

# Deep RAN: Time Series KPIs Prediction in a Live Cellular Networks with RNN

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**Abstract**— Predictive analytics is employed by telecommunication operators to get valuable insights to become better, faster, and make data-driven decisions. Particularly, to optimize, expand and modify the strategy of mobile network quality, many parameter changes or features are being implemented through mobile networks every day. One of the major challenges in network maintenance is to track the side-effects of mentioned changes, in order to avoid any anomalies due to configurations, by calculating the amount of degradation or improvement. Sometimes these changes coincide with the other network seasonality behavior, then, detecting the side effect factor will be more complex. Nowadays, the deep learning approach in general and especially Recurrent Neural Network (RNN) is a promising approach to predict time series trends in the industry. This prediction of KPI (Key Performance Indicator) has been conducted and implemented in a live Mobile network with around 130K cells, furthermore, training and creating this system has been done on 3 years of actual a mobile network dataset. In this paper, we propose the methods for prediction of the value of different network KPIs in future intervals, and also performance analysis of different methods is investigated.

**Keywords**—*Recurrent Neural Network, RNN, Deep Learning, Machine Learning, Keras, Time Series, LSTM, GRU*

## I. INTRODUCTION

Predictions are very important since they make decisions in many areas of scientific, economic, and industrial activities such as finance, stock exchange, meteorology, and telecommunication. In prediction, the historical data is used to build forecasts. This paper tries to predict the counter's value and KPIs in telecommunication networks. Since the nature of data in the telecommunication network is mainly time-series and this type of data has complex nature in its properties, such as seasonality, level, and the trend may bring various challenges to produce accurate predictions. In terms of seasonality, a time series may exhibit complex behavior such as multiple seasonal patterns, non-integer seasonality, calendar effects, etc. Thus, the traditional methods could not help us with forecasting precisely. In general, accurate time series forecasting and reliable estimation of the prediction uncertainty are critical for anomaly detection, optimal resource allocation, budget planning, and other related tasks. Moreover, the prediction is more challenging in during high variance segments such as holidays and sporting events because forecasting these occasional events depends on numerous external factors that can include weather, city population growth, or marketing [1]. Today's, by emerging machine learning in general and deep learning, in particular, we can forecast the time-series data more precisely. Since, there are different types of data in mobile networks such as the counters or KPIs that show the summation of the measurements like payload or traffic, or different sort of KPIs, illustrate the rate, other KPIs measure the conditions, and count of an event. So, a unique prediction system cannot perform precisely for the whole KPIs and counters. One of the most important roles of the Recurrent

Neural Network (RNN) as a deep learning technique is forecasting the future because it employs the memory in its architecture. This proposed RNN system tries to consider all factors and find the best performance for each type of KPI or counter. The strength of this application is that it uses in a real network, and trained RNN with long term dataset, for example the dataset which uses to train this application is for 3 years. Besides, because it is an applicable project so all the bugs has been recovered. This application has been implemented by Keras which is a high-level API capable of running on Tensorflow. The contributions of this work are as follows. Section II reviews previous related work; Section III presents different types of data in a mobile network; Section IV takes a look at RNN model; Section V represents the methodology by comparing the algorithms' performance and analyzing their sensitivity to various system parameters; Section VI shows the results of RNN configuration for each KPI; Section VII illustrates the real mobile network characteristics; and the last section expresses one of the practical conducted prediction which has been done in mentioned mobile network.

## II. RELATED WORK

The [1] introduces an LSTM system for time series prediction at Uber with multiple seasonal cycles is proposed, this methodology combines a series of multi-seasonal decomposition techniques to the enhancement of LSTM learning procedure. [2] works on Deep and Confident Prediction for Time Series at Uber in this paper the bayesian deep model has been introduced that provides time series prediction along with uncertainty estimation. In [3] a deep learning approach is proposed to predict the behavior of Energy Management System (EMS) devices. For this purpose, a Long Short-Term Memory (LSTM) has been employed, where the input is multivariate time-series data. The [4] works on different types of time-series data it develops the Recurrent Neural Network system for tree types of time series data, univariate time series, multivariate time series, and multi-step time series. Univariate type is a time series with a single time-dependent variable. But, more than one time-dependent variable are there in multivariate time series. Each variable depends not only on its previous values but also has some dependency on other variables. This dependency is used for forecasting future values in multi-step the predictions are computed by the estimated model for each prediction horizon. In [7], four machine learning algorithms have been presented to predict the throughput in mobile networks, and compare the Neural Network Regression, Algorithms based on Mean Throughput, Multiple Linear Regression, and Support Vector Regression. Authors in [8] try to predict the mobile traffic in public scenes by the SOS-vSVR method, and obtain optimal traffic prediction, an SOS (symbiotic organisms search) was adopted to configure the vSVR parameters. One method has been proposed to predict the network traffic based on a deep learning technique and the SCS (Spatiotemporal Compressive Sensing), the presented method adopts a discrete wavelet transform to extract the low-

