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RESEARCH ARTICLE

Data-Driven Model for Sliced 5G Network Dimensioning and Planning, Featured With Forecast and "what-if" Analysis

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ABSTRACT Network Slicing is an enabler for new use cases and an improved network performance, especially for 5G private networks, which opens new business opportunities for vendors and applications for customers. On the other hand, the slicing mechanism adds another level of complexity to network management that significantly increases total cost of ownership. Full automation is a must, which is also evident in the standardization work on autonomous and zero-touch mobile networks under the umbrella of 3GPP and ITU organizations. Moreover, there is a clear methodological gap in research related to mobile network slicing, i.e. capacity dimensioning and planning for such infrastructure. The concept of the network modeling tool has been updated with an emphasis on adding functionality of mobile network capacity dimensioning and planning, which is presented in this article. Data-driven framework with thoroughly verified methods is outlined (e.g., Prophet, Neural Networks, VARMAX and its univariate equivalent - ARMA). Special attention is paid to traffic forecasting as the basis for the dimensioning and planning process. We evaluate how to use the framework as a scenario simulator to estimate the impact of traffic changes in any slice on quality of service (namely throughput and delay) of all. Finally, we explain how this solution realizes the concept of Digital Twin-based network simulator.

INDEX TERMS 5G mobile communication, autoregressive processes, capacity planning, digital twins, network slicing, neural networks, quality of service.

I. INTRODUCTION

Wireless 5G technology with higher speeds, lower latency, and higher availability (than 4G) enables new services with stringent performance requirements, e.g., enhanced mobile broadband, ultra-reliable, low-latency communications, and massive machine-type communications [1]. Network Slicing (NS) is a solution to manage these requirements and to provide demanded Quality of Service (QoS). It is essentially a network virtualization technique [2], which logically divides physical network resources into logical network layers, called slices. Resources can be dedicated to specific slices in order to separate their traffic and/or to guarantee a certain level of QoS, and can be shared between slices to increase the efficiency of network utilization. Nokia Bell Labs estimates that this addition of another level of complexity to network management without automation will increase the total cost of ownership of the network by 30% versus that of the initial physical network [3]. On the other hand, full automation of NS can lead to a 32% cost reduction.

With network growth, Communication Service Providers (CSPs) have to regularly monitor and evaluate its capacity,

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and if that is declining, they perform a process of network (re-)planning including capacity dimensioning [4]. The dimensioning process is often done by vendor proprietary tooling, based on underlying product capabilities and internal know-how. It is also often done without any sophisticated approach, but with the use of spreadsheets [5]. Furthermore, this methodology is based on standard linear or queuing models [6] that are adjusted and verified with network simulations or laboratory tests. The impact of product extensions, such as new or extended functionalities, is added to the model as an additional linear block or coefficient, and this approach may give inaccurate results with complex deployments or the introduction of NS due to the effect of multicollinearity [5].

On top of the issues with the dimensioning methodology itself, there is an underlying concern that is related to its inputs. To properly estimate required capacity, CSP or vendor need to know what the traffic model would be, with the list of services, their data volumes, and QoS requirements for specific point in time in the future, e.g., from few weeks to several months depending on the deployment plans. For long-term planning, it is enough to take, e.g., CSP market penetration plans, but not for short-term estimations or for site specific scenario of time-variant wireless networks [1].

In this article, we evaluate possible data-driven models to forecast slice level throughput and delay. The multivariate approach is used to incorporate cell level specific radio and traffic conditions and have accurate forecasts per cell. We elaborate how such an approach can be used in dimensioning and planning processes for natural network evolution. Furthermore, we analyze how such approach can be used in "what-if" analysis for over-natural traffic growth scenarios, e.g., CSP plans to boost specific service usage or new service creation plans. It is verified that modification of traffic conditions in the model with simultaneous assumption of unmodified environmental conditions provides statements valid for throughput and delay processes observed in real-world system, which proves that the proposed analog can be used to explain and quantify that phenomena through data-driven simulation of the sliced wireless networks.

Overall, this approach is a first step to a materialization of the Digital Twin (DT) concept for communication networks. According to definitions in the literature [7], our DT is a virtual representation of a physical cell in the 5G base station. Training DT with real data measured in each cell separately creates dedicated/customized twins that can be used for cell traffic and delay forecasting and also for performing "what-if" analysis. It can be also used in optimization system suitable for recommendation of the capacity extensions, or for slice planning related parameter settings.

The paper is organized as follows. Section II describes research works that are related to 5G traffic forecasts, NS dimensioning and planning, and Network Digital Twin (NDT) concept. Section III explains the characteristics of the real network data that have been used in this research. Section IV elaborates the concept of using the forecasting model as a simulator for desired/expected scenarios. Section V describes the approaches to 5G data modeling that have been studied. Section VI is the summary of the results that have been achieved. Section VII concludes this study.

II. RELATED WORKS

A. 5G TRAFFIC FORECASTING

Network traffic can be forecasted using the so-called offline methods or online methods [8]. Offline methods collect information about the entire time-series and then make forecasts. Otherwise, online procedures learn only about a particular data segment and sequentially update the model parameters based on the revised data. Nowadays, plenty of papers about the 5G network dimensioning refer to Machine Learning (ML) methods. One of the most commonly used ML techniques is neural networks with Long Short-Term Memory (LSTM) units [8], [9], [10]. However, in the case of LSTM-based neural networks, many authors decide to make one-step-ahead forecast (i.e., prediction for the next time step), which is impractical. The concepts behind the one-step-ahead and multiple-step-ahead predictions are presented in Fig. 1 in [11]. For more details about one- and multiple-step-ahead forecasting, see [12] and [13]. Neural networks are powerful technology used for a broad spectrum of problems. Unfortunately, for the time-series forecasting problem, the creation of the proper structure and training of the neural network can be challenging. Some of the authors present models that should be further developed to improve the quality of forecasting.

The disadvantage of methods based on neural networks is the inability to present probabilistic uncertainty quantification [14]. The situation is different in the case of statistical methods. The idea of forecasting traffic using time-series models has been successfully used for several years - even in the case of earlier generations of telecommunications networks.

The most popular univariate time-series models for a network traffic forecasting are: Autoregressive Integrated Moving Average (ARIMA) models [15], [16], [17], [18] and the Exponential Smoothing techniques (or their advanced versions) [18], [19], [20]. Most papers utilizing time-series models consider only the one-dimensional case. Some of them mention the possibility of performing similar analyses for multivariate data.

In recent years, one can find also techniques that are based on time-series modeling and deep learning methods at the same time. In this way, they can exploit the strengths of both approaches. The authors of [21] introduce Thresholded Exponential Smoothing and Recurrent Neural Network (TES-RNN), that is, a method that uses Exponential Smoothing and RNN for motion prediction. Another example of using Artificial Intelligence (AI) procedures with time-series modeling for traffic forecasting is to use Discrete Wavelet Transform (DWT) to decompose the time-series and then model a linear component using ARIMA and forecast a non-linear traffic component by an LSTM [22]. The disadvantage of both methods is that Exponential Smoothing and ARIMA approaches work only for one-dimensional data.

Scientists also use other methods to forecast network traffic: e.g. classification methods, information theory methods, (hidden) Markov models, Gaussian processes, and Poisson models [9], [14], [23], [24]. In the literature, we can also find articles that use supervised methods to forecast network traffic [8], [25], [26], [27]. These methods include support vector machines, k-nearest neighbors, decision tree, linear regression, AdaBoost and random forest. A disadvantage of these methods is that we must additionally transform the dataset manually to indicate weekly patterns in the data. However, adding too many shifted values for each variable in the model can result in a curse of dimensionality. The curse of dimensionality means that increasing the dimensionality makes those data sparse. Considering the periodicity in both daily and weekly is significant, as network congestion has seasonal behavior. For example, thesis [9] shows how the average traffic value changes at certain times of the day. In addition, the author notes that intraday traffic volatility differs between weekend data and data collected during the working week. Therefore, taking these relationships into account can improve the quality of forecasting.

In our research, we focus on proposing multidimensional models for network traffic forecasting that take into account the occurrence of seasonal data patterns. In fact, the general model should include the existence of dependencies between Key Performance Indicators (KPI) and delay and throughput within all considered network slices. A review of the literature enables us to conclude that there is a research gap on this issue that needs to be developed.

