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Machine Learning-Based Traffic Prediction in 4G LTE Networks. Case Study of a Mobile Operator in Cameroon

[1,4]Eric Michel Deussom Djomadji, [2]Valery Nkemeni, [2,4]Tchagna Kouanou Aurelle and [3]Michael Issikamle

[1]*Department of Electrical and Electronic Engineering, College of Technology, University of Buea, Buea, Cameroon*
[2]*Department of Computer Engineering, Faculty of Engineering and Technology, University of Buea, Buea, Cameroon*
[3]*Department of Computer Engineering, College of Technology, University of Buea, Buea, Cameroon*
[4]*Department of Information and Communications Techniques, National Advanced School of Information and Communication Technologies, University of Yaoundé 1, Yaoundé, Cameroon*

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Corresponding Author:
Eric Michel Deussom Djomadji
Department of Electrical and Electronic Engineering,
College of Technology,
University of Buea, Buea,
Cameroon
Email: eric.deussom@gmail.com

Abstract: Mobile subscribers are increasingly demanding the availability of broadband services while the radio resources allowing them to be connected are limited. Understanding mobile Internet consumption trends and subscriber traffic demands is essential to enable the management of existing radio resources. However, it can be difficult to understand and describe the data usage patterns of mobile users because of the complexity of mobile networks. In this study, we study and characterize the data usage patterns and user behavior in mobile networks to perform traffic demand prediction. We exploit a dataset collected via a mobile network measurement and billing platform of the Historical Telecommunications Operator (HTO) network called U2020/MAE. We elucidate different network factors and study how they affect data usage patterns by taking mobile users of the HTO as a use case. Then, we compare mobile users' data usage patterns, considering total data consumption, network access, number of sessions created per user, throughput, and user satisfaction level with the services. Finally, we propose an application that employs a machine-learning model to predict traffic demand using the HTO data.

Keywords: LTE Core Network, Traffic, Machine Learning, Forecasting

Introduction

The evolution of mobile networks from 2-5G coupled with a permanent need for broadband services by mobile subscribers has led to a significant surge in mobile internet resources and traffic. The usage of applications like video streaming in both normal and high definition, online gaming, online conferences, and meetings by mobile subscribers has deeply improved this growing mobile data traffic. Many reports demonstrate that an important part of Internet traffic generated from mobile users' equipment is due to multimedia content (Gember *et al*., 2011; Huang *et al*., 2013; Maier *et al*., 2010; Shafiq *et al*., 2011). According to Ericsson (2020) report, video content alone accounted for 60% of mobile data traffic, with projections suggesting that this figure will rise to 74% by 2024 (Ericsson, 2018b). Additionally, it was anticipated in 2018 that by 2022, global traffic resulting from mobile data consumption will be twelve times higher than it was in 2018 (Ericsson, 2018a). Mobile carriers have evolved into a complicated entity designed to meet the ever-growing demand for mobile traffic (Damnjanovic *et al*., 2011). The rising demand for mobile data, coupled with increasing network complexity and the expanding number of connected users, presents significant challenges in both the control plane and user plane for radio resources management. Understanding mobile users' data usage patterns is a problem for content providers as a result of the increase in mobile users and mobile traffic demand. Mobile network operators then have the obligation to efficiently manage the available resources based on the data usage consumption and behavior of their subscribers. According to research and common usage of mobile devices, their energy consumption is greatly impacted by the type of active applications and their respective data usage pattern (Huang *et al*., 2013). It is crucial for service and content providers, as well as end users, to understand the data usage trends and behavior of mobile users across various markets and geographical areas. Mobile network carriers can use this information to predict the growing demand for mobile data usage (Cisco, 2017), and to do proper capacity planning and efficient network optimization of the available resources globally (Guo *et al*., 2018; Silva *et al*., 2018).

Additionally, it can be utilized to design adapted data bundles focusing on specific subscribers and their requirements (Moodley *et al*., 2020). This information can also help policymakers and content providers improve the quality of services and urban planning (Toole *et al*., 2012) and understand urban dynamics (Xia and Li, 2019).

