Provisioning of 5G Services Employing Machine Learning Techniques

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***Abstract* - This study proposes a modeling framework for optimal online 5G service provisioning, based on low computational complexity machine learning techniques such as Neural Network (NNs). NNs are trained to take optimal decisions adopting an offline Integer Liner Programming (ILP) model. This framework is used to solve the generic joint Fronthaul (FH) and Backhaul (BH) service provisioning problem over a converged high capacity and flexibility optical transport aiming at minimizing the overall energy consumption of the 5G infrastructure. Our modeling results indicate that the proposed approach adopting NN based real time service provisioning can provide very similar performance to the one derived adopting the high complexity but accurate ILP approach.**

Index Terms - Machine Learning, Optimization, 5G, ILP, LSTM, MLP, optical transport.

I. INTRODUCTION

As the demand for high-speed mobile internet access connectivity increases at a rapid pace, Radio Access Networks (RANs) deployments need to be transformed into open, scalable and dynamic ecosystems able to support a large variety of demanding applications and services in a flexible and efficient manner. The fifth generation (5G) mobile networks address this need through a set of hardware and software technology innovations targeting both the data and the control plane. Suitable solutions include the adoption of new centralized control and management frameworks based on Network Functions Virtualization (NFV)/Software Defined Networking (SDN) principles. In addition, new architectural models allow to migrate from highly distributed and inefficient structures to more centralized approaches relying on concepts such as the Cloud-RAN (C-RAN) approach. C-RAN and its more recent variant including the notion of dynamic functional splits [1] introduce the need for fronthaul (FH) services interconnecting remote units (RUs) with processing units to allow centralization and ultimately softwarization of the RAN. Through pooling and coordination gains of softwarized/centralized RANs, significant cost reduction as well increased scalability and flexibility over current RAN solutions can be achieved.

To successfully deploy the concept of softwarized RAN together with the increased backhaul (BH) requirements imposed by the current and upcoming 5G services at the data plane, there is a need for a high capacity transport network interconnecting the remote antennas with the compute resources where softwarized

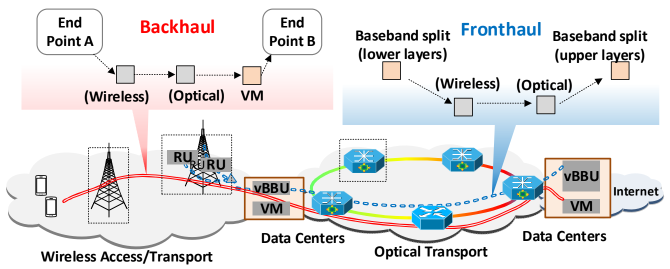

Figure 1: Provisioning of FH and BH services over a common 5G network infrastructure.

versions of the RAN protocol stack are executed. This will be enabled by a control plane solution able to manage and optimize the operation of a large number of highly heterogeneous network and compute elements, taking decisions related to: *i) optimal embedding* of service requests and creation of service chains over the converged network resources [2], [3], *ii) optimal infrastructure slicing* across heterogeneous network domains [4], *iii) optimal sharing* of common resources in support of Information and Communication Technology (ICT) and vertical industry services [5], *iv) optimal fronthaul* deployment strategies including optimal placing of central units with respect to remote units, functional split selection etc. [6], [7].

These problems are traditionally solved by a centralized controller considering in many cases multiple objectives and constraints (ranging from Capital and Operational Expenditure minimization, energy consumption, latency, resource availability etc.), adopting a variety of mathematical modeling frameworks based on integer linear [8] and non-linear [9] programming, stochastic linear and nonlinear programming formulations [10] etc. Although these schemes can be effectively used to identify the optimal operational points of the whole system, their increased computational complexity and slow convergence time makes them unsuitable for real time network deployments. To cope with the increasing computational complexity inherent in these models, alternative modular optimization schemes have been proposed. These aim at decomposing large optimization problems into smaller and easier subproblems that are able to handle a large number of variables.