B. NETWORK SLICING DIMENSIONING & PLANNING

There is already extended work on AI based solutions used in NS management. It can be used in all network management phases (preparation, planning and operation) [6]. Moreover, it has the potential of handling complicated decision-making problems in a dynamic network environment e.g. for transmission power allocation in cellular networks and resource allocation in network slices [1].

In [1], the authors show that ML algorithms enable cell level modeling basing on their specific characteristics, enabling heterogeneous network planning with consideration of local requirements [1]. Another example is where the planning of Radio Access Network (RAN) slices is done with the use of game theory [28]. Supervised DNN is proposed for spectrum allocation, aiming to minimize costs, maximize radio resource utilization, and guaranteeing desired service level agreements in [29].

C. NETWORK DIGITAL TWIN

In article [30], the authors have introduced the NDT concept that enables the development of more efficient network control and tools for modern communication networks, including, e.g. troubleshooting, traffic engineering, ''what-if'' analysis, network planning, anomaly detection - see. Fig 1, Fig, 2 and Tab. 2 in [30]. Moreover, they have argued that recent advances in ML enable building some of NDT's core components as a data-driven network models that can operate in a real time, including a routing optimization in a QoS-aware use case. The other researchers reported on a novel framework of digital twin manager dedicated to handle conflicting network applications [31], and also designed a digital twin suitable for ''what-if'' analysis in Border Gateway Protocol (BGP) optimization [32]. Finally, the paper [33] commenting on 5G/6G network softwarization and intelligentization, outline the role of digital twin architecture for network autonomy, predict an emergence of a service layer in 6G networks compatible with digital twin and able to realize proactive analytics, including generative intelligence functionality.

III. DATASET

The dataset used in this research consists of hourly averaged time-series from thirty-three 5G Base Transceiver Stations (BTS) working in a live network deployment. This data was collected from each BTS and each configured cell within the BTS, from a period of whole month - March'23. Each cell is specified by various configurational properties (e.g.: cell duplex mode, channel bandwidth, etc.) and performance measurements (KPIs calculated from counters). Counters describe the events in a mobile network on low level [34] (like the average downlink Radio Link Control (RLC) delay in gNodeB Distributed Unit per slice).
Subscribers in this network cluster have been divided into four groups:

- Slice A - mobile subscribers with high priority
- Slice B - mobile subscribers with medium priority
- Slice C - mobile subscribers with low priority
- Slice D - fixed wireless access subscribers with lowest priority

A. FEATURE SELECTION

The features used in modeling are shown in Fig. 1. Full name, description and unit for each variable is provided in Tab. 1.

Presented KPIs have been selected according to the best knowledge of the telecommunication expert. Thanks to them, it is possible to create multivariate models including traffic load and radio environment metrics [35] that have a direct effect on throughput and delay (described in next subsection).

The variables can be divided in two areas:

- traffic conditions: #UEs (number of User Equipments), DV (Data Volume), PRB (Physical Resource Block) utilization,
- environmental conditions: CQI (Channel Quality Indicator) and BLER (Block Error Rate).

Metrics marked in Fig. 1 as *Total* are calculated for all slices and metrics marked as *Slice* are calculated for each slice separately.

TABLE 1. The variables used in the modeling.

Abbreviation	Full name	Unit	Description
#UEs	Number of user equipments	#	The average number of user equipments which have buffered data in downlink direction
BLER	Block Error Rate	%	A ratio of the number of erroneous blocks to the total number of transmitted blocks
PRB utilization	5G PRB utilization for PDSCH	%	Utilization of PRBs for physical downlink shared channel (PDSCH)
CQI	Channel Quality Indicator	#	This indicates the average level of modulation and coding the UE could operate
DV	Data Volume	kbit	Amount of data send per particular network slice
-	Delay	microsecond	Calculated as time difference between the reception of the RLC SDU from PDCP layer and when first RLC SDU is sent over the air interface
TPut	Throughput	kbit/ms	Average downlink throughput volume at PDCP SDU level for a given network slice

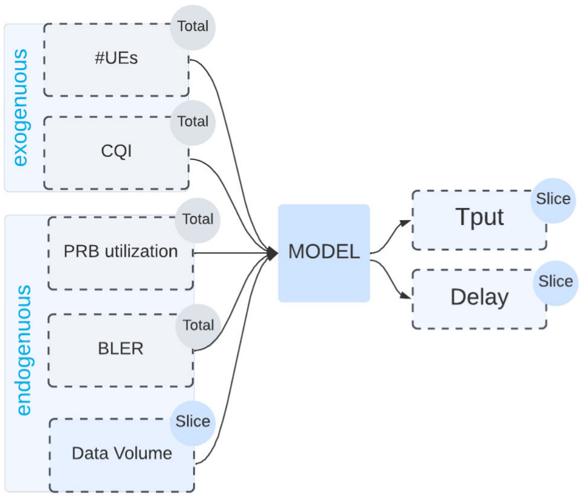

FIGURE 1. Model scheme for throughput and delay forecasting.

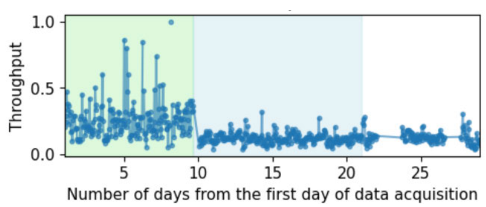

FIGURE 2. Pearson correlation matrix of the considered features.

B. CONFIGURATION CHANGES

Preliminary trajectory analyses have shown that some time-series contain structural changes (e.g., Fig. 2). The reason for most cases is a configuration change applied by the network operator. Due to this, it is necessary to collect configuration data that describes software changes or information about feature activations. Thanks to that, segments of the data with an unchanging structure can be extracted. In this research, the dates of the significant configuration changes in the network are checked to extract unchanged segments that are eventually used for modeling.

C. THE DEPENDENCIES OF FEATURES

The correlation analysis begun with the presentation of the correlation matrix. Fig. 3 shows Pearson correlation coefficient [36], that describes the linear dependence between the data. Data has been divided into stationary segments i.e., parts without configuration changes.

The correlation matrices show that linear relations for many pairs of variables can be observed. What is important, there is a high correlation factor for particular pairs of delays and throughputs for different network slices. Due to that, there is a need to create a general model to include the relationships between all slices.

D. INFORMATION ABOUT WEEKDAY

The inclusion of information about weekdays enables the examination of network traffic diversity between weekdays and weekends. This aspect was also raised by other authors [37]. Fig. 4 shows the boxplots for weekday and weekend of normalized throughput that is aggregated from all BTSs and cells within dataset (noralization is made as follows: the minimum value is subtracted and divided by the range).

Different ranges can be observed for weekdays and weekends. The variation becomes apparent with the analysis of the values for the following days separately. The most valuable information can be extracted when analyzing a single cell (e.g., Fig. 5, Fig. 6).

Similar analysis has been performed for delays. Fig. 6 shows that weekly patterns can differ for various cells. Weekly periodicity can be seen for individual weekdays. In Fig. 6, the 4th and the 11th of observations correspond to Sunday. We can observe that for them the throughput values are increased. In current research for short-term modelling the 24h cell level data is taken for training, however for long-term predictions (which are planned in future research), this weekday effect should be taken into account.

IV. FORECASTING AND DIMENSIONING FRAMEWORK

Following the emergent conceptions, a forecasting and dimensioning framework is proposed (Fig. 7) which is a data-driven model embodying the Network Digital Twin idea described in [30]. In fact, designed framework can work independently as a forecast and "what-if" analysis module relevant for (sliced) network dimensioning and traffic engineering or can serve as one of the core components of multifunctional NDT. This framework has been developed in modules to enable easy verification, management and scaling to specific use cases.