This study aims to analyze the various data flows within the network at a given time to predict network performance and support informed decision-making. To facilitate the optimization of traffic in a simplified manner, we propose the development of a platform that leverages data collected from the UGW of the HTO network over a specified period. This platform will utilize mathematical models, including linear and neural models, to generate accurate forecasts and enhance network management.

Related Works

The increasing demand for mobile data and the limited resources available to mobile network operators have driven significant research into traffic prediction and resource management in 4G LTE networks. Various methodologies, including machine-learning models, have been proposed and applied to address the challenges associated with traffic forecasting.

Abana and Tonye (2020) developed a multiple linear regression model to predict downlink user traffic in a 4G core network, considering various correlated variables. Their approach aimed to enhance network traffic management by providing a data-driven method for decision-making.

Zhani *et al*. (2012) conducted an extensive exploration of traffic forecasting techniques to optimize queue management in mobile networks. They ultimately proposed the α_SNFAQM method, an artificial mechanism based on traffic predictions. Although this method delivered accurate and reliable results, its complexity and the difficulty of interpreting its outputs posed challenges for practical implementation. There is a need for more interpretable models that could be more easily integrated into network operations.

Walelgne *et al.* (2021) investigated and characterized data usage patterns and behavior of users in mobile networks across six different countries: Japan, India, Germany, the United Kingdom, Brazil, and Finland. By employing machine-learning techniques such as linear regression, they were able to show how data usage patterns and the Service Level Score (SLS) of mobile users vary across the six countries. Their analysis produced insights into data usage trends in both cellular and Wi-Fi networks, offering a comparative view of data consumption per subscriber in each country.

Deussom Djomadji *et al.* (2022) leveraged machine learning to solve the problem of fraud by building a collaborative fraud detection model. Through Call Data Records (CDRs) and traffic data processing and analysis, they aimed to detect fraudulent activities in mobile core networks, particularly in the context of internet bundles. Their work demonstrated the efficacy of machine learning in identifying patterns indicative of fraud. Further extending the application of machine learning in another study the same authors (Djomadji *et al*., 2023a) focused on detecting SIM box bypass fraud in circuit switch telecom networks. Their model, which analyzed CDRs, was particularly relevant for addressing revenue losses in the international calls segment, where such fraud is prevalent.

Bernabe *et al.* (2022) explored the use of machine learning algorithms to reduce the downtime in LTE networks, improve network availability, and globally, the maintenance of 4G networks through alarm analysis. Their comparative study of different algorithms demonstrated the potential for machine learning to optimize network operations by enhancing the detection and resolution of network issues. In related research, Michel *et al.* (2023) applied machine learning to build alarm classification and correlation models which were used in an SDH/WDM optical network to improve its maintenance and reduce the time to repair. Their approach facilitated quicker identification of root causes for network faults, thereby reducing service downtime and improving overall network availability. This improvement is crucial for meeting Service Level Agreements (SLAs) between telecom operators and their customers.

Moreover, machine learning has been applied to resource allocation in 4G Radio Access Networks (RAN), as evidenced by several studies (Djomadji *et al*., 2023b). These approaches demonstrate the versatility of machine learning in optimizing network resource management, ultimately leading to more efficient and reliable mobile network operations.

Existing literature illustrates the growing importance of machine learning in predicting and managing traffic in mobile networks. However, the unique challenges posed by the complex and dynamic nature of 4G LTE networks necessitate continuous advancements in predictive models to ensure optimal resource allocation and network performance.

Materials and Methods

In this study, the target data to be exploited are labeled data. We used three algorithms namely linear regression algorithms, the Convolutional Neural Network (CNN), and the Long Short-Term Memory (LSTM) to achieve the prediction goals.

Linear Regression Algorithm

Also referred to as the linear model, is a statistical model that focuses on implementing prediction functions by minimizing the error. This algorithm exploits numerical values to identify a trend or a predictable evolution over time. It is widely applicable across various fields, including artificial intelligence (particularly in machine learning), statistics, and stock market analysis. In this study, we employ multiple linear regression to achieve our predictive goals.