Towards this direction, this study proposes a modular framework to enable optimal 5G service provisioning taking advantage of the optimal decisions taken through offline tools based on Integer Linear Programming (ILP) and less computationally intensive online tools based on Neural Networks (NNs). More specifically,

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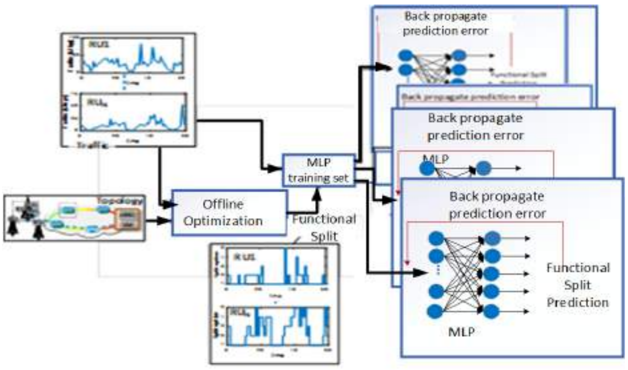

Figure 3: Construction of the training set that will be used for the design of the NN-based 5G optimization framework. The offline optimization block represents the ILP model, the solution of which gives the optimal baseband split for each RU. The optimal baseband splits as they have been obtained by the ILP and the traffic statistics as they collected by the RUs constitute the training set of the MLP-NN models. MLP-model learns to map each value of traffic statistics to the value of the optimal functional split through the backpropagation algorithm for each RU.

the offline ILP model is first used to create a set containing the optimal design policies for converged 5G network environments. NNs then use the output of the ILP as a training set. Once NNs have been trained, they can be used by the centralized controller for real time optimal decision making. To demonstrate the efficiency of the proposed technique, in the present study we consider the generic joint FH and BH service provisioning problem over a converged high capacity and flexibility optical transport network environment [4]. In this converged network part of the optimization problem is associated with identifying the optimal fronthaul service. This is directly related with the identification of the optimal split option adopted [4]. To solve the problem of optimizing the fronthaul services, a NN model is proposed to identify, in real time, the optimal functional split for each RU. Although NNs have been widely adopted to model various problems with remarkable performance in telecommunication networks (see [13]-[18]), to the best of the authors knowledge this is the first time where ILP and NNs are appropriately combined for the design of converged 5G Networks.

The rest of the paper is organized as follows. Section II provides a brief description of the problem under investigation, emphasizing on the offline ILP scheme and the proposed two-stage NN model. Optimal design strategies of the proposed NN model are provided in Section III whereas performance evaluation under a realistic network configuration is carried out in Section IV. Finally, Section V concludes the paper.

II. PROBLEM DESCRIPTION

This paper focuses on the generic case of a converged 5G infrastructure interconnecting a set $\mathcal{R}$ of R remote units (RUs) with a set $\mathcal{S}$ of S Central Units (CUs). This infrastructure, integrates wireless access and optical transport networks together with compute elements and is used to support FH and BH services. As already discussed for the FH services, we consider the dynamic functional split option approach, where the baseband signal processing tasks of the antennas can be divided,

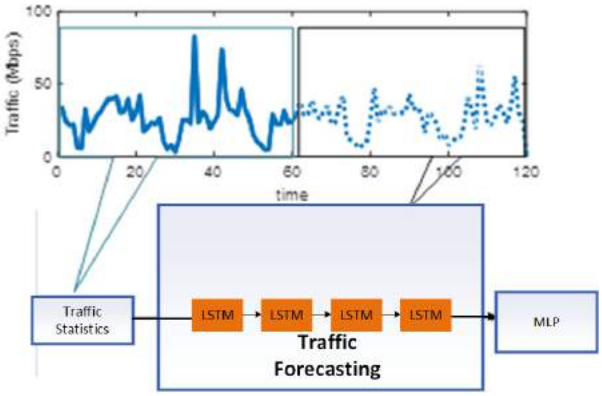

Figure 2: NN model-based, LSTM and MLP, for the optimization of the 5G network in the upcoming time instants. The input of the LSTM model is the traffic at time step t and the output is the traffic at next time step t+1. The value of traffic as derived from the LSTM is given as input to the MLP which can predict the optimal functional split in upcoming time instant.

