Using LSTM Network for Predicting Radio Mobile Networks' Behaviors

Cuong Pham-Quoc[1], Tuan Tang-Anh[2], Chien Tang-Tan[3]
[1] MobiFone Corporation, Hanoi, Vietnam
[2] Faculty of Electronics and Telecommunication Engineering, University of Science and Technology, The University of Danang, Danang, Vietnam
[3] Faculty of Computer and Electronics Engineering, Vietnam – Korea University of Information and Communication Technology, The University of Danang, Danang, Vietnam
Correspondence: Cuong Pham-Quoc, cuong.phamquoc@mobifone.vn
Received: 28/02/2023, revised: 23/06/2023, accepted: 30/6/2023
Digital Object Identifier:: 0.32913/mic-ict-research-vn.v2023.n1.1212

Abstract: Breakthroughs in artificial intelligence, machine learning and deep learning with great recent achievements have been strongly impacting the mobile communication industry. The traditional method of mobile network management and operation has been shifting toward automation and proactive monitoring. Forecasting radio mobile networks' behaviors in coexisting multi-layer technology mobile networks for improving resource allocation efficiency and optimizing network's key performance indicators becomes a critical task. The use of a Long-Short Term Memory (LSTM) network for predicting radio networks' behaviors based on real statistical data from operational support systems is suggested in this research. The promising results show the potential of our approach. The prediction results can help mobile network operators leverage networks' operating performance.

Keywords: *Long-Short Term Memory, predicting, behavior, radio mobile network, data.*

Tiêu đề: **Sử dụng mạng LSTM để dự báo hành vi mạng thông tin vô tuyến di động**

Tóm tắt: Những đột phá trong lĩnh vực trí tuệ nhân tạo, học máy và học sâu với các thành tựu vượt trội đã tác động mạnh mẽ đến ngành công nghiệp thông tin di động. Các phương pháp vận hành khai thác, quản lý mạng lưới truyền thống đang từng bước dịch chuyển sang hướng tự động hóa và chủ động giám sát. Việc dự báo các hành vi mạng thông tin vô tuyến di động trong mạng lưới thông tin tích hợp đa công nghệ nhằm cải thiện hiệu quả cấp phát tài nguyên và tối ưu các chỉ số chất lượng mạng lưới là nhiệm vụ cấp thiết. Nghiên cứu này đề xuất sử dụng mạng Long-Short Term Memory (LSTM) để dự báo hành vi mạng lưới dựa trên tập dữ liệu thống kê thực tế từ hệ thống hỗ trợ vận hành khai thác OSS (Operational Support System). Các kết quả dự báo cho thấy tiềm năng của phương pháp mà bài báo đề xuất, Với những kết quả đạt được có thể giúp các nhà mạng di động tối ưu hiệu năng vận hành khai thác mạng lưới.

Từ khóa: *Long-Short Term Memory, dự báo, hành vi, mạng thông tin vô tuyến di động, dữ liệu.*

I. INTRODUCTION

Nowadays, with a tremendous volume of data and advances in computing power, deep learning (DL) has played a key role in complicated challenges. It is anticipated that next-generation mobile networks would combine DL and advanced machine learning (ML) to complete tasks that previously seemed impossible [1]. The world's leading telecommunication vendors, such as Nokia and Ericsson have applied AI and DL to provide technical solutions for Mobile Network Operators (MNOs) to operate and manage their networks more efficiently [1, 2].

For optimizing Capital Expenditure and Operating Expenditure with high-quality services, MNOs need a well-planned network strategy. To devise such a network strategy, MNOs should have an in-depth insight into the characteristics of their networks' behaviors. Big data generated by state-of-the-art network systems, when paired with DL techniques, can dramatically enhance network design and management [3].

In order to find insights and make important actions for mobile networks, a huge dataset must be gathered, organized, and analyzed using data analytic and mining techniques. The method of employing data analysis to predict uncertain outcomes is the subject of this work. The objective of this research is using LSTM network to predict radio mobile networks' behaviors with real data obtained from the NetAct operational support system (OSS) system [4].