CNN Algorithm

A Convolutional Neural Network (CNN) is a type of artificial neural network primarily used for image recognition and processing, they are particularly performant for finding patterns in images to recognize objects, classes, and categories. CNNs are a subset of neural networks and can be used also for classifying audio, signal data, and time series.

LSTM Algorithm

Long Short-Term Memory (LSTM) is a Recurrent Neural Network (RNN) architecture used in the field of deep learning. Unlike traditional feedforward neural networks, LSTM networks have feedback connections, making them particularly well-suited for tasks involving classification, processing, and forecasting based on time series data. LSTMs are designed to handle lags of unknown duration between important events in a time series and they were developed to address the gradient problems often encountered when training conventional RNNs.

To train the system for the most accurate traffic prediction in a 4G network, we employed a data science approach. Using a dataset collected from the databases of a mobile operator's operation and maintenance center over a specific period, we applied the machine learning algorithms discussed in the previous sections to determine which algorithm would yield the most reliable results.

The approach involved the following steps:

- ✓ Preprocessing the dataset
- ✓ Normalizing/coding the variables
- ✓ Determining the model and its parameters
- ✓ Training the model
- ✓ Testing and interpreting the results

Environment and Tools Used

To implement the machine learning algorithms, we utilized the Python programming language, specifically version 3.9. Python is a preferred language for developing artificial intelligence applications due to its ease of installation, interpreted nature, speed, and lightweight performance. The Python interpreter, along with its extensive standard library, is freely available as both source code and binaries for all major platforms through the official website python.org and can be freely redistributed. For this project, we used the Anaconda distribution of Python, which includes all the essential tools and libraries needed for machine learning, such as NumPy, Matplotlib, scikit-learn, Jupyter, and Spyder, among others.

Dataset Processing

Data was collected directly from the operator's core network monitoring platform. In this study, we focus on the file containing traffic-related data. This file is in plain text format, where each entry is recorded on a separate line. The entries include various metrics such as the amount of data consumed in both downlink and uplink, the number of simultaneously active subcarriers, the period of data collection, and the total data consumption, among others. The dataset comprises 2160 rows and 14 columns. Figure (1) shows the structure of the dataset after extraction from the U2020/MAE server and Fig. (2) presents the Python code used to list the columns of the dataset as an illustration.

Before proceeding to the coding of the algorithm capable of performing the traffic prediction, we have performed some analysis with the tools offered by the ANACONDA environment, through its libraries Numpy and Matplotlib in order to specify the columns that we will use in our work.

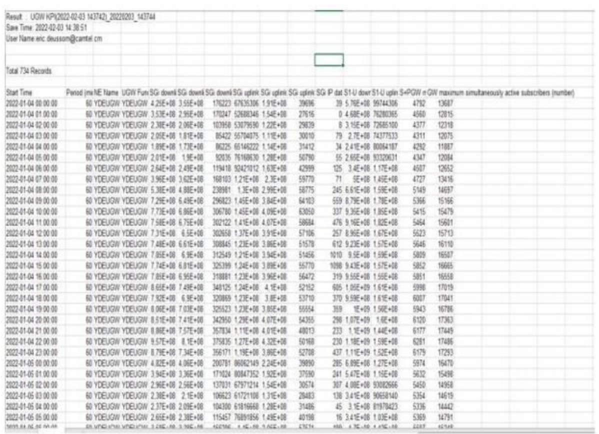

Fig. 1: Data extract from the Huawei U2020/MAE server

```
df.columns

Index(['Start Time', 'Period (min)', 'NE Name', 'UGW Function',
       'SGi downlink user traffic in KB (kB)',
       'SGi downlink user traffic peak throughput in KB/s (kB/s)',
       'SGi uplink user traffic in KB (kB)',
       'SGi uplink user traffic peak throughput in KB/s (kB/s)',
       'S1-U downlink user traffic in KB (kB)',
       'S1-U downlink user traffic peak throughput in KB/s (kB/s)',
       'S1-U uplink user traffic in KB (kB)',
       'S1-U uplink user traffic peak throughput in KB/s (kB/s)',
       'S+PGW maximum simultaneously active bearers (number)',
       'SGi Total Peak Throughput (Mbits/s) (Mbit/s)'],
      dtype='object')
```

Fig. 2: Columns of the Dataset as an illustration

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Learning and Creation of Prediction Models

After creating the datasets for training, the next step involves applying a learning model to the data. Since the data to be predicted is labeled, we utilized the algorithms mentioned earlier to develop the prediction models.

