Reinforcing mobile network planning with forecasted input data obtained by a machine learning approach

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Abstract— **Mobile network planning (MNP) is an essential task of each mobile operator for meeting communication needs and ensuring qualities of networks for subscribers. In addition, a good MNP strategy guarantees to optimize operators' Capital Expenditure (CAPEX) and Operating Expenditure (OPEX). This paper investigates and proposes machine learning (ML) approaches with linear regression model and autoregressive integrated moving average (ARIMA) model for reinforcing MNP by forecasting data of number of subscribers in cellular systems based on real statistical information from operation support systems (OSS). Training and testing data are taken from home location register (HLR) for verifying and analyzing the results. With these predicted data, they can be used as an additional input to enhance MNP's results for reinforcing network development strategies and leveraging qualities of network rollout in the future.**

Keywords— **forecast, MNP, subscriber, linear regression, ARIMA.**

I. Introduction

Nowadays, artificial intelligence (AI) in general and ML in particular that play a key role in digital transformation revolution with great recent achievements such as Tesla's self-driving cars, Google's OCR systems, etc. AI and ML are gradually penetrating into all areas of life and the telecommunication industry is not out of this trend. Giant telecom vendors in the world such as Nokia Siemens Networks (NSN), Huawei Technologies and Ericsson have been embedding ML technologies into network managements and operations [1].

Mobile communications have made great leaps to connect people and communities by various multiple access technologies from analog telecom systems (1G) to complex digital telecom systems (5G, 6G and beyond) so far. On average, every 10 years a new generation of mobile technologies is introduced [2] that brings improvements in experience, performance, efficiency and capability. Operating, managing and optimizing multi-layer multi-platform technology mobile network tasks are very complicated and beyond the ability of human to fully comprehend and control. ML intelligence offers the best opportunity to achieve the high levels of automation necessary to manage the complexity and optimize system performance [3].

Network planning is the first and most supreme step for any mobile network deployment. The quality of planning determines, user experiences and return on invested capital (ROIC). Traditional network planning tools concentrate on the coverage for voice services which is relatively simple to predict [1]. Today, mobile network system creates a tremendous amount of big data so that user experiences depend heavily on optimized parameters like data throughput and latency. ML and predictive models provide predicted data as inputs for network planning tools so that the network is more likely to meet not only the coverage target but also the user experience requirements of all subscribers.

In this paper, we focus on predictive analytics which encompasses a variety of statistical techniques from data mining, predictive modelling, and ML, that analyze current and historical facts to make predictions about future or otherwise unknown events that turns data into actionable information.

This paper is concerned with linear regression (LR) model and ARIMA model which are used to predict number of subscribers in cellular systems with the intention of robust MNP using limited datasets taken from NetAct OSS systems.

II. Brief Description on Mobile Network Planning

MNP is the most critical phase in the life cycle of a mobile network system as it includes traffic forecasting and capacity planning to balance network investment (OPEX, CAPEX), end user experience and long-term network performance.

The telecom industries have commercially witnessed the mobile communication evolution from 1G to 5G so far. Regardless of the mobile technology, the overall MNP process consists of three main steps: pre-planning (aka dimensioning), detailed planning and post planning (aka optimization) as illustrated in Fig. 1 [4]. The output of the dimensioning phase is an approximate number of 2G's BSs, 3G's NodeBs, 4G's eNodeBs or 5G's gNodeBs required to cover an area of interest.

Since there are many mobile technologies which co-exist in the operator networks at the same time with diverse types of subscribers and services, the good MNP strategy can help operators develop network strategies and action plans that will attain business goals and provide input to the subsequent design

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and integration network. The more inputs operators have, the better the MNP is.

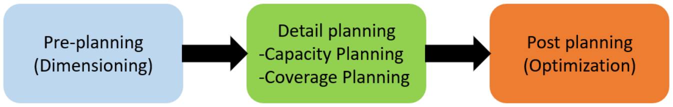

Fig.1. Three main steps of MNP process [4]

Fig.2 illustrates an interface architecture of typical existing mobile network system that has different radio access networks (RAN) (2G/3G/4G/5G) and associated core networks, all of which are connected to the operator's OSS to operate and manage.