Up to now, mobile communication networks have experienced a huge change [5] which is a journey from analogue cellular systems (1G) to state-of-the-art cellular systems (5G, 6G and beyond 6G). A new generation of mobile technologies debuts roughly every ten years [6], which enhances capability, performance, effectiveness, and experience. Although each generation differentiates itself from the previous one by its standards, capacities, techniques and new features, the general network design has the common foundation of the Radio Access Network (RAN), the core network and the back-haul network [7]. These commercial mobile network technologies that are 2G, 3G, 4G and currently 5G are all connected to the MNO's OSS via signaling interfaces to operate, exploit and manage. RANs' behaviors consisting of customers' attempts, network events, major alarms, etc. are gathered to monitor, optimize and leverage network performance.

There has been extensive research on applying DL and ML to support the operation, management and exploitation of mobile networks as [8] in which a deep generative adversarial network with LSTM cells was proposed to detect anomaly KPIs in the cellular networks. In addition, it is suggested to employ a Random Forest based method to determine the primary reason for the decline in 5G radio quality [9]. Recent research has demonstrated the great potential of utilizing DL/ML to improve the quality of mobile communication networks.

Periodically, network's performance counters record and store behaviors related accessibility, retainability, mobility, etc. These counters are triggered by events generated by user equipment or network elements like base station transceivers (BTS), eNodeBs (eNBs) or serving gateway (S-GW) and so on [10]. Then, counter data which is integer values is sent to OSS's server via control planes for monitoring operation and optimization.

The 4G/LTE radio mobile network behaviors including Random Access Channel (RACH) attempts, Radio Resource Control (RRC) attempts, E-UTRAN RACH Setup attempts, etc. are logged by numerous counters. In this paper, based on the collected data, we examine the prediction of the network behaviors by using proposed LSTM network. The results has showed potential of our approach in different scenarios.

So this paper is structured as follow: In section 2, we discuss our research methodology. Section 3 presents the experiment results. Finally, section 4 concludes the paper and discusses future works.

II. RESEARCH METHODOLOGY

1. The LSTM Network

The LSTM network that is an advanced form of the recurrent neural network architecture combats against the problem of vanishing gradients. The LSTM-based network is ideal for prediction of temporal sequences, and are replacing many traditional approaches to DL. In LSTM networks, each module, which is called memory cell contains three different gates. An input gate, an output gate and a forget gate denote as i_t, o_t and f_t, respectively.

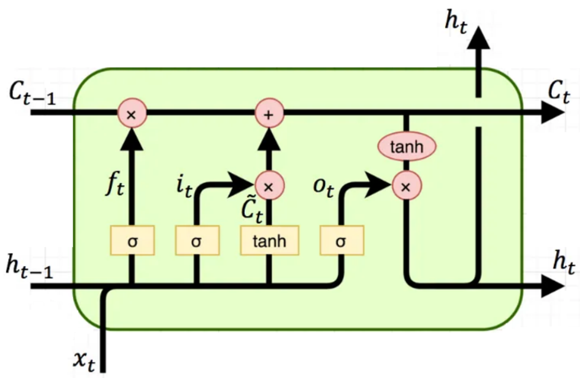

Figure 1. A basic LSTM memory cell unit [11].

The three gates in Fig. 1 are calculated as (1) to (3).

$$f_t = \sigma(W_{fx}x_t + W_{fh}h_{t-1} + b_f) \tag{1}$$

$$i_t = \sigma(W_{ix}x_t + W_{ih}h_{t-1} + b_i) \tag{2}$$

$$o_t = \sigma(W_{ox}x_t + W_{oh}h_{t-1} + b_o) \tag{3}$$

Where σ is the nonlinear activation function. The expression for an intermediate state is:

$$c_t = tanh(W_{cx}x_t + W_{ch}h_{t-1} + b_c) \tag{4}$$

Updates are made to the hidden state and memory cell as (5) and (6), respectively.

$$c_t = f_t \odot c_t + i_t \odot c_t \tag{5}$$

$$h_t = o_t \odot tanh(c_t) \tag{6}$$

where $tanh$ is the nonlinear tanh activation function. The symbol $\odot$ is used to denote Hadamard product.