allocating some functions at the RUs and the remaining ones at the CUs. As discussed in [4], the decision to execute these functions locally or remotely depends on various parameters including the network topology, the availability of resources, the service characteristics etc. For the BH services, we consider content delivery type of services, where mobile devices offload their compute intensive tasks to the cloud [4]. For this type of services, specific compute and network resources need to be also reserved across the converged 5G infrastructure. A graphical representation of this concept is shown in Figure 1.

To date, the problem of joint FH/BH service provisioning over a common infrastructure has been formulated and solved based on Integer Linear Programming (ILP) [19]. Specifically, assuming that $\mathcal{D}_F, \mathcal{D}_B$ is the set of FH and BH demands, respectively, $\mathcal{E}$ is the set of links, κ_e, the cost per link e in the infrastructure with $e \in \mathcal{E}$, κ_s the remote processing cost at $s \in \mathcal{S}$, κ_r the processing cost at the RU $r \in \mathcal{R}$ measured in Giga Operations per Second- GOPS, $u_{FH,e}, u_{BH,e}$ is the link e capacity allocated for FH and BH services, $\pi_{FH,s}$, $\pi_{BH,s}$ is the processing capacity for the FH/BH services and $\mathcal{U}_e$ is the capacity of link e, then, the joint FH/BH optimization problem can be formulated as follows:

$$\min \mathcal{F}\,(\boldsymbol{u},\boldsymbol{\pi}) = [\mathcal{FH}(\boldsymbol{u},\boldsymbol{\pi}),\quad \mathcal{BH}(\boldsymbol{u},\boldsymbol{\pi})] \quad (1)$$

where

$$\mathcal{FH}(\boldsymbol{u},\boldsymbol{\pi}) = \sum_{e\epsilon\mathcal{E}} \kappa_e\, u_{FH,e} + \sum_{s\epsilon\mathcal{S}} \kappa_s \pi_{FH,s} + \sum_{d\epsilon\mathcal{D}_F} \kappa_d\, \pi_{FH,d} \qquad (2a)$$

$$\mathcal{BH}(\boldsymbol{u},\boldsymbol{\pi}) = \sum_{e\epsilon\mathcal{E}} \left[\mathcal{U}_e - u_{FH,e} - u_{BH,e}\right]^{-1} + \sum_{s\epsilon\mathcal{S}} \left[\mathcal{C}_s - \pi_{FH,s} - \pi_{BH,s}\right]^{-1} \quad (2b)$$

subject to capacity, functional split and demand constraints. $(2a)$ minimizes the expected cost for the FH services while $(2b)$ the

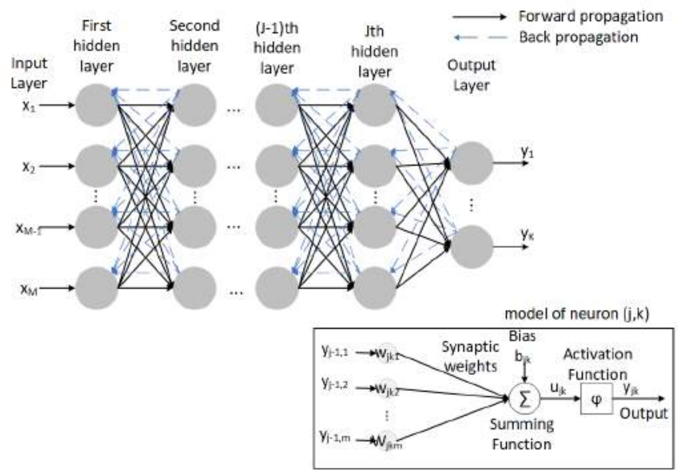

Figure 4: Graphic illustration of an MLP NN structure with backpropagation algorithm.