pass component of network traffic that describes the long-range dependence of itself [9]. In [10] the authors leverage two large-scale real-world datasets to analyze the prediction of mobile data traffic. Three techniques have been compared in [11] to predict the traffic in mobile networks based on the machine learning approach. In this paper TBATS, Double polynomial and LSTM-RNN have been tested. The [12] has proposed a stochastic model to forecast user throughput in mobile networks. Authors in [13] discuss the possibility of applying AI (Artificial Intelligence) technology to network operation and presents some use cases to show good prospects for AI-driven network operation.

### III. MOBILE NETWORK COUNTERS

The performance of a mobile network has been analyzed and monitored with KPIs and PMs (Performance Management) or counters. The PMs (and, hence, KPIs) come from the aggregation of all connections in a mobile cell during a reporting output period (ROP), usually, an ROP defined as a 15 minutes interval but its subcategories are hourly, daily, monthly, or yearly. In general KPIs has been calculated by PMs or counters, on the other hand, a KPI contains different counters or PM.

The PMs are classified in different types, the supported counter types in the mobile networks are listed below [6]:

- PEG (Peg counter): it increases by 1 at each a specific activity. For example, the *pmErabEstabAttInit* counter is a PEG counter in LTE and it stands for the total number of initial E-RAB Establishment attempts.
- GAUGE (Gauge counter): This counter can be increased or decreased depending on an activity in the system. The *pmErabMax* counter in LTE is a GAUGE counter and it defines as a peak number of simultaneous E-RAB usage.
- ACC (Accumulator counter): An Accumulator counter increases by the value of a sample. It points out the total sum of all values taken during a certain time. For example, the *pmErabLevSum* is an ACC counter which denotes the peak number of simultaneous E-RAB usage.
- SCAN (Scan counter): It somehow looks like the ACC.
- PDF (Probability Density Function): This counter is a list of bin values. If the value falls within a certain range, the counter increases. *pmErabEstabAttInitQci* is a PDF counter and defines as the total number of initial E-RAB setup attempts per QCI.

From the time-series side, each type of PM or KPI has its own characteristics, and it should be considered separately, furthermore, a unique prediction system cannot be used for all sorts of PMs. In addition to these categories, some KPIs indicate the rate of measurement such as CSSR (Call Setup Success Rate) or RAB (Radio Access Bearer) Establishment Success Rate, in spite of these KPI which fluctuates around 100%, certain Rate KPIs are near to zero, for example in DCR (Drop Call Rate) should tend to the zero. Many KPIs point out a value such as throughput, or payload and have an increasing or decreasing trend in the long term. Another sort of KPI shows the average of measurement. Comprehensively, this paper tries to consider all

types of KPIs and counters, and predicts them separately.

### IV. RNN DEEP LEARNING MODEL

The most important characteristic of RNNs is using the memory to process sequences of inputs. It means, unlike the CNN (Convolutional Neural Network) architecture, where there is no memory to capture the temporal correlation, RNNs have the capabilities to capture the sequential correlations and information. There are 3 types of recurrent neural networks, the simple RNN, long short term memory unit (LSTM) and gated recurrent unit (GRU). Another advantage of RNNs is going to be the size of data in input, i.e. there is no limitation for the input and output size and structure. Mainly the GRU and LSTM have been used in this work to model the network KPI's temporal behaviors.

In LSTM and GRU networks, there is a cell memory. After training the neural network, the network can select the information to save to pass through the networks, and which part of the information can be ignored. Hence, there is a forget gate and memory cell [14].