Prediction

We used 4 features from our dataset to find the underlying causes:

- "Period"
- "S1-U downlink user traffic in KB (kB)"
- "S1-U uplink user traffic in KB (kB)"
- "S+PGW maximum simultaneously active bearers (number)

We used the aforementioned algorithms to make predictions using the input data from the dataset, resulting in Figs. (3-6), which are presented below for each algorithm.

We notice that the value predicted by this model does not merge with the value we have in input, i.e. there is no overlap between the point in green representing our input value and the "cross" in orange representing the value predicted by our model. We can say that the error is quite large in the use of this model. In contrast to CNN, as presented in Fig. (4), linear regression provides better accuracy in that the difference between the actual input value and the predicted value is minimal. This model therefore provides a more accurate prediction than the CNN.

The model based on the LSTM offers a better correlation than those used above. Indeed, it allows us to obtain a very precise prediction of the values we submitted as input, we have the illustration in Fig. (5).

Interpretation

- Considering the curves and graphs obtained after the test, we notice that the results obtained are strongly dependent on the input data, so it is urgent to perform the pre-processing of the data beforehand.
- The analysis of these different curves shows that only the traffic test curve using the LSTM recursive neural network model provides us with better accuracy because the prediction points are more similar to the real value points. Thus, finally, to provide better performance we will develop our application based on LSTM recursive neural networks.

Evaluation of Our Prediction Models

To effectively evaluate the models used, we employed error curves as a performance criterion. The results are presented in Figs. (6-8). For the CNN, the maximum error value is 0.245 obtained after testing our model on real data and it decreases as the model becomes more efficient. The value obtained at the end of the training is the sum of the errors between the real data and the predicted values.