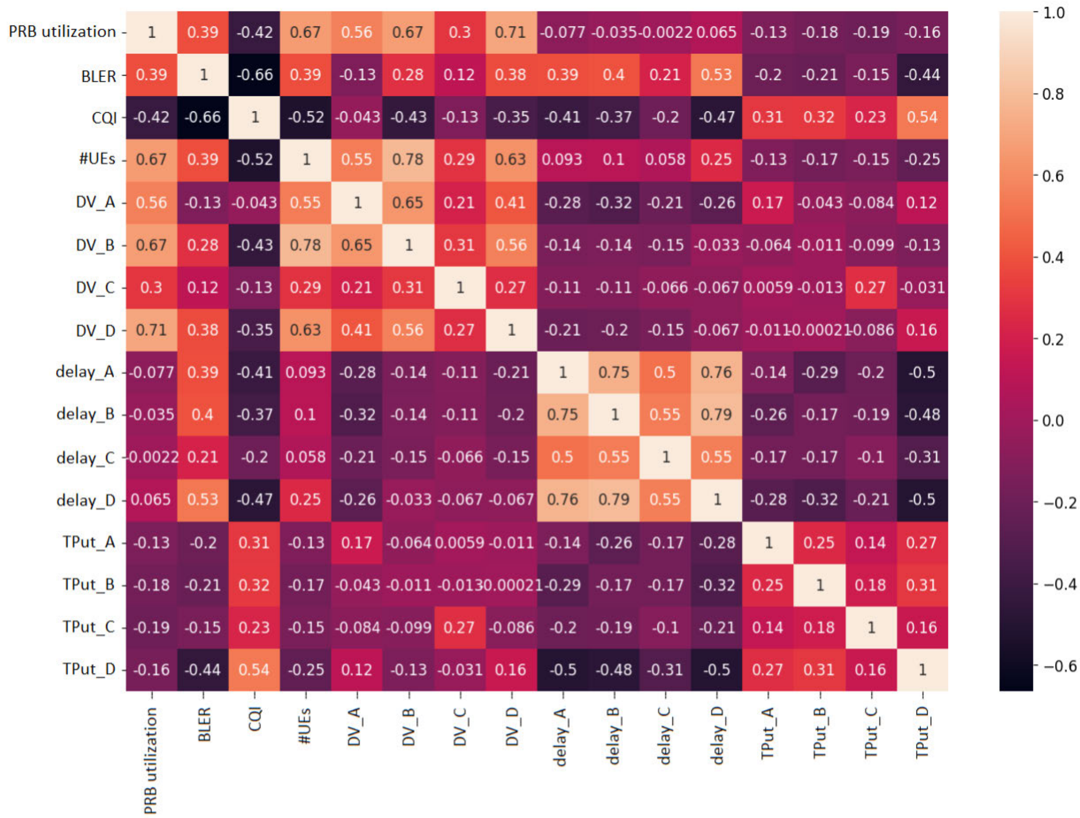

FIGURE 3. Illustrative trajectory of normalized throughput for Slice D.

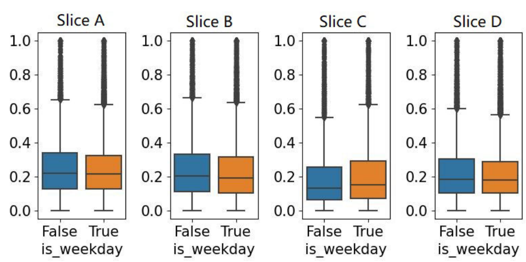

FIGURE 4. Boxplots for normalized throughput by network slice.

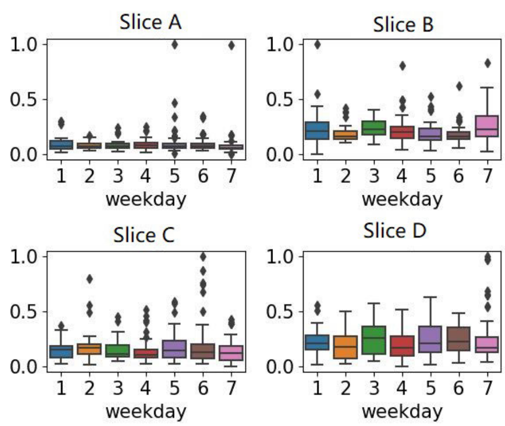

FIGURE 5. Boxplots for normalized throughput by network slice (cell-1).

It is worth to mention that the DT-based simulations require integration with the data platform [38], to perform model retraining whenever the relation between the inputs and outputs might change (e.g. configuration change, software upgrade, etc.) or might be different (e.g. configurations that have not been in the training data). Therefore, it has to be taken into account how the connection between the physical and the digital network should be maintained. In our case, the plan is to incorporate it into a continuous delivery cluster similar to the one described in [34].

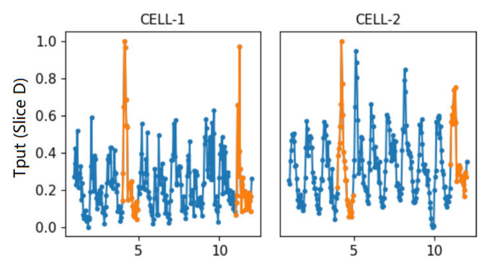

FIGURE 6. Normalized throughput for Slice D for two selected cells.

A. SCENARIO FORECASTING MODULE

The heart of this module is the forecasting model, which is trained on real traffic and environmental data. This multivariate model forecasts throughput and delay with cell and slice granularity. Once used in the dimensioning process, it makes the need for an a priori defined traffic model obsolete [39]. Several methods have been verified and as

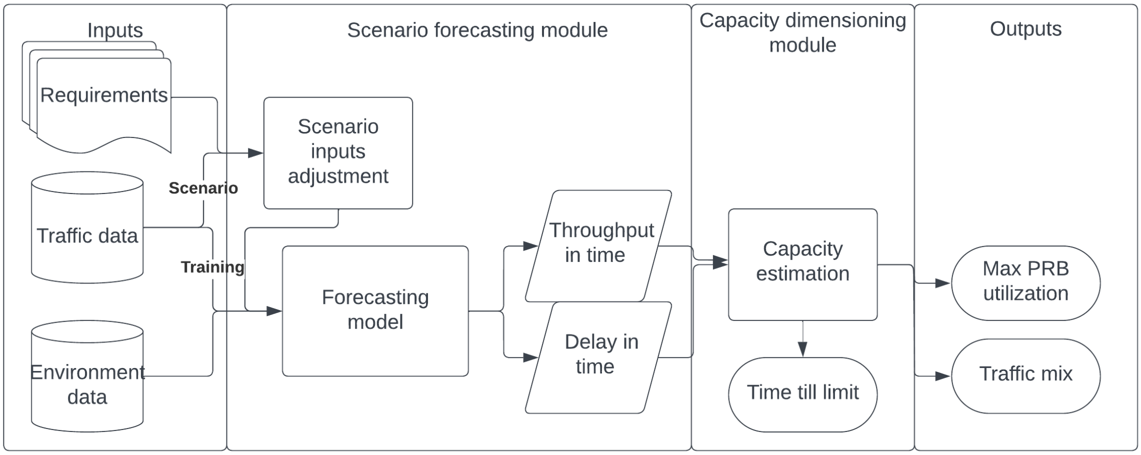

FIGURE 7. **Forecasting and dimensioning framework.**

a result the most promising have been described in the following sections.

The "what-if" scenario simulation can be performed with the use of such a pre-trained model. According to the scenario requirements, the historical model inputs are modified to estimate slice throughput and delay in the future. Because some of the input features are correlated (as described in III-C), any modification of the inputs must consider their relation (which is elaborated in VI-C).

B. CAPACITY DIMENSIONING MODULE

Usage of real data pre-trained cell models in the dimensioning process leads to accurate traffic forecasting and enables capacity estimation for future development of the network. Taking the assumption that the service usage will grow with the same pace as of now, the model can be taken to predict the future capacity. In this work, short-term forecasting (24h) is evaluated, because of the limited amount of data with unchanged BTS configuration (III-B). However, long-term forecasting is planned to be evaluated in future work.

To estimate required capacity and infrastructure, throughput and delay are forecasted per slice. Afterwards, for each cell configuration and each slice, it is checked when the slice capacity or slice QoS delay requirements will be reached. Knowing the time of reaching capacity limits, system configurational changes can be proactively done to increase slice capacity. This approach can also be used for long-term dimensioning (planned in future work), in a way that the forecasted time of reaching delay limit will show when the network extension will need to be made and capacity at the end of the forecast will show how large the infrastructure extension should be.