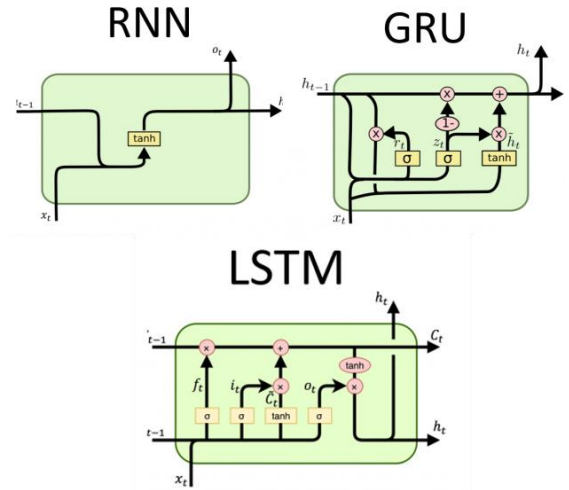


Fig 1. Recurrent Neural Network types.

Fig.1 illustrates the different types of RNN networks. In LSTM the follows notations have been defined:

$h_t, C_t$  : Hidden layer vectors,  
 $x_t$  : Output vector,  
 $b_f, b_i, b_c, b_o$  : Bias vector,  
 $W_f, W_i, W_c, W_o$  : Parameter matrices, and  
 $\sigma, \tanh$  : Activation functions.

### V. METHODOLOGY

In time series prediction, with given a univariate time series  $\{y_1, \dots, y_T\}$  including T observations, the N next observations of the time series  $\{y_{T+1}, \dots, y_{T+N}\}$ , has been predicted. Time series in different applications or fields can have variety resolutions (e.g. hourly, daily, monthly, yearly) with considering the T interval. In this project model, the time series data are Data Payload, Success Rate KPIs, Drop Rate KPIs, and Throughput in the daily interval, and horizon (T) has been considered for 7 days, this predicted time can be changed.

The proposed methodology for time series prediction is performed in three steps.

### A. Data preprocessing

In this step, the data should be separated into two parts train and test, since there is not any explicit labeled dataset, so the  $y_{T+N}$  are considered as the target or labeled data for  $y_T$ , which the N is next time when we want to predict. Before the dataset uses for train and test part it should be normalized.

### B. Training the model

The training part should consider all types of KPIs, thereby we cannot use one RNN network for all sorts of data. For an RNN configuration, we have different parameters like Activation Function, Optimizer, Loss Function, size of the hidden layer, batch size, number of the epoch, and type of RNN, for example simple RNN, LSTM or GRU. For this project all these parameters have been combined and tried, to see which of them has the best performance.

### C. Evaluation

In this section profound analysis has been illustrated for the payload KPI, then based on this procedure the other KPIs have been processed. This system has been trained with all different available combinations for find the best result. Then the RMSE (Root-mean-square deviation) has been calculated to evaluate and compare these different combinations to find the best system for each KPI. The TABLE I shows the average RMSE for each parameter, for example in RNN model rows, the 458 equal to the average of RMSE for all other parameters which using the GRU.

TABLE I. AVERAGE OF RMSE WITH DIFFERENT ALGORITHMS AND PARAMETERS

		Average of RMSE
RNN Model	GRU	458
	LSTM	562
Activation Function	Tanh	150
	Relu	756
	sigmoid	429
	softmax	634
Optimizer	Adagrad	389
	Adadelta	440
	Adamax	461
	Adam	196
	RMSprop	212
	sgd	1381
	Nadam	365

TABLE II. RMSE RESULT WITH DIFFERENT ACTIVATION FUNCTIONS AND OPTIMIZERS

RMSE in LSTM with 40 Hidden layer		Activation Function			
Optimizer		relu	sigmoid	softmax	tanh
	Adadelta	50.0802	717.866	386.268	26.2446
	Adagrad	86.1045	542.79	1513.89	23.6462
	Adam	175.858	246.41	267.773	208.198
	Adamax	279.579	356.74	381.273	52.2745
	Nadam	165.266	116.517	99.2077	144.938
	RMSprop	166.641	198.218	270.228	114.563
	sgd	85.5328	2710.5	3193.28	93.7166
RMSE in GRU with 40 Hidden layer		Activation Function			
Optimizer		relu	sigmoid	softmax	tanh
	Adadelta	92.6716	339.238	516.909	170.179
	Adagrad	71.7681	463.059	439.995	5.26802
	Adam	240.912	80.1843	263.753	73.6884
	Adamax	239.792	198.739	318.687	120.23
	Nadam	232.385	231.546	121.561	96.9658
	RMSprop	265.241	116.154	239.814	120.376
	sgd	126.107	1512.97	3134.74	76.687

The TABLE II demonstrates, RMSE per each combination, for this specific KPI the “Tanh” in activation functions, the “Adagrad” as an optimizer in GRU system has the best result. The next step is finding the optimum size of the hidden layer. Fig. 2 illustrates our analysis in another side, in this study 40 hidden layer is going to be the best performance for the Adagrad, Tanh, and GRU combination.