associated costs for the BH services. A description of the ILP-based modeling approach together with the relevant implementation details is given in [19] . Using as inputs network topology details and traffic statistics, the location where each function/task will be processed together with the required network and compute resources can be determined. Although the above-mentioned optimization framework can effectively identify the optimal operational point of the whole system, its increased computational complexity and its slow convergence time makes it impractical to optimize the operation for real time network deployments. To address this limitation, a two-step Neural Network-based optimization framework is proposed. This framework allows real time identification of the optimal operational strategies per RU. In the first step, using a specific set of training data, a novel Multilayer Perceptron (MLP) - based NN model is constructed that in-real time can identify the optimal operational policies for the whole 5G infrastructure. A high-level view of this process is shown in Figure 3 for a specific case where the MLP-NN is used to identify the optimal split per RU. To achieve this, a training set combining data from history traffic statistics as well as data extracted from the offline - optimization framework described above is considered. An algorithmic approach that allows the identification of optimal MLP-NN architecture is provided in the following section.

Once the model has been trained, the MLP-NN model is combined with a trained Long Short-Term Memory (LSTM) NN model used for traffic forecasting. This aims at identifying the optimal operating conditions for the 5G infrastructure in the upcoming time periods. The flowchart of this process is provided in Figure 2.

III. REAL TIME OPTIMIZATION FOR 5G

A. *Artificial Neural Network Preliminaries*

Artificial NNs are defined as systems of interconnected computational units, known as neurons, that interact with the environment. Each neuron has a non-linear, differentiable function, known as activation function, used to compute a weighted sum of the outputs of the previous-layer. In NNs, knowledge is stored in interneuron connection strengths, known as synaptic weights using a learning algorithm. The learning algorithm is a function that updates the value of synaptic weights during the learning operation. The Backpropagation algorithm is the most popular learning algorithm for training NNs and comprises two phases, the forward phase and the backward phase. Through the first phase, the signal is transmitted from the input to the output on a layer by layer basis, keeping the synaptic weights' unaltered. In the second phase, the comparison between the network's output and the desired response leads to an error signal. The error signal is propagated backwards through the network, starting from the output, and then the synaptic weights are re-evaluated to minimize the loss function. The loss function is a function that calculates the divergence between predicted and expected network's response values [12]. Figure 4 shows a typical MLP neural network with J hidden layers over which the backpropagation algorithm is applied.

Table 1: Overview of the Backpropagation Algorithm applied to the MLP-NN

Parameters:
M = dimensionality of the input space and number of neurons in hidden layers, $m = 1,2, \ldots, M$
J = *number of hidden layers*, $j = 1,2, \ldots, J$
K = *number of neurons in output layer*, $k = 1,2, \ldots, K$
N = *number of epochs*, $n = 1,2, \ldots, N$
$\boldsymbol{w_m}$=*synaptic weight vector of neuron m*
$\boldsymbol{d}$ = *desired response vector*
y = *neuron output*
$\boldsymbol{\delta_k}$ =*local gradient at neuron k*
η = *learning rate*
$\boldsymbol{e_k}$ = *error*

Initializations:
Set the synaptic weights of the algorithm to small values selected from uniform distribution.

Computations:
- **If neuron k is an output neuron then**:

(3.1) $\boldsymbol{u_k(n) = \sum_{m=1}^{M} w_{km}(n) \cdot y_{Jm}(n) + b_k}$

(3.2) $\boldsymbol{y_k(n) = \varphi(u_k(n))}$

(3.3) $\boldsymbol{e_k(n) = d_k(n) - y_k(n)}$

(3.4) $\boldsymbol{E(n) = \sum_{k\epsilon C} e_k{}^2(n)/2}$

(3.5) $\boldsymbol{\Delta w_{ki}(n) = -\eta \frac{\partial E(n)}{\partial w_{ki}(n)}}$