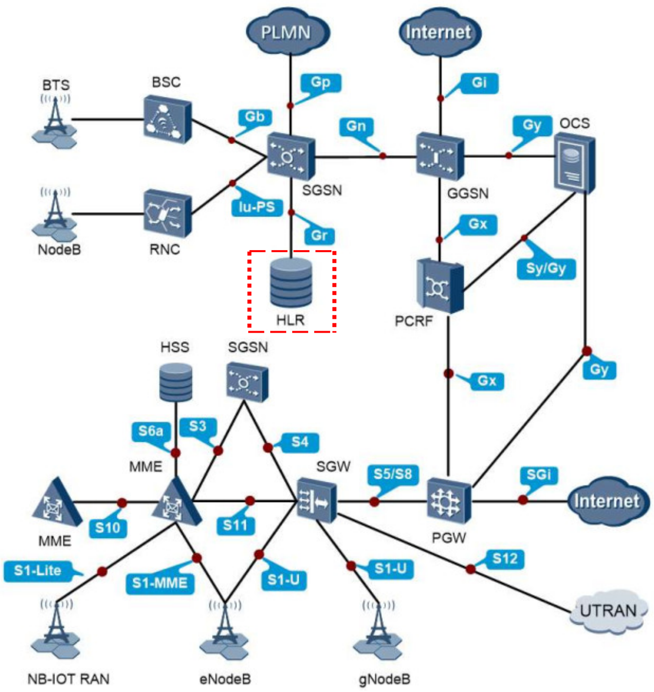

Fig.2. The interface architecture of typical existing mobile network system

The HLR in this architecture is a reference database used for storage and management of subscriptions which include 2G, 3G, 4G and 5G subscriber profiles. It is considered the most important database since it stores permanent data about subscribers, including a subscriber's service profile, location information, authentication parameters and activity status. This information is entered into the database by the network provider when new subscribers who buy subscriptions in the form of subscriber identification modules (SIMs) are added to the system. This paper investigates the prediction of the number of subscribers to supplement an extra input for enhancing quality of MNP based on dataset collected from HLR.

III. The Machine Learning Approach for Reinforcing MNP

A. *The Linear Regression Model*

The LR model is a ML model which algorithm based on supervised learning which is employed for modelling a linear relationship between dependent variable value y and a given independent variable x [5]. Using the notation defined in the Table 1, the purpose of LR is to find the weight vector ϕ and bias b that given some a new data point x_i, sampled from the same distribution as the training data will predict the target y_i with the lowest error [6].

TABLE 1: SYMBOL DESCRIPTION

Symbol	Description
m	Number of samples in dataset
i	Index of each sample
$x^{(i)}$	Input data point of i^{th} sample
x	Input vector
X	Collection of datapoints (The entire dataset)
$y^{(i)}$	Corresponding label of i^{th} sample
d	Number of features
$\overline{y}$	Mean value of observed data
Λ	Prediction results
ϕ	Weight vector
b	Bias
$l^{(i)}$	The i^{th} squared error
ζ	Minibatch of training
σ	Predetermined step size of parameter update process

Prediction results can be expressed as Λ:

$$\Lambda = \phi_1 x_1 + \ldots + \phi_d x_d + b \qquad (1)$$

The model compactly using a dot product can be written as:

$$\Lambda = \phi^T x + b \qquad (2)$$

For a collection of data points X, the prediction Λ is as:

$$\Lambda = Xw + b \qquad (3)$$

The squared error is calculated by:

$$l^{(i)}(\phi, b) = \frac{1}{2}\left[\Lambda^{(i)} - y^{(i)}\right]^2 \qquad (4)$$

Determining the accuracy of a model on the whole dataset by averaging the loss on the entire training set.

$$L(\phi, b) = \frac{1}{m}\sum_{i=1}^{m} l^{(i)}(\phi, b) = \frac{1}{m}\sum_{i=1}^{m}\frac{1}{2}\left[\phi^T x^{(i)} + b - \Lambda^{(i)}\right]^2 \quad (5)$$

Finding parameters (ϕ^*, b^*) which minimize the total loss across all training samples:

$$\phi^*, b^* = \underset{\phi, b}{argmin}\, L(\phi, b) \qquad (6)$$

LR uses gradient descent algorithm to optimize the learning model via iteratively reducing the error by updating the parameters in the direction that incrementally lowers the loss function [5]. Sampling a minibatch ζ consisting of a fixed number of training data stochastically. The update process can be written mathematically as:

$$\left(\phi,b\right)\leftarrow\left(\phi,b\right)-\frac{\sigma}{|\zeta|}\sum_{i\in\zeta}\partial_{(\phi,b)}l^{(i)}\left(\phi,b\right) \quad (7)$$