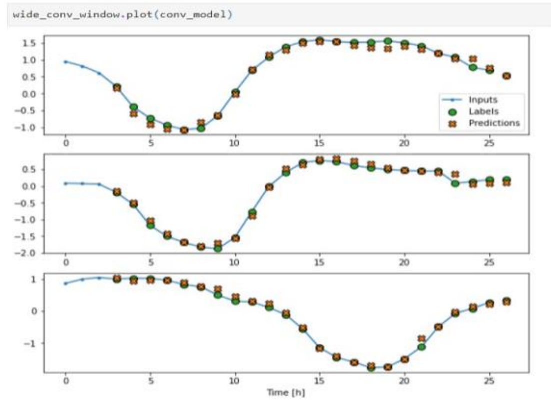

Fig. 3: Test with the CNN

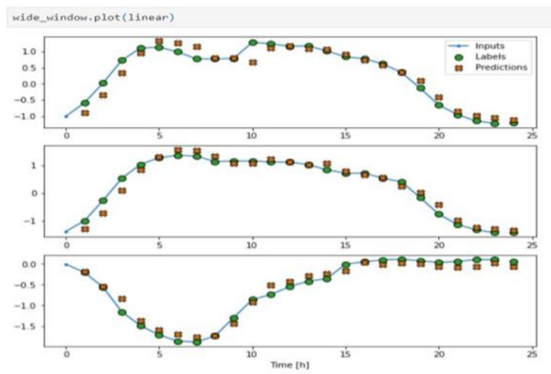

Fig. 4: Test with linear regression

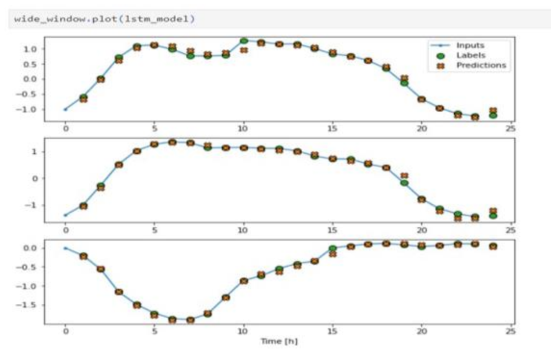

Fig. 5: Test with the LSTM

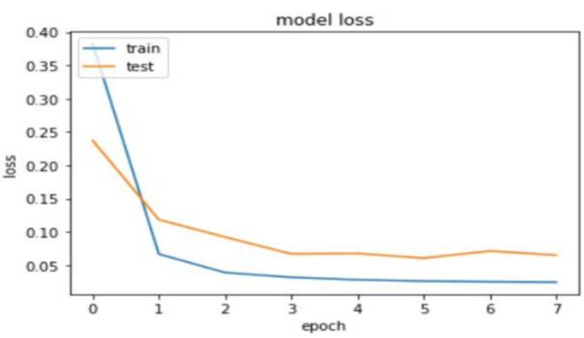

Fig. 6: Slope curve for the CNN

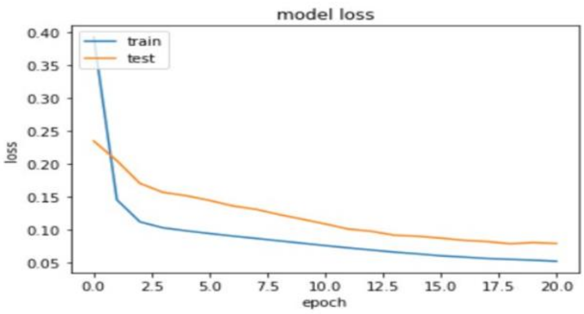

Fig. 7: The slope curve for the linear regression

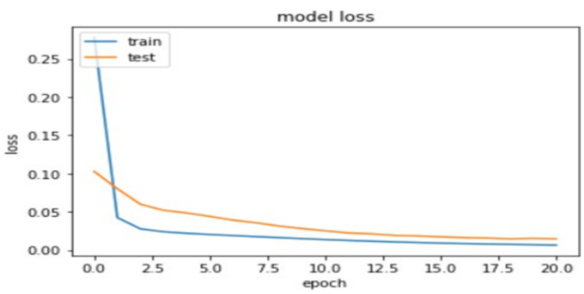

Fig. 8: The slope curve for the LSTM

Table 1: MAE value of each algorithm

Algorithms	MAE values
CNN	0.1928
Linear regression	0.067
LSTM	0.0412

The linear regression model yields a slightly lower maximum error value compared to the CNN, with a maximum loss of 0.237. The LSTM model performs the best among all the models used, achieving a maximum error value of 0.11, which decreases more rapidly than the others.

Interpretation

Looking at the different loss values obtained above, we realize that the LSTM offers better performance because it offers a smaller maximum loss than the other models and decreases more rapidly than the other models. Indeed, the loss informs us about the robustness of our model and the more the loss value tends towards 0 the better.

The values obtained being all lower than 1, we conclude that the different models offer good performances but the priority is given to the LSTM.

The Mean Absolute Error (MAE) is a common metric used to assess forecast accuracy in time series analysis. The different MAE values obtained for each model are presented in Table (1).

Interpretation

The MAE as its name indicates is the average of the absolute errors. From the results obtained above, we notice that the LSTM performs better than the other models used.

Results and Discussion

After implementing each of the previously presented machine learning algorithms, all models achieved a certain level of accuracy, as detailed in Table (2).

The LSTM-based model outperforms the others with an accuracy of 95.88%, making it the preferred choice for making predictions. The results of the comparative analysis are summarized in Table (3).

We can conclude that the LSTM-based model offers superior performance and will be used for the development of the prediction tool.