(3.6) $\boldsymbol{\frac{\partial E(n)}{\partial w_{ki}(n)} = -e_k(n)\varphi'_k\big(u_k(n)\big) \cdot y_{ji}(n)}$

(3.7) $\boldsymbol{\delta_k(n) = e_k(n)\varphi'_k\big(u_k(n)\big)}$

(3.8) $\boldsymbol{\Delta w_{ki}(n) = -\eta\, \delta_k(n) \cdot y_{ji}(n)}$

(3.9) $\boldsymbol{w'_{ki}(n) = w_{ki}(n) + \Delta w_{ki}(n)}$

else if it is a hidden neuron at layer j:

(3.10) $\boldsymbol{u_{jm}(n) = \sum_{m=1}^{M} w_{jm}(n) \cdot y_{j-1,m}(n) + b_{jm}}$

(3.11) $\boldsymbol{y_{jm}(n) = \varphi\big(u_{jm}(n)\big)}$

(3.12) $\boldsymbol{e_k(n) = d_k(n) - y_k(n)}$

(3.13) $\boldsymbol{E(n) = \sum_{k\epsilon C} e_k{}^2(n)/2}$

(3.14) $\boldsymbol{\Delta w_{ji}(n) = -\eta \frac{\partial E(n)}{\partial w_{jm}(n)}}$

(3.15) $\boldsymbol{\delta_{jm}(n) = \varphi'_{jm}\Big(u_{jm}(n)\Big) \cdot \sum_{k=1}^{K} \delta_{jk}(n) \cdot w_{jk}(n)}$

(3.16) $\boldsymbol{\Delta w_{jm}(n) = -\eta\, \delta_{jm}(n) y_{j-1,m}(n)}$

(3.17) $\boldsymbol{w'_{jm}(n) = w_{jm}(n) + \Delta w_{jm}(n)}$

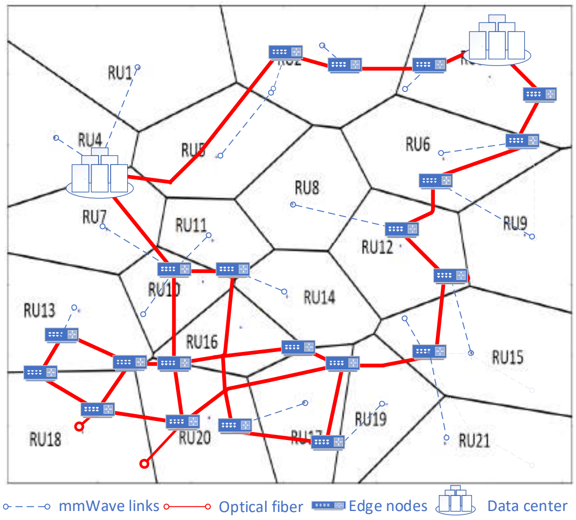

Figure 5: 5G network topology under investigation

The modeling details of the backpropagation algorithm for the MLP network are summarized in Table 1. Specifically, if neuron k is an output neuron, then the linear combiner output $u_k(n)$ is calculated by the weighted sum of the inputs $\cdot\, y_{Jm}(n)$ with the respective synaptic weights $w_{km}(n)$ using equation (3.1) (see lower part of Figure 4). $u_k(n)$ is then applied to an activation function φ, which limits the amplitude of the output of neuron k (3.2) resulting to the final output of neuron k at the n iteration, namely $y_k(n)$. The estimation error at the output of neuron k is calculated through (3.3), while the total instantaneous error $E(n)$ of the whole network is calculated using (3.4). The error is propagated backward and the correction Δw_{ki} is applied to the synaptic weight w_{ki} (3.5) - (3.9). A similar set of equations is applied for the hidden neurons (3.10) - (3.17).