2. Implementing and Evaluating the Proposed LSTM Network

The MNO's OSS is utilized to gather the data needed to train and validate the proposed LSTM network. Since the coexisting multi-layer multi-technology mobile network has a high data volume, the amount of data that can be collected

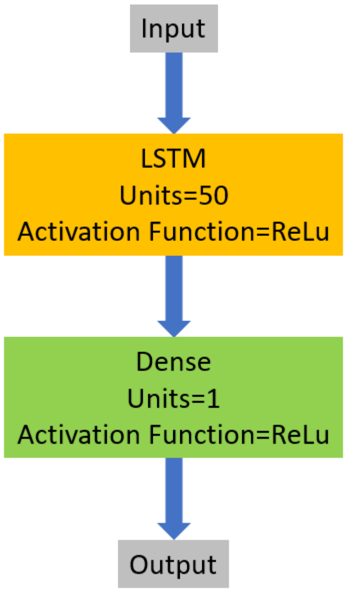

Figure 2. The proposed LSTM network's architecture.

and stored in the OSS is constrained owing to the servers' limited storage capacity. The LSTM network is trained and tested using a dataset with three different KPIs, including E-UTRAN RACH Setup Attempts, RRC Setup Attempts, and E-UTRAN Data Radio Bearer Attempts across time. It was gathered over the period of two weeks at a 15-minute granularity from one Nokia's eNodeB located in Thua Thien Hue province in Vietnam. The entire dataset which includes 1344 samples is split into two subsets with a ratio of 80% and 20% for training and testing, respectively. The network's behaviors prediction model is implemented using Python and Keras library.

A single hidden layer with 50 neurons and an output layer make up the proposed LSTM network to predict a single numerical value, as illustrated in Fig. 2. The Adaptive Moment Estimation (Adam) [12] version of stochastic gradient descent and Mean Squared Error (MSE) are used to optimize the network. Adam calculates an adaptive learning rate for each parameter and it is superior to other adaptive learning rate algorithms in terms of convergence [13].

The hidden layer and output layer are designed to utilize Rectified Linear Unit (ReLU) as the activation function in order to benefit from ReLU, which combats against the vanishing gradient problem and enhance deep neural network learning efficiency [14]. The definition of ReLU function is expressed (7):

$$f_{ReLU}(h_{i,k}) = max(0, h_{i,k}) \tag{7}$$

Other important hyper-parameters in our experiment, including Optimizer, Loss, Batch size and Epochs, are listed in Table I.

Table I
THE PROPOSED LSTM NETWORK'S MAIN HYPER-PARAMETERS.

Hyper-parameters	Values
Optimizer	Adam
Loss	MAPE
Batch size	50
Epochs	1000

Mean Average Percentage Error (**MAPE**), also known as the mean absolute percentage deviation, which is a statistical measure to define the accuracy of a learning algorithm on a specific dataset, is used as the metric to assess the prediction model's error rates across various datasets. The smaller the error is, the better the model is. If and only if the **MAPE**'s value equals zero, the model is ideal.

MAPE that is calculated as (8) can also be expressed in term of percentage.

$$\mathbf{MAPE} = \frac{1}{p}\sum_{q=1}^{p}\left|\frac{A_q - F_q}{A_q}\right| \tag{8}$$

In (8), where A_q means the actual value and F_q is the predicted one. The vertical bars represent absolute values, while p denotes the number of observations.

III. EXPERIMENT RESULTS

This section provides the visualized fit-level prediction results for three 4G/LTE KPIs that describe network behaviors as from Fig. 3 to Fig. 5. As seen in these figures, our approach can predict almost all the sudden changes and overall network behavior trend which are some of the most important factors of monitoring and optimizing network operations.

As we can see, the LSTM network has a promising precision for predicting RANs' behaviors [16]. MNOs are developing and gradually transiting to a Software Defined Networking (SDN) based mobile network architecture paradigm [17]. That means they can flexibly deploy multiple mobile network technologies in the same physical elements such as radio frequency modules, antenna modules, base-band modules, etc. Therefore, thanks to forecast information related to RANs' behaviors, SDN controllers can decide to activate suitable RAN technologies to reduce cross interference and improve qualities of mobile services [18].

Moreover, investigated results of error rates of each prediction are calculated and synthesized in Table II.