The expression (8) can be rewritten explicitly as:

$$\phi\leftarrow\phi-\frac{\sigma}{|\zeta|}\sum_{i\in\zeta}x^{(i)}\left[\phi^{T}x^{(i)}+b-y^{(i)}\right] \quad (8)$$

$$b\leftarrow b-\frac{\sigma}{|\zeta|}\sum_{i\in\zeta}x^{(i)}\left[\phi^{T}x^{(i)}+b-y^{(i)}\right] \quad (9)$$

B. The ARIMA model

The ARIMA model, also known as the Box-Jenkins model, which is a type of model that captures a suite of different standard temporal structures in the time series data. The acronym of ARIMA is expository as brief description below [7]:

- Autoregressive (AR) mentions a model which shows a changing variable that regresses on its own lagged observations.
- Integrated (I) refers the difference of raw observations to allow for the time series to become stationary.
- Moving Average (MA) means the dependency between an observation and a residual error from a moving average model applied to lagged observations.

A non-seasonal ARIMA model is achieved by incorporating differencing with autoregression and a moving average model that is classified as ARIMA(α,β,γ) model [8], where:

- α is the order of the autoregressive part.
- β is the degree of first differencing involved.
- γ is the number of lagged forecast errors in the prediction equation.

An $AR(\alpha)$ is the auto-regressive model of order α that can be expressed as the form:

$$X_t=\sum_{i=1}^{\alpha}\Psi_i X_{t-i}+w_t \quad (10)$$

where X_t is stationary, $w_t \sim wn\left(0,\sigma_w^2\right)$ and Ψ_i are model parameters.

A $MA(\gamma)$ is the moving average model of order γ that can be written as:

$$X_t=\sum_{j=1}^{\gamma}\theta_j w_{t-j}+w_t \quad (11)$$

where w_t and are paramters.

The finite MA model is contrary to the AR model because the observation is just a weighted moving average over past forecast errors.

The I process in ARIMA refers to the differencing process which is a popular and widely used data transform to make time series data stationary. Differences of order β are defined as:

$$\nabla^{\beta}=\left(1-B\right)^{\beta} \quad (12)$$

where ∇ is considered as the first difference and B is the backshift operator. $\left(1-B\right)^{\beta}$ can be algebraically extended for higher integer values of β.

Finally, the general ARIMA(α,β,γ) model can be written as:

$$\Psi\left(B\right)\left(1-B\right)^{\beta}X_t=\theta\left(B\right)w_t \quad (13)$$

where $\Psi(B)$ and $\theta(B)$ are the autoregressive operator and the moving average operator, respectively.

IV. NUMERICAL RESULTS

A. Model Implementation

This paper uses data obtained from the real HLR/OSS to train and test the LR and ARIMA models. Data is integer values of 2G, 3G and 4G/LTE subscribers registered in the operators' HLR of Danang city over time, which was collected during approximately three years from the 30th of August 2017 to the 15th of August 2020 with 1-day granularity. The whole dataset is divided into two sub-datasets at ratio 80% and 20% for training data and testing data, respectively.

The implementation of the LR and ARIMA prediction model is done by Python programming language with Skicit-Learn, Numpy and Pandas libraries.

The R squared (R^2) is chosen as the metric to measure how close each data point fits the regression line or how well the models fits the data, which is expressed as [9]:

$$R^2=1-\frac{SSR}{SST}=1-\frac{\sum_i\left(y_i-\Lambda_i\right)^2}{\sum_i\left(y_i-\overline{y}\right)^2} \quad (14)$$

In the equation (14), SST is the total sum of squares that represents the total variation of the dependent variable around its mean value and SSR is the sum of square of residuals which can be thought of as the "unexplained" variation in the variable. R^2 equals 1 that means the model explains all of the variation in the response variable. Therefore, the larger the R^2, the better the prediction model fits observed data.

B. Result Analysis

In this section, we present the visual results of fit levels of prediction as graphs from Fig. 3 to Fig. 5 and multi-step prediction of number of 2G, 3G and 4G/LTE subscribers that is performed for four later time instants. In addition, the accuracy of each prediction per type of subscriber is calculated and shown in Table 2. The x-axes of all graphs represent the time with 1-day timesteps.