Our objective is to identify an MLP network that maps any input x to the corresponding output y. Output y is obtained from the solution of the corresponding ILP formulation, while x represents the set of history observations. As an example, consider the scenario for which we apply to the MLP a training set that comprises a set of pairs (x, y), where x represents the traffic statistics for a particular RU at a given point in time, while y represents the functional split. The optimal functional split per RU over time has been obtained through the solution of the ILP model described in Sec. II. This training set is given as input to the MLP neural network in order to learn how to map each input x to the corresponding output y. Once the system has been trained, the MLP can predict the functional split given any new data without solving the corresponding ILP. The parameters of the MLP model can be derived executing the algorithm of Table 1 for different parameters' values (batch size, number of hidden layers etc.). At the end of the experiments, the combination of parameter value is chosen according to their ability to maximize the prediction accuracy.

B. Traffic forecasting using Long Short-Term Memory Neural Networks

Long Short-Term Memory (LSTM) is a special case of Recurrent Neural Network (RNN) capable to learn long-term dependencies, since it can remember information that was acquired in previous steps of the learning process. LSTM contains a set of recurrent blocks, known as memory blocks, each of which has one or more memory cells. Each cell is composed of three basic units, the input, output and forget gate that are responsible to decide whether to forget, keep, update or output information that has been acquired previously. LSTM is the most successful model for predicting long-term time series [1].

In the present study, the LSTMs are optimally designed to forecast the traffic load of each RU based on history traffic data available. The LSTM input vector corresponds to the traffic at an arbitrary time step t while the LSTM output vector corresponds to the traffic at time step t+1. To train the LSTMs, the dataset containing history measurements of each RU is split into two parts, the training set and the test set. The training set is used during the training of the LSTM network, while the test set is used to validate the effectiveness of each LSTM designed. To identify the optimal LSTM architecture for each RU, an extensive set of experimentations is performed. Given that the LSTM architecture can be fully characterized by the number of hidden layers, neurons, epochs and the batch size, our objective is to the identify how these parameters can be optimally combined to minimize the forecasting error. This process is summarized as follows:

Step 1- Batch size. The batch size is the number of training instances used in each iteration. The weights are updated after each batch propagation. We choose the value for the batch size that minimizes forecasting error keeping all other parameters constant.

Step 2- Number of epochs: The number of epochs determine the maximum number of passes over the training dataset. Various values for the number of epochs are tested in order to identify the optimal one that minimizes the forecasting error.

Step 3- Number of neurons. In this step, our objective is to identify the optimal number of neurons that achieves optimal traffic forecasting accuracy.

Step 4 – Number of hidden layers. The last parameter that we study is the number of hidden layers. As before, after extensive experimentations we choose the number of hidden layers that

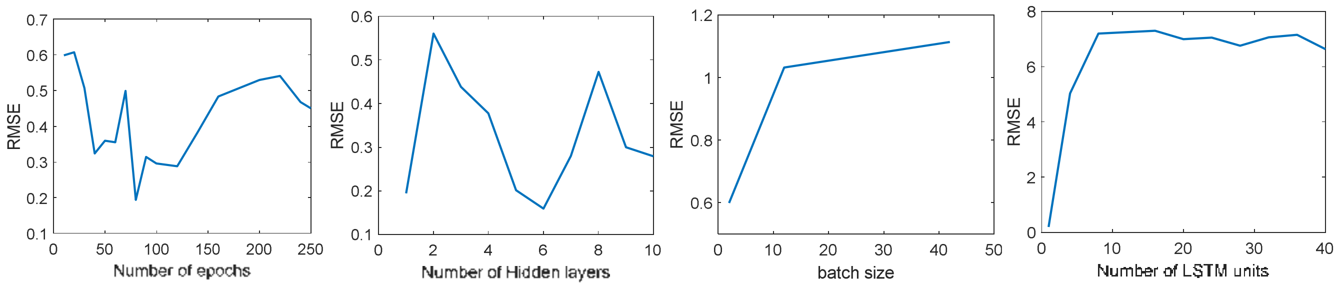

Figure 6: Learning curves of the LSTM for RU16

Table 2:Parameter Settings of Neural Networks for the RU16

	Batch Size	Number of Epochs	Hidden Layers of the Network	Number of Neuron for Output Layer	Activation Function for Hidden Layers	Activation Function for Output Layer
LSTM	2	80	6 hidden layers with 1 neuron each layer	1	Relu	-
MLP	2	600	1 hidden layer with 10 neurons	5	Relu	Softmax