With the extension of "what-if" analysis, capacity dimensioning can be performed for simulated scenarios assuming different ways of network traffic demand evolution, e.g., higher grow for specific slice due to planned new offering from CSP.

V. METHODS

Several multivariate predictive models for throughput and delay forecasting have been verified (e.g., Prophet model for a single variable forecasting). Initial selection has been narrowed to the multivariate ARMA model and neural networks.

A. VARMAX

A time-series $\{\boldsymbol{X_t}\}$ is a m-variate ARMA(p,q) process (called also vector ARMA, VARMA) if it is formulated in the following way:

$$\Phi(B)\boldsymbol{X_t} = \Theta(B)\boldsymbol{Z_t}, \tag{1}$$

where $\{X_t\}$ is a **stationary solution** of difference equations (1), where

- $\Phi(z) := I - \Phi_1 z - \ldots - \Phi_p z^p$, where $\Phi_1, \ldots, \Phi_p$ are $m \times m$ matrices,
- $\Theta(z) := I - \Theta_1 z - \ldots - \Theta_q z^q$, where $\Theta_1, \ldots, \Theta_q$ are $m \times m$ matrices.

Moreover:

- I is $m \times m$ identity matrix,
- B is the backward shift operator,
- $\{\boldsymbol{Z_t}\}$ is multivariate white noise sequence.

For more details about VARMA model, definition of multivariate white noise, and methods for estimation of parameters, see [40]. In this research, VARMAX model, that is vector ARMA model with additional exogenous components, has been used. The utilized tools enable to fit of multivariate model using Maximum Likelihood Estimation (MLE) via the Kalman filter by the assumption that $\{\boldsymbol{Z_t}\}$ has multivariate Gaussian distribution.

Data preprocessing starts with seasonal decomposition to achieve stationarity. The MLE-based procedure selects the model coefficients for the appropriate model orders $(p,\ q)$. Different pairs (p, q) have been evaluated and the one that minimizes the information criteria has been selected. The information criteria considered are as follows: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan-Quinn Information Criterion (HQC) [41]. Finally, the VARMAX(p, q) model is fitted for selected p and q. The test set is the last 24h of data. The other data is considered as a training set.

B. NEURAL NETWORKS

The second part of our research focuses on testing various neural networks structures containing different layers and units. The multi-step forecasting approaches are developed. Due to the length of available data, forecasts for the next 24h based on the last 24h are made. The last 48 hours for both segments are test data. The other data are the training and validation set. The maximum number of training epochs is set to 1000. However, if the loss for the training set does not decrease per 20 epochs, the learning is stopped. The data is normalized and seasonally decomposed before training the neural networks. Preliminary tests indicate that breaking delay and throughput into seasonal and residual factors lower the loss. Seasonal decomposition is made in the same way as in the case of VARMAX. The effectiveness of time-series decomposition before neural network training is confirmed by the other authors [42].

1) LSTM

Recursive neural networks are often used for time-series forecasting. However, for long sequences, the so-called gradient-vanishing problem can occur, which is associated with the low values of partial derivatives calculated for weights, which causes them not to update. For recursive networks, a long time horizon T means that observations x_1 and x_T are distant. To counteract the vanishing gradient LSTM unit can be used. The network utilized these units is a modification of standard RNN. In general, LSTM introduces three logic gates: *Input gate, Forget gate*, and *Output gate* that decide which information is to be "remembered" and which is "forgotten" in subsequent steps. For more details about RNN and LSTM, see [43] and [44].

The structures of neural networks mentioned in this section use only LSTM units and dense layers. Neural networks with the number of LSTM layers not exceeding 3 have been tested. The use of shallow structures is justified by the shorter training time of the model. Furthermore, they can be developed in the case of inefficiency (i.e., high loss). The considered set of hyper-parameters is presented in the Tab. 2.

Based on the conducted tests, it can be concluded that the best model has only one hidden layer (Fig. 8) with Adam as an optimizer, Mean Absolute Error (MAE) as a loss function, and learning rate equal to 0.01. This structure is chosen as the most accurate because the values of MAE and MSE are the lowest for most samples.

2) CNN-BILSTM

The structures based on a composition of convolutional layers and Bidirectional LSTM (BiLSTM) has been considered

TABLE 2. Hyperparameters for structures utilized LSTM block.

Hyperparameter name	Hyperparameter values
LSTM-number of layers	1, 2, 3
LSTM-units	[50], [50, 50], [50, 50, 20]
LSTM-dropout rate	0.2
LSTM-activation	tangent
LSTM-recurrent activation	sigmoid
Learning rate	0.01, 0.001
Optimizer	SGD, Adam
Batch size	24
Loss	MAE, MSE

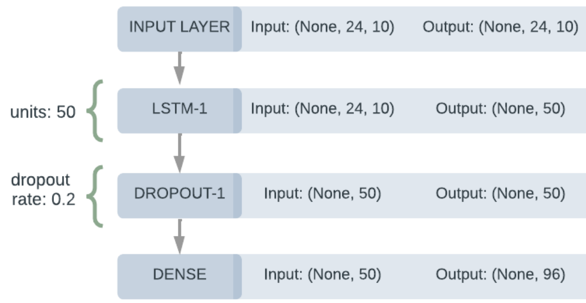

FIGURE 8. The neural network structure that uses LSTM unit(s).

in this work. In a convolutional neural network (CNN), neurons are connected only to a filter - a particular area in the preceding layer. It is a difference between classical dense neural networks - for them all neurons are fully connected. For more details about CNN and BiLSTM see [43] and [45], respectively. As in the previous subsection, different combinations of parameters can be checked. The most accurate model has the structure visible in Fig. 9. The parameters of the structure are shown in Tab. 3.

VI. RESULTS AND DISCUSSION

A. MODEL PER NETWORK SLICE

First, we focus on developing the method of modeling throughput and delay for each network slice separately. The scheme of the model for each network slice is the same as in Fig. 1. In general, throughput and delay depend on the past values of endogenous KPIs and present values of exogenous variables. In addition, throughput and delay also depend on their past values. For modeling and simulation, we use Python.

1) VARMAX

As we mentioned earlier, for the VARMAX model, the data should be complete and stationary in a weak sense. Every component of a multidimensional time-series is decomposed using a simple approach based on the moving average. The period is 24 hours.

The important step after seasonal decomposition is stationarity verification. We propose to test the stationarity using the Augmented Dickey-Fuller (ADF) test [46]. The results of forecasting for one illustrative cell for slice A are visible

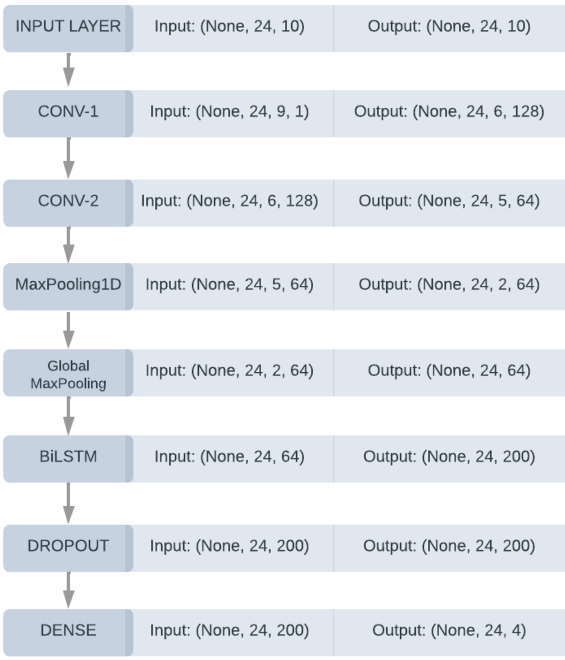

FIGURE 9. The neural network structure that used CNN-BiLSTM unit.

TABLE 3. Parameters for the best CNN-BiLSTM structure.