Presentation of the Traffic Forecasting Tool

Following the testing of the models, we developed a traffic prediction tool. This tool is a dashboard that implements the LSTM model and is divided into several modules, including a connection interface, parameter and data management interfaces, and other components used for making predictions. Figures (9-10) respectively present the login interface and the parameters and data management interface.

As shown in Fig. (11-12), the tool also enables business experts to evaluate the performance of the model by conducting a training test, ensuring that the results obtained are reliable and not erroneous. As illustrated in Fig. (13), the test allows users to track the evolution of the curves representing the predictions made by our solution, as well as the MAE, which reflects the average of the squared errors resulting from the predictions. Figure (14) shows the prediction interface, where users can specify the day for which the prediction is to be made. By clicking the "Predict" button, the tool provides the predicted data reflecting the flow of exchanges in the network as depicted in Fig. (15).

Table 2: Summary of the accuracy of the different models

Algorithms	Accuracy (%)
CNN	80.72
Linear regression	93.3
LSTM	95.88

Table 3: Summary of model evaluation

Evaluation metric	CNN	Linear regression	LSTM
Error value			
Accuracy			

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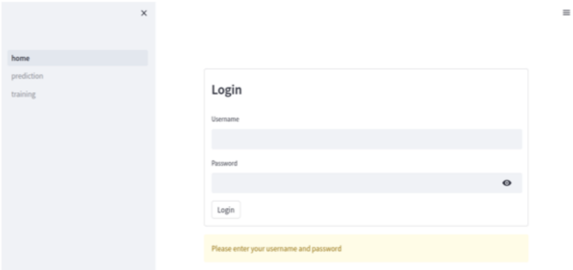

