed shown in Fig. 15-a and Fig. 15-b, we observed the training behavior of ResNet DNN. From Fig. 15-c, which refers to DNN InceptionTimePlus for the read dataset in the Fabric testbed, there was a subtle drop in the training and test losses, indicating that DNNs could extract patterns from the time series for prediction. As with Fig. 15-d, which refers to the dataset written in the Fabric testbed, there is a visual indication that the loss decreases as the epochs advance.

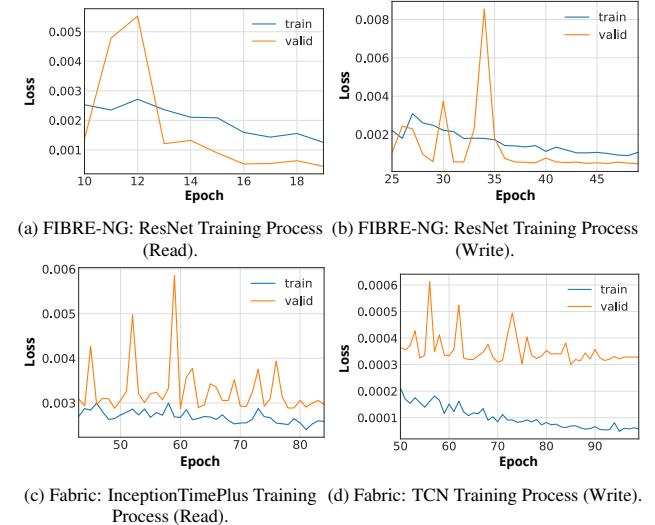


Figure 15: Training and Test behavior for Read and Write datasets on FIBRE-NG and Fabric Testbeds.

The results presented in Table 13 and Table 14 summarize the performance of DNNs in the context of FIBRE-NG, utilizing the RMSE metric. The InceptionTimePlus network stands out with the lowest RMSE for both reading (0.011) and writing (0.016), indicating superior performance compared to other networks. The ResNet also shows competitive results, with RMSE values of 0.010 for reading and 0.012 for writing. In contrast, the XCM and OmniScaleCNN exhibit the highest RMSE values, suggesting lower accuracy in their predictions. Additionally, the table reveals the variability of the results, reflected in

the standard deviations (StDev), which vary across the different architectures, with most maintaining relatively low deviations, especially in reading tasks.

Table 14: Summarizing the DNNs performance for FIBRE-NG using RMSE.

Neural Network	Read Mean	Read StDev	Write Mean	Write StDev
FCN	0.017	0.008	0.021	0.007
FCNPlus	0.013	0.005	0.014	0.005
InceptionTime	0.013	0.005	0.024	0.027
InceptionTimePlus	0.011	0.003	0.016	0.007
OmniScaleCNN	0.020	0.009	0.035	0.025
ResCNN	0.021	0.019	0.026	0.013
ResNet	0.010	0.000	0.012	0.004
ResNetPlus	0.014	0.005	0.017	0.005
TCN	0.019	0.007	0.015	0.005
XCM	0.025	0.007	0.035	0.012

Having the DNNs learn over the epochs operating on the datasets generated in the two testbeds, it is possible to admit that the DNNs are efficient in dealing with the seasonality of a production-ready network. Then, slicing orchestrators can couple such models into their slicing management control loop and modernize the delivery of service verticals with a guaranteed SLA.

We seek to observe the behavior of DNNs in predicting Cassandra latency by contrasting the real and predicted in the test portion of the time series. Fig. 16 shows the DNNs and their prediction process performance, considering the lowest value of the MAE metric for both the Write or Read operations presented in Table 11 and Table 12. Thus, modern slicing orchestrations can adopt a threshold for the difference between actual and predicted and assess whether the network slices it manages comply with the agreed SLA.

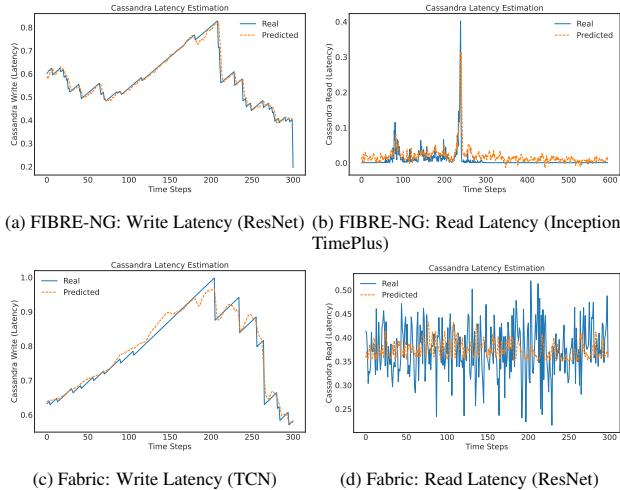


Figure 16: Latency prediction for better DNNs for Write and Read operations in testbeds.

To further our analysis, we examined the performance of DNNs for the four datasets generated in the two testbeds using the MAPE metric. As illustrated in Fig. 17-a, for the FIBRE-NG testbed, ResNet demonstrated the highest performance on the Write dataset with a MAPE of 0.024. Conversely, for the Read

dataset, DNN InceptionTimePlus exhibited superior performance, as depicted in Fig. 17-b.