- Fit levels of 2G network's subscriber prediction model

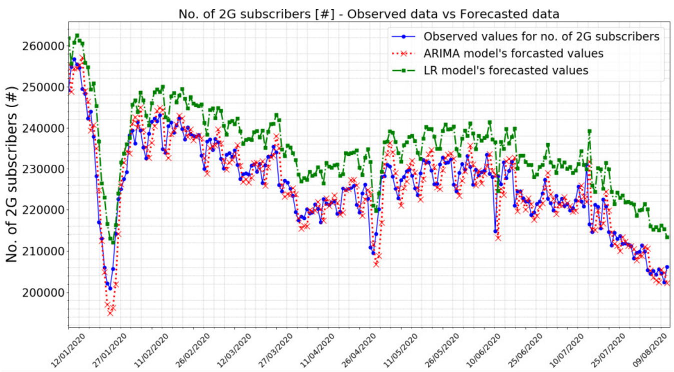

Fig. 3. Number of 2G subscribers - observed data versus forecasted data

- Fit levels of 3G network's subscriber prediction model

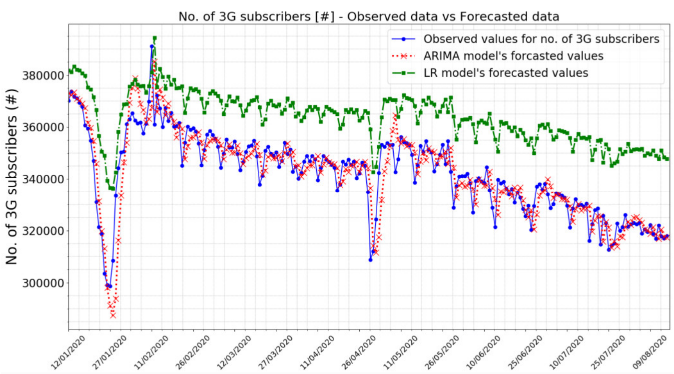

Fig. 4. Number of 3G subscribers - observed data versus forecasted data

- Fit levels of 4G network's subscriber prediction model

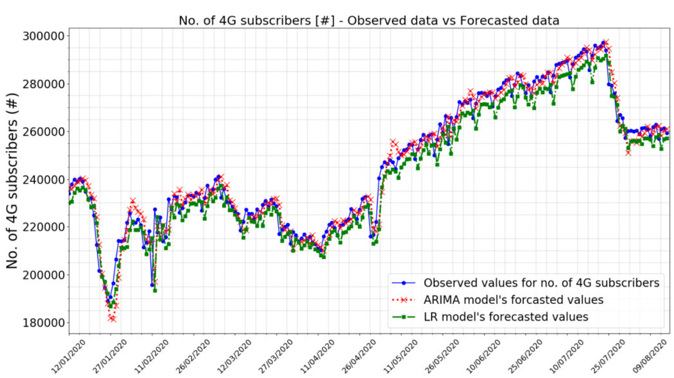

Fig. 5. Number of 4G/LTE subscribers - observed data versus forecasted data

From the Fig.3 to Fig.5, it is visually obvious that the ARIMA model has better prediction performance than the LR model's. The main reason for that is due to the ARIMA model having the integrated process which makes time series variables stationary. The Table 2 summarizes the score of prediction of each model.

TABLE 2: ACCURACY OF EACH FORECAST

Model	Accuracy measured by R squared of forecast		
	No. of 2G subscribers	No. of 3G subscribers	No. of 4G subscribers
ARIMA	0.83	0.75	0.96
LR	0.16	-1.18	0.94

According to Table 2, the ARIMA's R^2 scores varying from 0.75 up to 0.96 are equivalent to the accuracy of forecast ranging from 75% to 96%. Therefore, the ARIMA model has an acceptable precision for forecasting the number of subscribers over time. In other words, the ARIMA's R^2 scores from the experiment indicate a high degree of fitting prediction equations.

The LR's R^2 scores fluctuate from -1.18 to 0.94. The negative values of R^2 score means that predictions are worse than using simple mean, thus the model fails to make forecasts. However, the LR's R^2 score for forecasting number of 4G/LTE subscriber is good with 94% accuracy. According to the degree of reliability target, we suggest to use the ARIMA model for predicting number of mobile subscribers based on the coefficient of determination in order to enhance the quality of MNP

Fig. 6 to Fig. 8 illustrates prediction results as graphs of four future data points of the number of subscribers for four later time instants.