Hyperparameter name	Hyperparameter value
CONV1 (filters, kernel size)	(128, 4)
CONV2 (filters, kernel size)	(64, 2)
CONV-activation	relu
Pooling size	2
BiLSTM-number of layers	1
BiLSTM-units	100
BiLSTM-activation	relu
BiLSTM-recurrent activation	relu
Dropout rate	None
Batch size	24
Learning rate	0.001
Optimizer	Adam
Loss	MSE

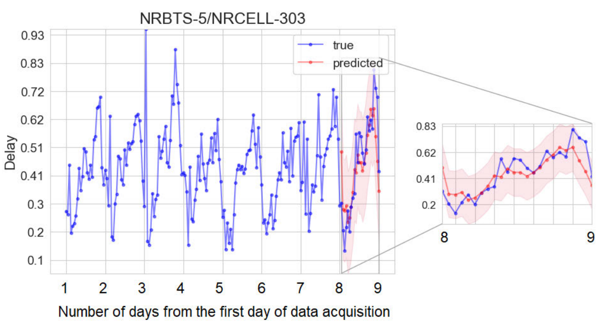

FIGURE 10. The forecast for normalized delay for Slice A using VARMAX(2,0).

in Fig. 10 and Fig. 11. For this cell, the optimal orders are $p = 2$, $q = 0$ (for these values, the smallest AIC was noticed).

The results presented previously are made for data which is seasonally decomposed and differentiated (if necessary). However, reducing the number of variables can be beneficial,

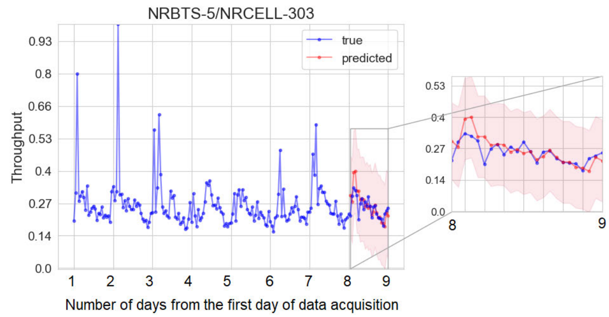

FIGURE 11. The forecast for normalized throughput for Slice A using VARMAX(2,0).

because it could make parameter estimation faster. Two scenarios of input data preparation for VARMAX modeling have been considered (Tab. 4). In the first scenario, a standard

TABLE 4. Scenarios for VARMAX modeling.

Scenario	PCA	Endogenous*	Exogenous
1	False	throughput, delay, data_volume, BLER, PRB utilization	#UEs, CQI
2	True	throughput, delay, PCA_1, PCA_2	#UEs, CQI

preprocessing is used while in the second one - the Principal Component Analysis (PCA) is used to make the dimensionality reduction. For more information about PCA, see [47].

Fig. 12 shows the comparison of the computational time for both scenarios. The computational time for Scenario 2 takes into account making PCA, modeling and forecasting. Moreover, the values of normalized MAE (nMAE) calculated for all cells are similar for both scenarios (for both throughput and delay).

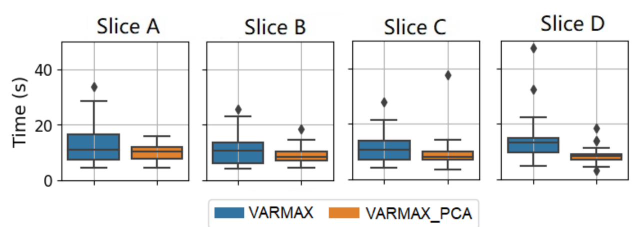

FIGURE 12. Comparison of computational time between VARMAX and VARMAX PCA.

It can be seen in the boxplots of normalized MAE (Fig. 13). Thus, the algorithm from Scenario 2 may have a practical application due to the fast computational time. The downside is that using PCA makes the parameters of the model less interpretable.

2) NEURAL NETWORKS

For neural networks data is decomposed in the same way as for the VARMAX model. The set of hyperparameters

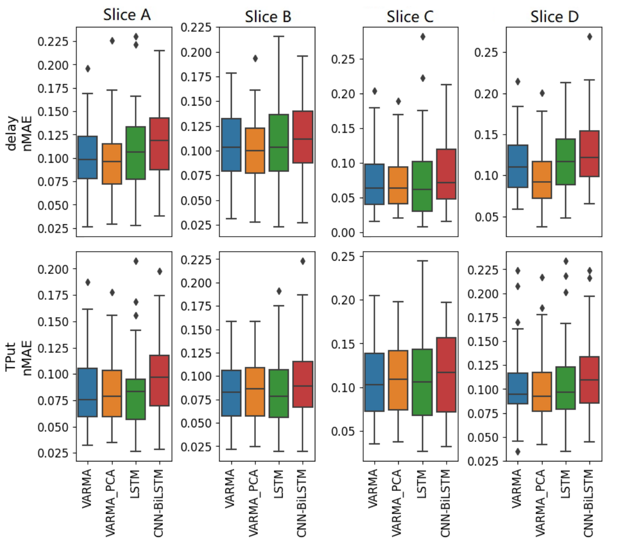

FIGURE 13. Normalized MAE for delay (upper panel) and throughput (bottom panel) per network slice. MAE is normalized by dividing by range.

(i.e., structures described in Sec. V-B) is chosen based on additional tests. In the first step, broader hyperparameter space is considered, but for smaller datasets. Based on this, the best hyperparameters set for our research has been selected (Tab. 5).

TABLE 5. List of the best structures used LSTM units.

Model	units	Learning rate	Optimizer	Loss
1	[50]	0.01	adam	mse
3	[50]	0.01	adam	mae
5	[50]	0.001	adam	mse
7	[50]	0.001	adam	mae
9	[50, 50]	0.01	adam	mse
11	[50, 50]	0.01	adam	mae

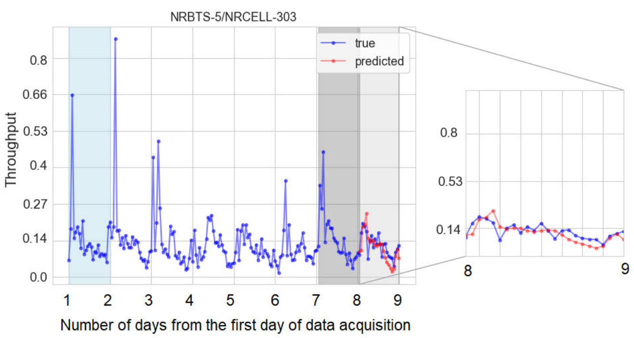

FIGURE 14. Throughput forecast for Slice A using model_3.

For the illustrative cell used in Sec. VI-A1, Model 3 outperforms the others, as it minimizes normalized MAE and normalized Root Mean Square Error (RMSE). The throughput and delay forecasts for Slice A are shown in Fig. 14 and Fig. 15.

The target is to select a model that minimizes the learning time and the prediction error. Based on these criteria, a probable nominee for the winning structure is Model 3.

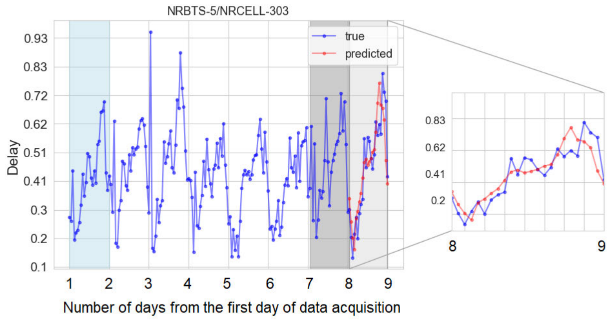

FIGURE 15. Delay forecast for Slice A using model_3.

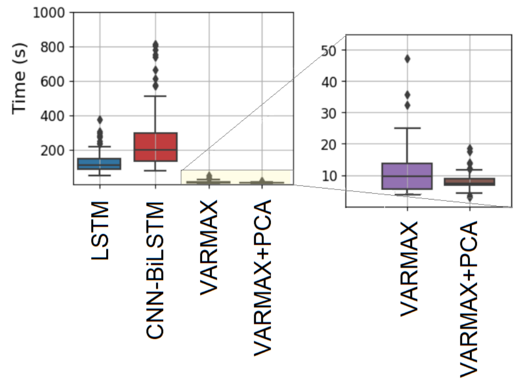

FIGURE 16. Comparison of the modeling and forecasting time (Slice D).

The same type of analysis has been done for CNN-BiLSTM. The results obtained for a particular BTS and cell could depend on the specificity of the selected multivariate time-series.

For that reason, in the next step evaluation metrics are calculated and modeling time for the remaining samples and for each network slice is compared (Fig. 13 and Fig. 16).