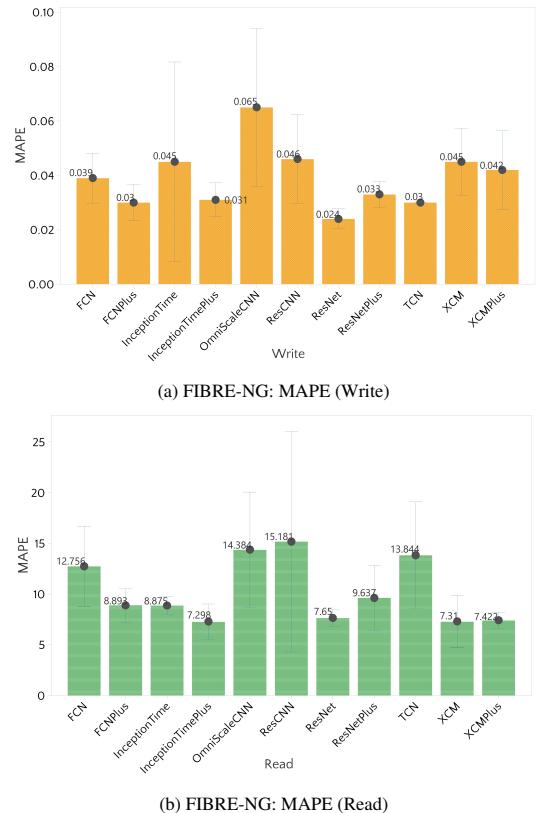


Figure 17: Mean Absolute Percentage Error (MAPE) for FIBRE-NG in Write and Read operations.

Furthermore, our analysis revealed that the DNN exhibiting optimal performance for the Write dataset in the Fabric testbed was FCNPlus (Fig. 18-a), achieving a MAPE of 0.015, with standard deviation serving as the criterion for resolving ties.

In the Fabric Read scenario, and according to Fig. 18-b, the MAPE showed very low and homogeneous values across the models, indicating high prediction accuracy. The low variability suggests that the prediction task for this operation was relatively simple, resulting in insignificant percentage errors. Models such as FCN, ResNet, and TCN performed practically identically, whereas XCM and XCMPlus showed slight variations, but still within a very small error range.

Considering this empirical analysis of the behavior of DNNs and the MAPE metric, it is possible to admit that DNNs are technologies that perform intelligent network slicing. It is possible to couple such capabilities into different building blocks to act at different phases of the lifecycle of a network slice. Using the MAPE metric, it is possible to have a percentage dimension of the error of DNNs that reiterates its ability to be embedded in prediction Application Programming Interfaces (APIs) based on microservices, such as SFI2 Orchestration Architecture.

Our approach primarily focused on evaluating a distributed database to assess the feasibility of training ML algorithms on a large-scale testbed. In addition, our method can be extended to

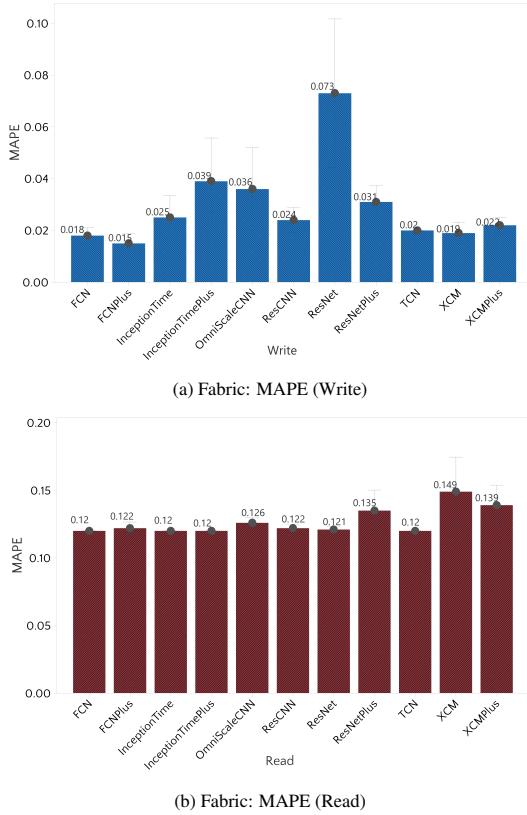


Figure 18: Mean Absolute Percentage Error (MAPE) for Fabric in Write and Read operations.

a broader range of applications that require access to computing and network-monitoring platforms. This extension would enable the integration of diverse performance metrics, facilitating accurate application performance forecasting and supporting life-cycle decision making in network slicing architectures.

6. Concluding Remarks

In this study, we shed light on how ML techniques, specifically DNNs and basic ML algorithms, can be jointly employed with slicing orchestration architectures to leverage and guarantee SLA for tailored applications in nationwide testbeds. To achieve this, we propose a method for generating and aggregating datasets regarding the latency of **Write** and **Read** operations in a distributed database. We found that there are approaches in the literature that combine computational intelligence for the different phases of the network slice life cycle; however, they have not yet considered how these AI techniques behave in production-ready networks deployed on nationwide testbeds.

Among the findings, we found that DNNs and even basic ML algorithms are promising technologies that can be built or natively embedded in slicing architectural building blocks to perform zero-touch orchestration in production-ready networks. Furthermore, we verified that forecasting network slicing latency with a low error rate is possible by monitoring generic and easily collected metrics related to the computing or network resources on which the network slice is deployed. Furthermore,

we believe that embedding the DNN or basic ML models in SFI2 AI management to cope with stringent application vertical requirements is a promising path.

One of the constraints of this study is that it focuses on generic networks and computing metrics. We aimed to incorporate more heterogeneous metrics into the dataset construction process to assess the generalization of these metrics and achieve low error rates in our predictions. Currently, we are working on analyzing the separation of metrics to validate the impact of each on the final ability to estimate SLA conformance and the employment of Reinforcement Learning.

In addition, we plan to explore methods such as queueing theory, extreme value analysis, or bursty traffic models to better capture extreme network conditions using supervised learning methods and other DNNs and attention-based mechanisms to determine their efficacy in such contexts. Our results offer valuable insights and opportunities for the further exploration of intelligent native slicing architectures.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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