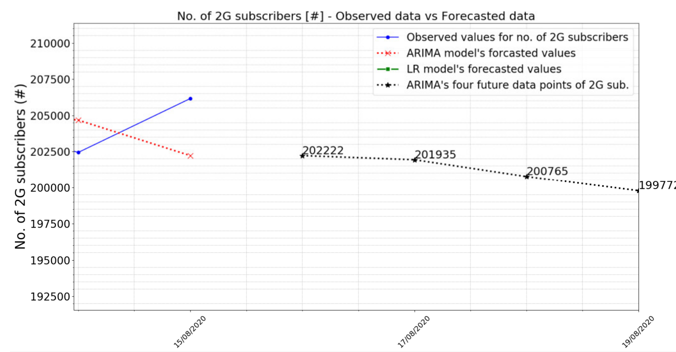

Fig. 6. Four future data points of 2G subscribers

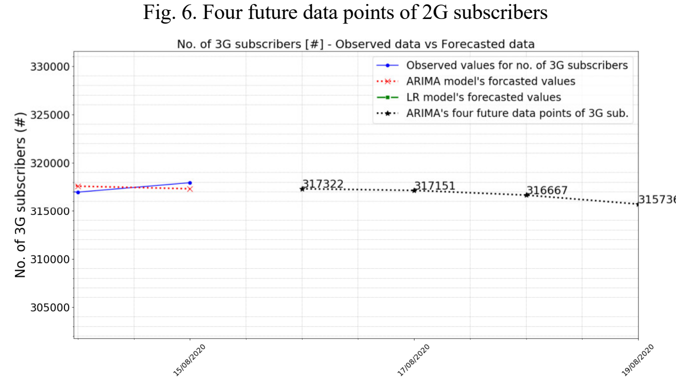

Fig. 7. Four future data points of 3G subscribers

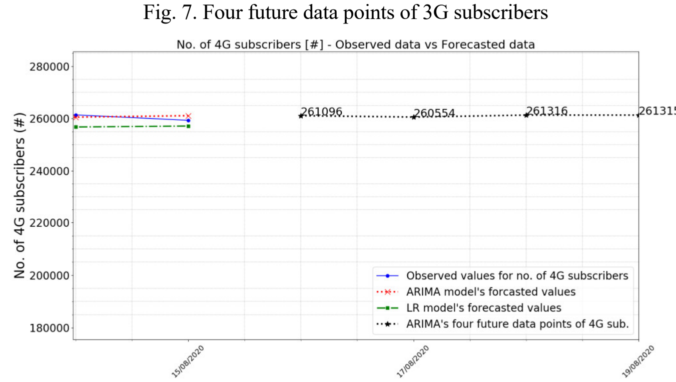

Fig. 8. Four future data points of 4G subscribers

The Table 3 synthesizes prediction results of four future data points of three types of mobile subscribers.

TABLE 3: FUTURE DATA POINTS OF EACH FORECAST

Prediction data point	Forecast values [#]		
	No. of 2G subscribers	No. of 3G subscribers	No. of 4G subscribers
16th Aug. 2020	202,222	317,322	261,096
17th Aug. 2020	201,935	317,151	260,554
18th Aug. 2020	200,765	316,667	261,316
19th Aug. 2020	199,772	315,736	261,315

According to prediction data as Table 3 with accuracy varying from ~75% to ~96%, the quality of MNP strategies can be improved. For example, according to the forecasted number of 2G subscribers, the MNOs can find out a suitable time to switch off 2G signals with the aim of making room for reserving the frequency spectrum which is freed up from 2G systems for broadband networks such as 4G/LTE, 5G and beyond 5G without auctioning new spectrum [10]. Beside this, MNOs is currently developing and gradually transiting to a software defined networking (SDN) based mobile network architecture paradigm [11] that means they can flexibly deploy multiple mobile network technologies in the same physical elements such as radio frequency (RF) modules, antenna modules, baseband modules, etc. Therefore, thanks to forecast information related to number of subscribers, SDN controller can decide to activate suitable RAN technologies to reduce inter-cell interference and improve the qualities of mobile services. Based on the ML approach solutions to mobile networks we can wisely apply it into the other prediction of counters reflecting other information which is helpful for making MNP more robust such as data volume, voice traffic, etc. to proactively roll out technical solutions [1].

V. CONCLUSION

This paper proposes using ML approach to forecast number of mobile subscribers in cellular systems based on real statistical information from networks' HLR in OSS with a view to supplement one more input that reinforce MNP processes. The accuracy of the model is up to 96% so that it is suitable for forecasting number of subscribers with the real dataset size. With forecasted data of networks, telecom operators can dynamically allocate resources and proactively deploy technical solutions with the intention of meeting not only the coverage target but also the user experience requirements of all customers.

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