3) COMPARATIVE STUDY OF UNITS MODELS

Our research shows that, depending on the network slice, the VARMAX model (with or without PCA) or the LSTM-based network can be a better predictor (Fig. 13). The forecast made by the more complex CNN-BiLSTM network is less accurate. Moreover, CNN-BiLSTM has the longest modeling and forecasting time (see, Fig. 16).

B. GENERAL MODEL FOR ALL NETWORK SLICES

Taking into account the need to test the impact of changing individual variables on traffic, a general model has been created. It contains information about all network slices within a specific cell. One approach could be to aggregate unit models, but a general model (including variables for all network slices) is more interpretable. The general model schematic is given in Fig. 17. The time-series decomposition and the order selection procedure for the VARMAX model is the same as in Sec. VI-A.

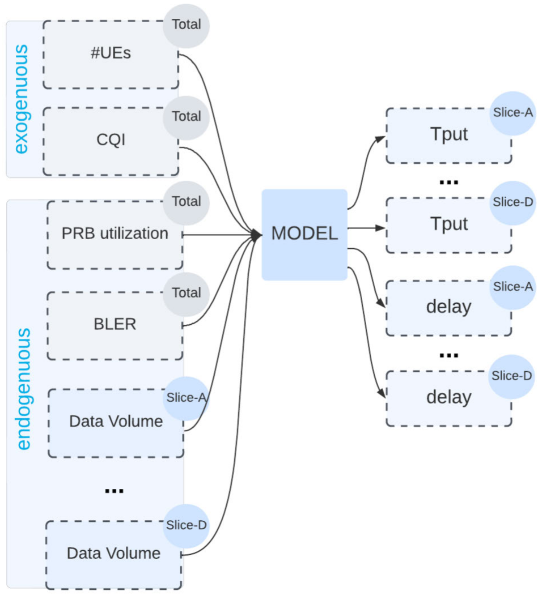

FIGURE 17. Schematic of the general model including each network slice.

For a general model based on neural networks, the same structures as in Sec. VI-A are tested. The most accurate LSTM-based neural network is Model 11 and CNN-BiLSTM-based: Model 2. The analysis of computational time of model fitting and forecasting leads to the same conclusions as for unit models: VARMAX is the fastest, and CNN-BiLSTM-based neural network is the slowest (Fig. 18).

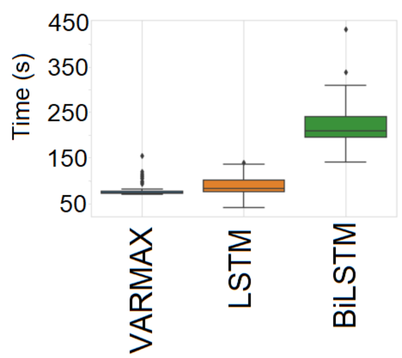

FIGURE 18. Comparison of the modeling and forecasting time.

Boxplots with normalized RMSE error are shown in Fig. 19. It can be seen that the differences between the general VARMAX model (G) and the unitary model (U) are low for each network slice. It is different for LSTM-based models. However, it is worth noting that the best structures for units and general differ in the parameters set (for the unit case, the best structure is Model 3, and for general the best results provides Model 11). Furthermore, the selection of initial weights is random, which can affect network training. Generally, the lowest error is for different variants of VARMAX models or LSTM-based networks. General models can successfully replace individual equivalents. It is worth adding that in some cases VARMAX using PCA enables us to get the best forecasts. However, the results are not easily interpretable if the dimensionality reduction is utilized during the modeling. Depending on the functionality that should be obtained, one may consider including PCA in the model or not.

It is impossible to assess (based only on visual inspection) whether the differences between the prediction errors of different models are statistically significant. At the end of the research, the Friedman test and the Nemenyi post hoc test were used to check when prediction errors vary significantly. For more details on the tests, see [48]. The statistics and p-values for the Friedmann test are visible in Tab. 6.

TABLE 6. The Friedmann test. Metric: normalized MAE, normalization by dividing by range.

Variable	Slice	Statistic	p-value
Throughput	A	78.35	7.81E-15
	B	73.17	9.15E-14
	C	56.93	1.88E-10
	D	41.38	2.43E-07
Delay	A	96.78	1.18E-18
	B	40.88	3.06E-07
	C	73.24	8.84E-14
	D	66.33	2.31E-12

P-value is close to 0 for each network slice. This means that the null hypothesis can be rejected. Therefore, for each network slice, at least one model normalized MAE differs significantly.

For verification of the differences between the pairs, the Nemenyi post hoc test is performed. The results for Slice A are presented in Tab. 7. If the p-value is less than 0.05 it means that the two algorithms differ significantly at the significance level of 0.05. Otherwise, there are no statistically significant differences.

The results for the remaining slices are similar (also for delay). General and unit models created by the same methods do not differ significantly in any case. The most common differences are between CNN-BiLSTM (both U and G) and other methods. The prediction errors for the VARMAX model and the LSTM-based network are statistically different only for throughput in Slice A.

C. THE CONCEPT OF SIMULATED SCENARIO

1) REAL DATA EVALUATION

To check the validity of the simulator and to assess its limits of applicability/ability to preserve the physical context, experiments on the actual data have been conducted. First, the moments of increasing DV from the data have been extracted. There are two types of changes during these moments, a single peak and a change in the DV, after which the DV remains elevated. Both types were marked accordingly. An illustrative example of a single jump in DV-B is shown in Fig. 20.

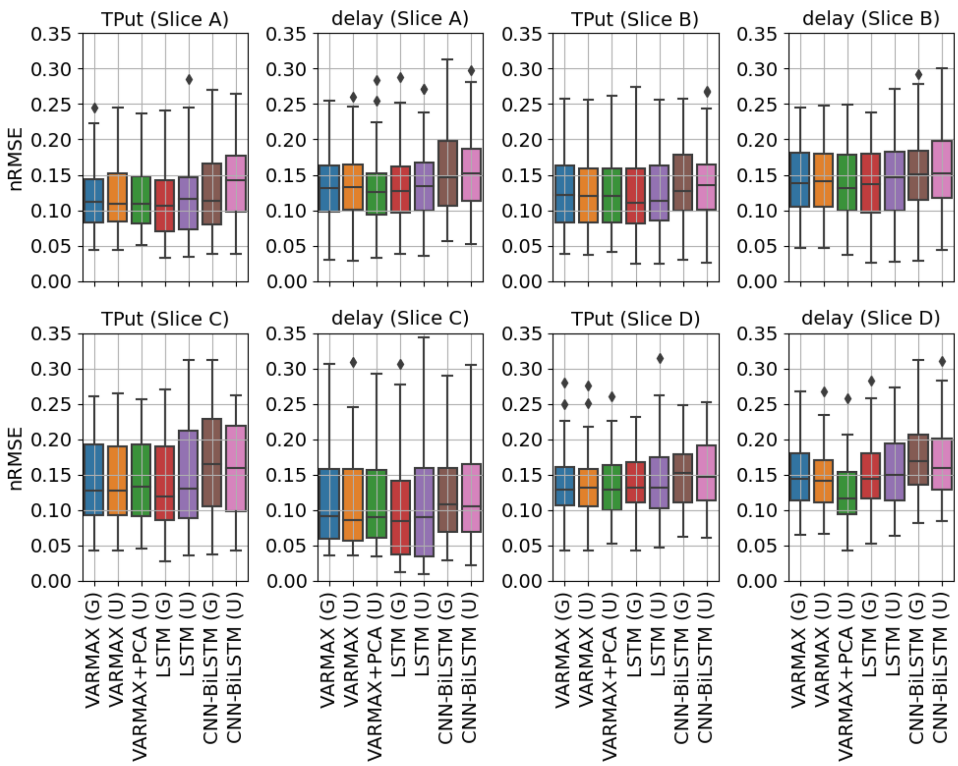

FIGURE 19. Comparison of normalized RMSE per slice. RMSE is normalized by dividing by range; (G) - general model, (U) - unit model.

TABLE 7. P-values for the Nemenyi post-hoc test. Metric: normalized MAE, normalization by dividing by range. Variable: throughput, Slice A.