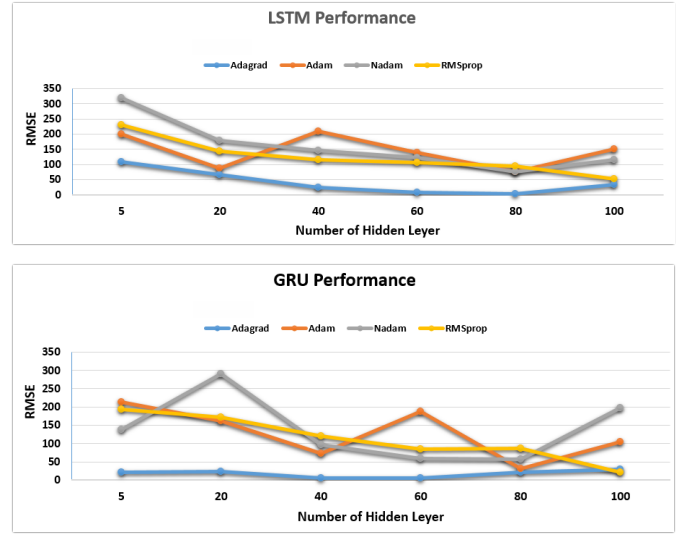


Fig. 2. Tanh activation function with verity optimizer’s performance on LSTM and GRU system in different hidden layer size.

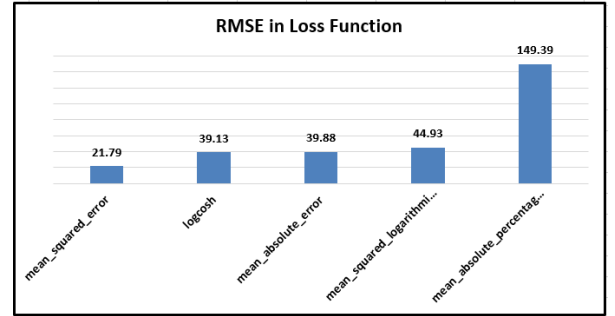


Fig. 3. RMSE in tanh, Adagrad, GRU system for different loss functions

Different types of Loss Function have been tried on the GRU with tanh, Adagrad, for Payload KPI. The result has been shown in Fig. 3. In this system Mean\_Squared\_Error has the best performance. Apart from these five loss functions squared\_hinge, hinge, and categorical\_hinge have been tried but the results were somehow outlier so they don’t consider to this evaluation.

The final proposed system with appropriate parameters predicted the payload in a cluster of sites very accurately, Fig. 4 shows this accuracy.

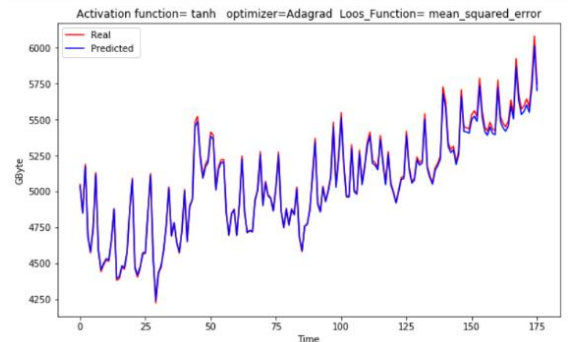


Fig. 4. Actual and prediction of Payload of sites cluster with the proposed RNN system.

## VI. RNN CONFIGURATION FOR EACH KPI

In previous section the best configuration has been found for the Payload KPI, but in a Mobile networks we have many important KPIs, which need to forecast. The TABLE III shows the network configurations with all possible and effective parameters.

TABLE III. RNN CONFIGURATION

	Payload or Traffic	Throughput	Drop Rate	Establish Success Rate
Optimizer	Adagrad	Nadam	Adam	Adagrad
Loss Function	MSE	MAPE	MSE	MSLE
Activation Function	Tanh	Tanh	Relu	Relu
Hidden Layer	50	43	30	10
Batch size	15	15	11	25
RNN	GRU	GRU	LSTM	GRU
Epoch	300	200	200	70

MAPE: mean\_absolute\_percentage\_error

MSE: mean\_squared\_error

MSLE: mean\_squared\_logarithmic\_error

The flowchart in Fig. 5 is showing the application performance in different KPIs.