Fig. 9: Tool login interface

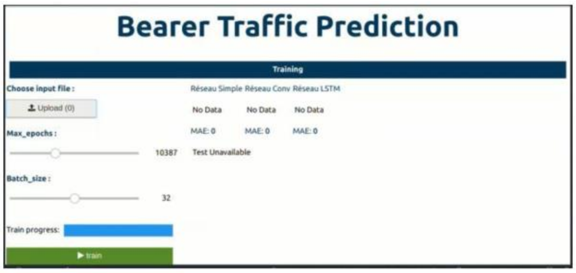

Fig. 10: Parameter and data management interfaces

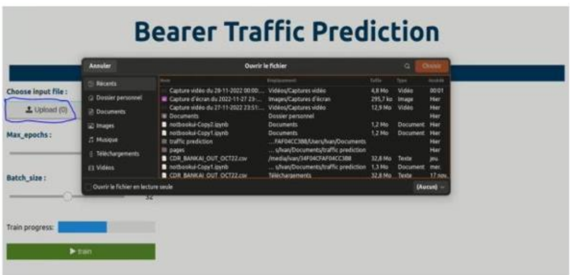

Fig. 11: Interface for importing the data

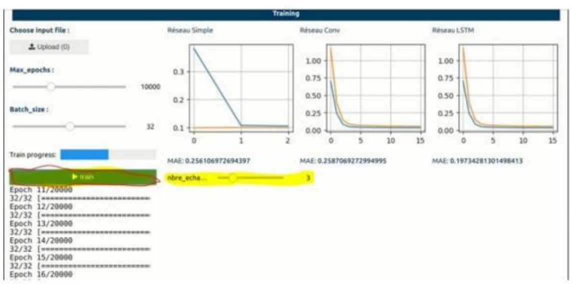

Fig. 12: Interface for model testing

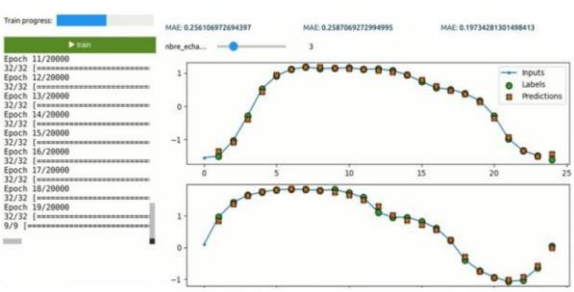

Fig. 13: Visualization of predictions during training

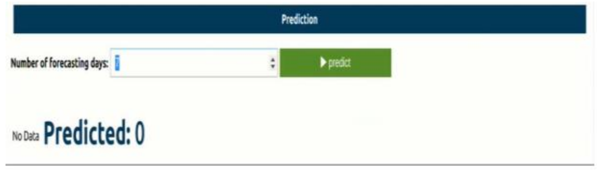

Fig. 14: Traffic prediction interface

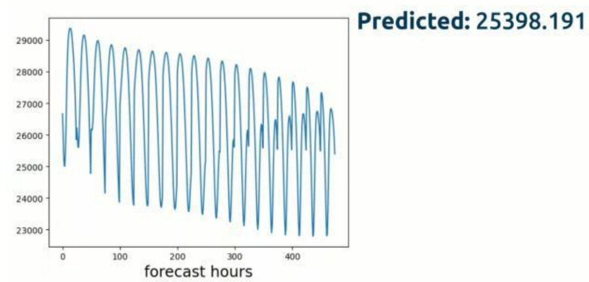

Fig. 15: Traffic prediction for a given date

Impact on Business/Marketing

The benefit of the proposed tool lies in its potential financial benefits for the company, although the precise monetary impact cannot be disclosed due to the unpredictable nature of data consumption in a network operator's environment, especially with the increasing growth of mobile usage. However, by utilizing this tool, the operator can:

- ❖ Propose new services and offers to its subscribers
- ❖ Optimize network load balance and resource utilization by offering existing services during periods of low traffic
- ❖ Detect sudden variations in traffic and respond effectively by proposing appropriate services and identifying the causes of these variations (e.g., fraud, illegal resource usage, etc.)

With further improvements to our traffic prediction model before its release and testing phase (where increased data processing will enhance its accuracy), we anticipate that the company's gains from mobile data consumption will increase by a significant percentage. Additionally, the deployment cost of our tool is relatively low compared to the substantial financial benefits it is expected to generate, addressing the key concern about the necessity and value of our tool.

Technical Impact

Traffic prediction in a cellular network is a crucial step in the development of an efficient system. It plays a vital role in enhancing network protection, preventing congestion through effective control schemes, and identifying anomalies. Thus, the proposed solution will contribute to:

- Detect anomalies in mobile data usage and consumption
- Avoid network congestion by anticipating the deployment of new resources
- Help determine the changes to be made within the network to ensure good quality of service and a better user experience. Indeed, 4G performance is divided by 2 between the time when the network is most available and the time when it is most congested. This saturation degrades the quality of service in terms of speeds perceived by users.
- Estimate and obtain the largest favorable resource
- Allocate bandwidth through convenient provisioning while maintaining maximum network utilization

Conclusion

To enhance traffic forecasting in 4G networks, relying on an adequate forecasting tool is essential. The traditional manual approach, which involves extracting and processing data through Excel, has proven insufficient given the voluminous and unstructured nature of network parameters. With the advent of Big Data and Machine Learning, data forecasting has undergone a significant transformation. This study was undertaken to predict traffic demand using the HTO data, enabling proactive decision-making to expand network capacity and prevent congestion. In order to achieve our goal, first, we reviewed how the 4G network works. Then, we studied the prediction methods. And finally, we followed the Machine Learning pipeline. This study allowed us to extract a use case diagram, a class diagram, and an activity diagram from which the solution is derived in other to build the tool proposed.

In conclusion, the objectives outlined in the introduction section have been successfully met. The developed tool reduces analysis time and generates forecast curves for traffic performance indicators. Specifically, data loading into the platform takes approximately two minutes per file and the generation of forecast data takes about two minutes, making the process both efficient and effective.

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Author's Contributions

Eric Michel Deussom Djomadji and Michael Issikamle: He participated in all experiments, coordinated the data-analysis and contributed to the writing of the manuscript.

Valery Nkemeni and Tchagna Kouanou Aurelle: He contributes in reviewing the article and it critically for significant intellectual content.

Ethics

This article is original and contains unpublished material. All authors have read and approved the manuscript and no ethical issues are involved.

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