	LSTM (G)	LSTM (U)	CNN-BiLSTM (G)	CNN-BiLSTM (U)	VARMAX (G)	VARMAX (U)	VARMAX +PCA (U)
LSTM (G)	1.000	0.018	0.001	0.001	0.008	0.001	0.009
LSTM (U)	0.018	1.000	0.248	0.001	0.900	0.900	0.900
CNN-BiLSTM (G)	0.001	0.248	1.000	0.064	0.387	0.900	0.361
CNN-BiLSTM (U)	0.001	0.001	0.064	1.000	0.001	0.001	0.001
VARMAX (G)	0.008	0.900	0.387	0.001	1.000	0.900	0.900
VARMAX (U)	0.001	0.900	0.900	0.001	0.900	1.000	0.900
VARMAX+PCA (U)	0.009	0.900	0.361	0.001	0.900	0.900	1.000

The complete procedure is as follows:

- fit model for data before DV change (blue part),
- set initial state for simulation by taking true values of data volumes for each slice and PRB utilization (red part). Input values for BLER are forecasted by the standard procedure described in Sec. V-A,
- forecast next 24 hours (green part).

The simulations are based on the VARMAX(1,0) model. We also performed tests for neural networks based on LSTM units, however, the results turned out to be worse.

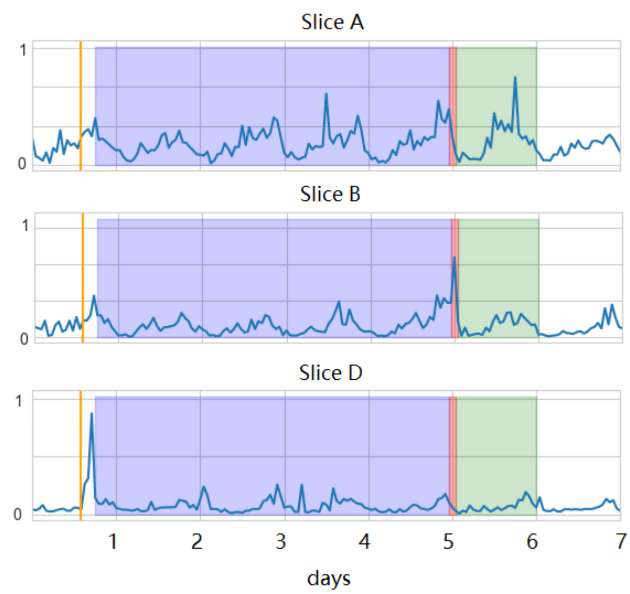

FIGURE 20. The illustrative trajectories for data volumes per network slice.

However, testing of deeper structures of neural networks can be considered as a future work.

Information on the actual value of PRB utilization is included in the initial state. The reason is that with DV change, the utilization of radio resources changes correspondingly. A simulation that contains only changes in DV would

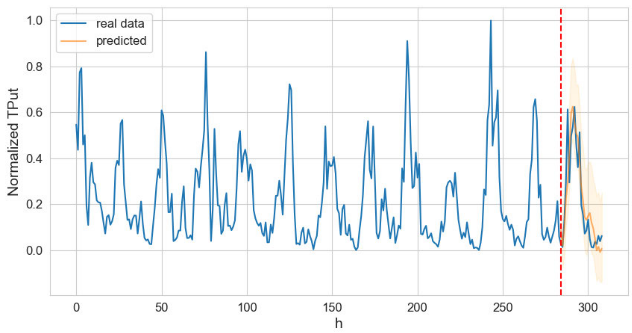

FIGURE 21. Throughput forecast for Slice A using VARMAX.

TABLE 8. The values of information criteria and evaluation statistics for a sample from Fig. 21.

AIC	BIC	HQIC	MAE	RMSE	R2
-6001.57	-5195.14	-5678.26	4.13	5.25	0.77

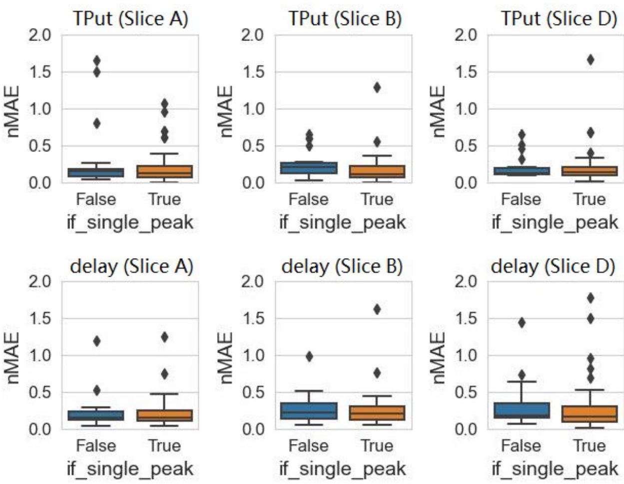

FIGURE 22. Normalized MAE, normalization by dividing by range.

TABLE 9. Simulation scenarios.

Variables	% of DV's change
DV (A), PRB utilization	50, 100, 150, 200
DV (B), PRB utilization	50, 100, 150, 200
DV (A, B, C), PRB utilization	50, 100

not reflect reality. An example forecast based on real data is shown in Fig. 21. In this scenario: DV_A increases by 267.2%, DV_B increases by 7.98%, DV_D increases by 13.7%, and PRB utilization increases by 80.75%. It is worth noting that a large increase in DV in Slice A is associated with a significant increase in PRB utilization.

The values of information criteria and evaluation statistics for a sample from Fig. 21 are presented in Tab. 8. As can be seen, the errors are low and R^2 is high.

To compare the results for all samples, two metrics are used, namely MAE and RdR score introduced in [49]; RdR score is a normalized value based on DTW and RMSE. It tells us whether the forecast based on "our model" outperforms

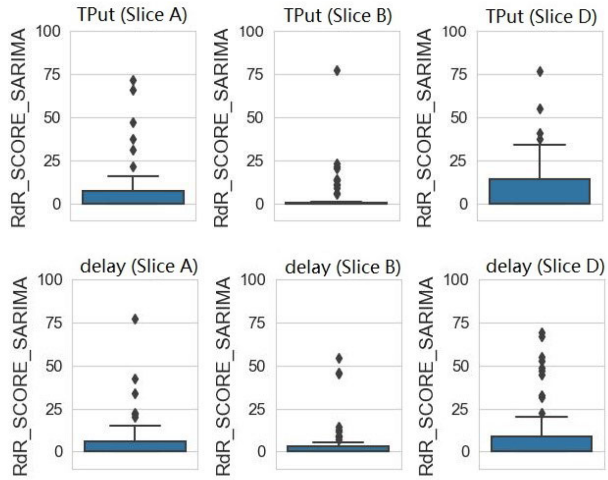

FIGURE 23. Modified RdR score for all selected samples; reference: ARMA.

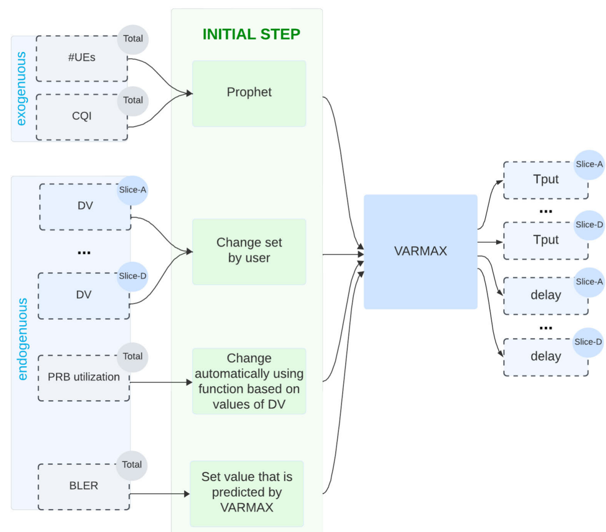

FIGURE 24. Schematic of the simulator.

the results obtained for other considered approaches. After small modifications, another version of RdR score was considered, such checks if "our model" is better than its univariate equivalent (ARMA for data after seasonal decomposition). In general, modified RdR score can be defined as follows:

$$RdR_{score} = \frac{RMSE_{score} + DTW_{score}}{2}, \tag{2}$$

where

$$RMSE_{score} = 1 - normalized(RMSE),$$
$$DTW_{score} = 1 - normalized(DTW).$$

The value of $normalized(RMSE)$ is the RMSE for "our model" normalized by subtracting the minimum value of the reference and dividing by the reference range.