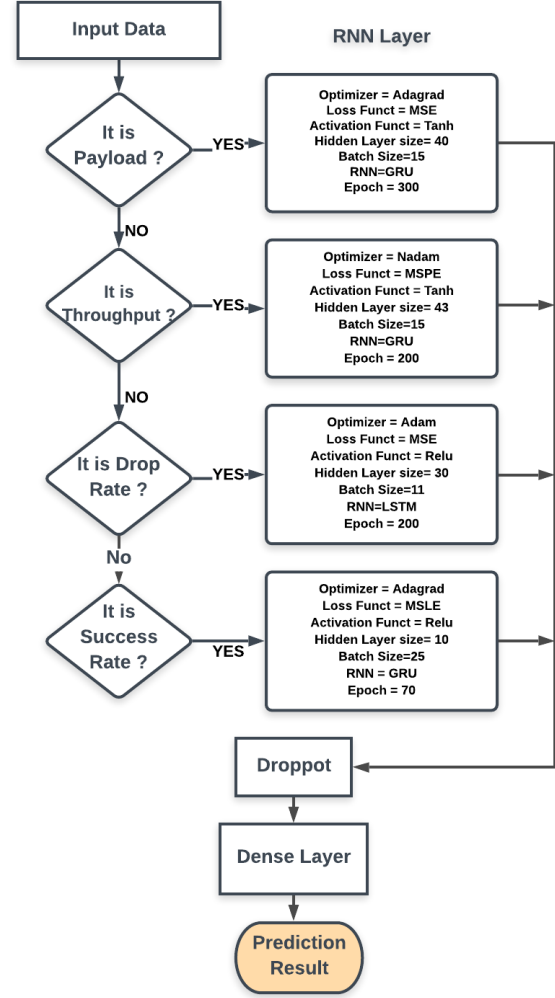


Fig. 5. The flowchart of the implemented application for different KPIs

## VII. MTN IRAN-CELL CHARACTERISTICS

This application is a suitable platform for being used in Mobile Operators like MTN Iran-cell, which is officially titled Iran's biggest data operator; Iran-cell is pioneering in equipping its subscribers with the fastest and most advanced data network in the country. Besides, Iran-cell owns the largest 2G-3G-4G-4.5G RAN and modernized core mobile network, and fixed wireless TD-LTE internet services in the Middle East. It connects over 45 million people in Iran via 260,000 cell carriers in different technologies [14].

1) *Performance and Optimization Challenges:* As the Mobile networks advance to such large scales, the configuration, operation, optimization, and management teams will be in dire need to have intelligent tools to handle the new and diverse problems. Furthermore, such huge mobile operators these types of networks will also collect gigantic amounts of data in order to monitor, maintain and improve network stability, performance to provide better services by performing optimization actions to satisfy subscribers' expectation. In traditional approaches, some applications are used just to monitor main KPIs or revenue streams of the operator to ensure operator obligations are met

and investment is protected. Based on our experiences, some most important KPI can be observed and monitored in these applications [14].

2) *Application Specification:* The input to our proposed platform is a set of RAN KPIs as time-series data. Main Tools characteristics are as follows:

- A) The proposed platform is scalable since it is capable of predicting regardless of the type of KPI. It means, it is possible to input any type of KPI to the trained neural network to forecast data.
- B) The technology which is used can be different network to network, so it can be used for all kinds of technologies such as 2G, 3G, 4G, 4.5G, and 5G.

## VIII. PRACTICAL EXPERIMENT IN LIVE MOBILE NETWORK

In a scenario, we had activated the roaming of two Mobile Operators between some specific sites and we wanted to know if our traffic increases or we lose the traffic in these sites, in general, we don't know this implementation in the network is useful or harmful. By using this proposed RNN method the KPI trend can be predicted to see the impact. Fig.6 shows the result of this deep learning system on the payload KPI, it illustrates with this implementation (Blue) and without this activation (Orange), in other words the orange line shows the prediction trend.

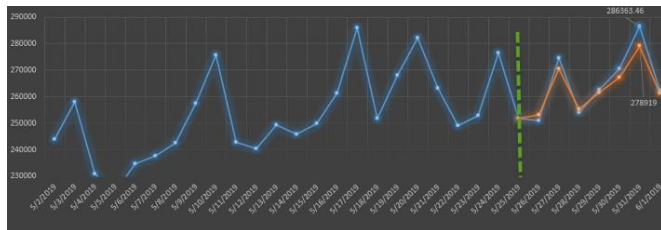


Fig.6. The practical prediction system result in a live network

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