Table II shows computed MAPE values of each behavior prediction:

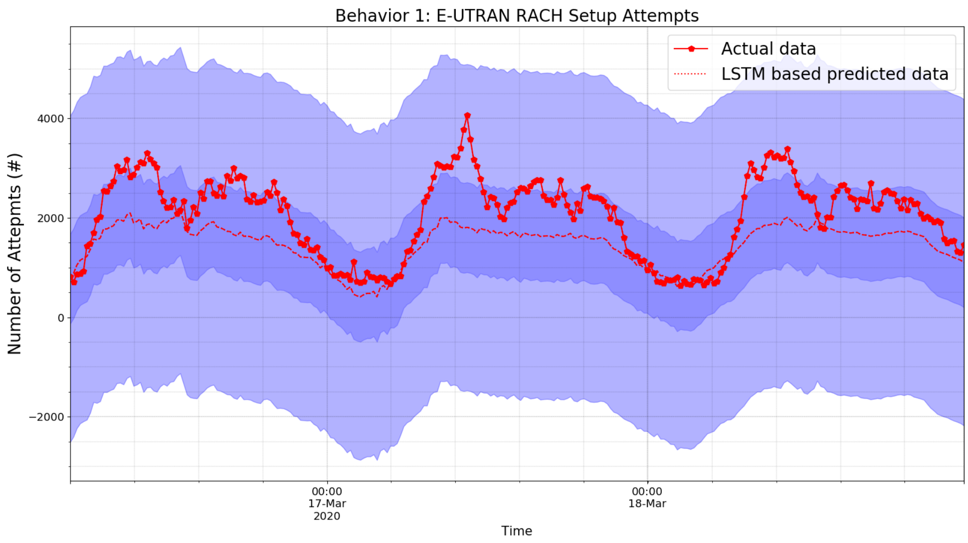

Figure 3. E-UTRAN RACH Setup attempts - predicted data versus actual data

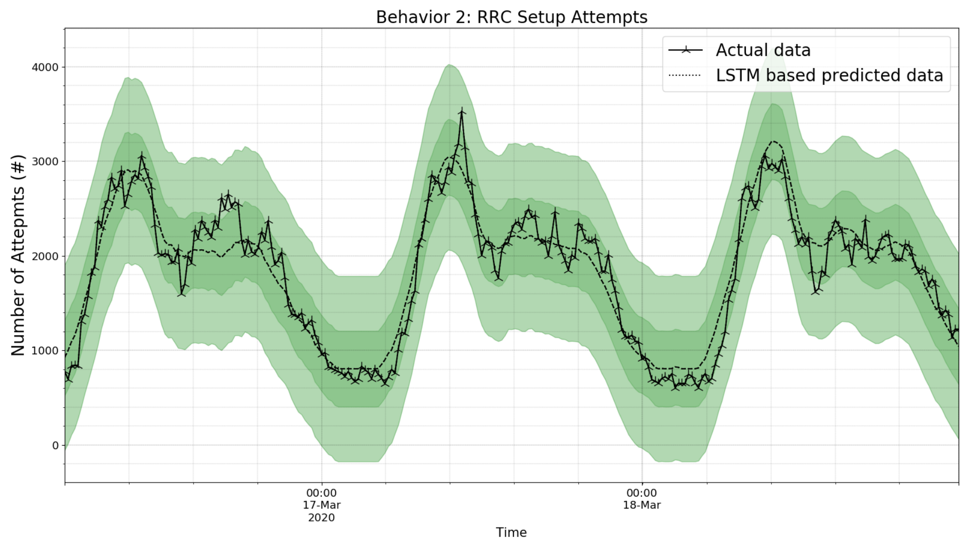

Figure 4. RRC Setup attempts - predicted data versus actual data

Table II
ERROR RATES OF EACH PREDICTION.

Behaviors	MAPE (%)
E-UTRAN RACH Setup Attempts	27
RRC Setup Attempts	10
E-UTRAN Data Radio Bearer Setup Attempts	12

According to Table II, the MAPE values varying from 10% to 27% are equivalent to the accuracy of forecasts ranging from 73% to 90%. Because of the limited training dataset retained on OSS, we can expand the dataset by utilizing data aggregation techniques to increase prediction accuracy. However, with the limited dataset, the quite high accuracy shows strong potential of our approach in predicting network behaviors.

Compared with conventional predictive models including LR and ARIMA in [18], the proposed LSTM network gives similar predictive accuracy, but the complexity of the time series dataset is more complex. The forecasting methods in [18] can only handle data with a stable and regular nature. The proposed LSTM network, on the other hand, can predict more complex data with acceptable accuracy.

Based on the proposed LSTM network, MNOs can put it in use in different prediction scenarios related to separate mobile technologies such as 3G, 4G, 5G and beyond 5G to have forecast information available for deploying appropriate technical solutions.