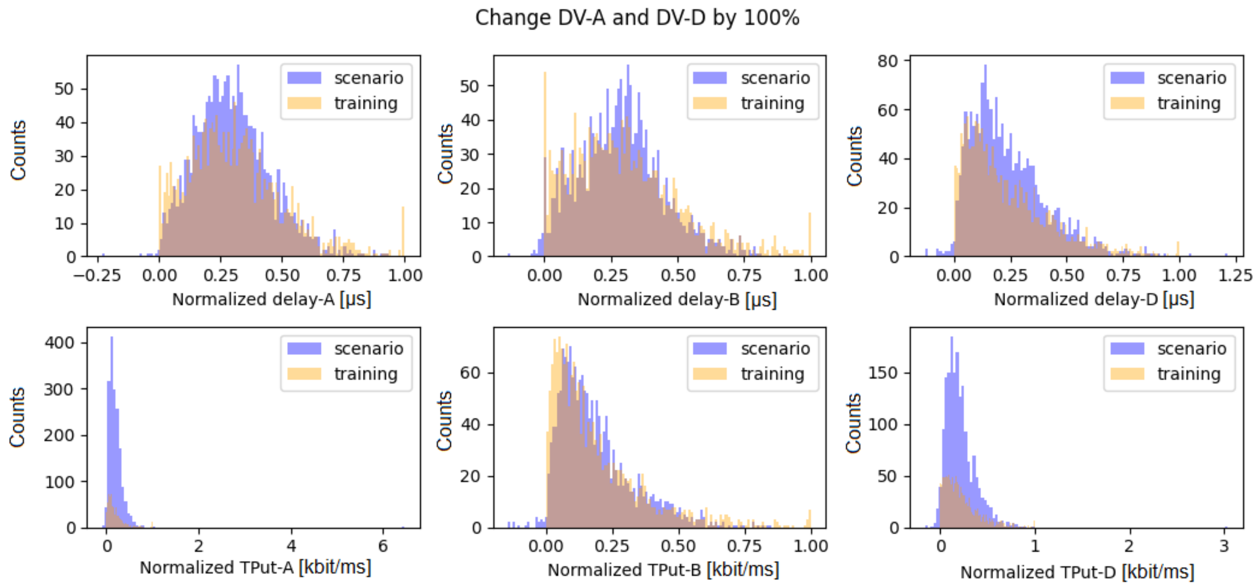

FIGURE 25. **Comparison of the histograms of normalized throughputs and delays: forecasts (simulated scenario) vs. training set (the last 24h).**

The reference limits are the values of the RMSE for an ARMA. The definition of $normalized(DTW)$ is analogous. MAE is normalized by dividing by range to make the results for all samples comparable.

The normalized MAE values are shown in Fig. 22. As can be seen, the forecasts have a small normalized MAE. Slightly worse than the others are the errors of the model for the delay in Slice D. However, the median of errors is small.

The conclusion of these boxplots is that it is possible to make a simulation that reflects reality using VARMAX. Nevertheless, it was also verified if the VARMAX model performs better in simulation case than univariate approach (ARMA). To do that, the RdR is recalculated as follows: $max(0, RdR \cdot 100\%)$. The results for all samples are visible in Fig. 23. After comparison of the results for VARMAX simulation and its one-dimensional equivalent (ARMA), significant improvement can be seen for both delay and throughput for Slice A and Slice D and imperceptible improvement for Slice B.

2) SIMULATIONS

Evaluation of the model allowed us to determine its effectiveness in the problem considered. The next step is to perform simulations in which the DV values are modified by the user. The considered cases are presented in Tab. 9. The schematic of simulator is visible in Fig. 24.

Each endogenous variable is forecasted in the VARMAX model, but the values of exogenous variables should be known at the current time for which we perform forecasting. According to telecommunication know-how and after preliminary analysis, the assumption is made that exogenous variables (#UEs and CQI) do not change its behavior when DV changes.

One dimensional Prophet model introduced in [50] has been selected to forecast the #UEs and CQI in the simulator. We selected Prophet because it is a simple and computationally efficient method dedicated to univariate time-series prediction. What is important, the Prophet considers the occurrence of seasonal components in time-series.

To set the initial state in the case of endogenous variables, the following procedure has been established. For the case where there is no modification to the DV at time $T-1$, the prediction of endogenous variables at time T is made using the VARMAX model and the initial state is just the entire data set at time $T-1$. It can be assumed to be an initial reference state. If the user wants to simulate a situation in which the DV for a given slice changes by $x\%$, then we set the initial state as $(100+x\%) \cdot y$. Here y is a predicted value of DV at time T (the reference state). For BLER it is assumed that the initial state is equal to its reference state.

If the initial values of DVs are calculated, then it is possible to determine the value of PRB utilization. It was mentioned that PRB utilization can be represented as a function of data volumes. Various approaches for PRB utilization forecasting have been considered, including: prediction using functional dependence (polynomials, exponential function, logarithm) or random forest models, multiple linear regression, ridge, and lasso. For more details on these models, see [43]. The chosen methods are simple models that are computationally efficient. KPIs are correlated, and predicting the dependent variable is not a complicated task (therefore a simple solution is preferred). The best results were obtained using a random forest, which takes as input the DV in each Slice, BLER, CQI and #UEs.

In this paper, a single simulated scenario is presented. Fig. 25 shows the values of normalized throughputs and delays: the last 24h of the training set vs. predicted values. The results correspond to the scenario in which DV-A and DV-D increase by 100%. The predicted values show that Slices A and D have increased TPut and delay, which corresponds to increased DV. Slice B also has a slight increase in delay, which is due to the fact that the underlying resources are shared. Furthermore, the distribution of the delay for Slice D increased (more samples with higher delays) and this is caused because this is the slice with the lowest priority and all the traffic affects it. Finally, all these results are in line with the understanding of telecommunications of this scenario, which additionally proves the correctness of the approach.

VII. CONCLUSION

The paper contributes to the fundamental problem of complex system modeling and simulation [51], [52], [53], especially for the application in wireless communication. An advancement in computational power, numerical, and AI/ML methods, and the huge amount of available experimental data open new opportunities to study the emergence of complex processes, which is a prerequisite to understand and manage complex systems. In this sense, we provide evidence that it is possible to retrieve and aggregate the knowledge from experimental data in a form of empirical model but with a phenomenological context. This results in customization of the analog consisting of mimicking detailed characteristics of the complex systems, feature typically unavailable for mechanistic modeling [52]. This legitimizes the use of our data-driven approach in the context of digital representation of a real-world object (here: 5G network). Finally, knowledge generalized in the form of data-driven digital twin enables descriptive and predictive inference, and also some actions which are now handled manually with the use of expert knowledge, e.g., 5G network planning and dimensioning.

In this article, we have described a framework for the network dimensioning and planning process. Several multivariate methods for traffic forecasting have been evaluated, from which VARMAX and LSTM presented the best fit to the real network time-series. Cell environmental conditions have been considered on top of the traffic model data. Two approaches to cell level network slicing modeling have been compared: slice specific and common for all slices. The general model, which presents good accuracy, is more elastic, and can be used for scenario simulation of the impact of traffic changes in specific slice(s) or all slices, which was also outlined in the article. The described framework can be used for "what-if" analysis, e.g., to evaluate what capacity extensions should be recommended and planned on the slice and cell level for a specific scenario.

An extension of cell level modeling to BTS and network level is planned as a next step of reported research. Furthermore, the robustness for a selected approach and a long-term planning case will be evaluated once a longer real data sample is acquired. In addition, we can also simulate the data generated in the adopted model for any arbitrary period and scenarios (i.e. when some parameters of the model change). This is the added value of using such a model. In this case, the evaluation of long-term forecasting can be performed if long-term data are available. We outlook that forecasting of other metrics, such as energy consumption and success rates (or loss rates, e.g. PDR), can be also added to the framework in the future. However, as these signals have other characteristics, we expect a need to use different models. Regarding the simulation intelligence approach [51], initiated here for the dimensioning and planning of a 5G wireless network, it is possible to extend the data-driven model with a broker module dedicated to optimized resource management in the sliced network [54].

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