The operators can proactively monitor their mobile net-

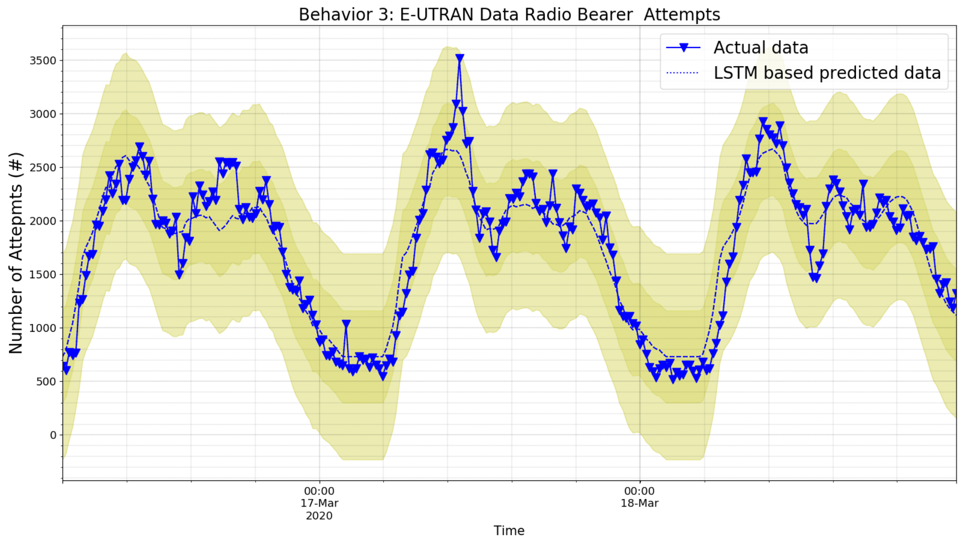

Figure 5. E-UTRAN Data Radio Bearer Setup attempts - predicted data versus actual data

works and take advantage of user-experience-driven network features by using the predicted information [2]. In addition, self-learning and adaptive networks are being researched [7] and developed to enhance qualities and capabilities of future cellular networks for satisfying subscribers' experiences.

IV. CONCLUSION AND FUTURE WORK

Based on actual statistical data from network counters in OSS, this research proposes using the LSTM network to forecast network behaviors in radio mobile network systems. With a size-limited dataset, the model's accuracy shows its potential in forecasting a majority of counters that reflect network behaviors. With the help of network's behavior predictions, operators can have a better overview of the radio networks to allocate resources, implement technical solutions and optimize networks. In the future, we will optimize our model to improve the predicting accuracy for each network behavior and for several network behaviors together to have a better overview of the whole network.

ACKNOWLEDGEMENT

This research was supported by Funds for Science and Technology Murata and The University of Danang - University of Science and Technology under Grant number T2021-02-07MSF.

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Cuong Pham Quoc received the B.Eng. degree in Electronic and Telecommunication Engineering from the University of Danang, University of Science and Technology, (DUT), Vietnam, in 2016. In October 2016, he joined the MobiFone Testing and Maintenance Center, MobiFone Coporation. In 2019, he received the M.Eng. degree in Electronic Engineering from the University of Danang, University of Science and Technology, (DUT), Vietnam. His research interests include mobile communications, radio network optimization, machine learning and deep learning.
Email: cuong.phamquoc@mobifone.vn

Tuan Tang Anh received his B.E. degree in electronic and communication from Danang University of Science and Technology, Vietnam, in 2013 and his Ph.D. degree at University of Leeds, United Kingdom, in 2019. His research interests include SDN, security, intrusion detection, machine learning and deep learning.
Email: tanganhtuan@dut.udn.vn

Chien Tang Tan received his Bachelor degree in Physics - Electronics from the University of Science, Ho Chi Minh City, Vietnam, in 1979. He joined the Department of Electronic and Telecommunication Engineering, the University of Danang, University of Science and Technology. In 2003, he received his Ph.D. Eng. degree in Telecommunications Engineering from Hanoi University of Technology, Vietnam. He was promoted to Associate Professor in 2010. He is currently senior lecturer at the Faculty of Computer and Electronics Engineering, Vietnam – Korea University of Information and Communication Technology, The University of Danang, Vietnam. His research interests include electromagnetic compatibility (EMC) and signal processing.
Email: ttchien@ac.udn.vn