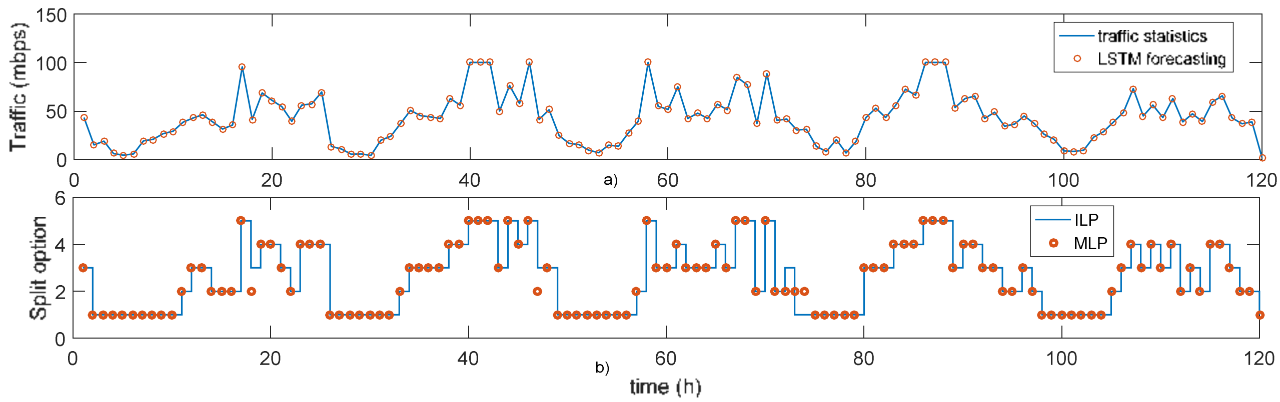

Figure 7: a) Traffic forecasting for RU16 using LSTM. b) Optimal functional split prediction for RU16 using the results obtained from the ILP and the MLP.

minimizes the forecasting error calculated through the root-mean-squared-error formula (RMSE).

IV. NUMERICAL RESULTS

A. *Topology description and assumptions*

The validity of the proposed NN-based optimization framework is evaluated using the optical transport network topology presented in [4] over which 21 RUs are deployed. The coverage area of each RU is shown in Figure 5. For this topology, mobile devices served by the corresponding RUs generate demands according to real datasets reported in [11]. Each RU is connected to the optical transport through microwave point-to-point links with 2 Gb/s bandwidth, and 45W power consumption. The optical transport has a single fiber per link, 4 wavelengths of 10 Gb/s each per fiber, and minimum bandwidth granularity of 100 Mb/s [4]. The processing requirements of the mobiles devices and the RUs are supported through a set of DCs. For this network topology, our objective is to design a NN model that approximates the optimal ILP described in Sec. II and solved in [4]. To keep the analysis tractable, the results provided are correspond to the optimal functional split of RU16, however, similar studies have been conducted for all compute/network elements of Figure 5 focusing on other parameters of interest such as, network capacity for optical links, compute capacity for DCs, locations where demands are processed for demands etc.

B. *Neural Network/Learning topology optimization*

To design the two-stage NN model using the LSTM/MLP models, the methodology presented in Sec. III is applied to all network components. For each component, our objective is to design an NN that approximates with very high accuracy the optimal policies obtained through the corresponding ILP model.

To identify the optimal NN models, the learning curves showing the RMSE as a function of the number of epochs, hidden layers, neurons and batch size are first obtained. Based on these curves, the optimal values of the parameters that minimize the corresponding error can be readily determined. A typical set of learning curves for the LSTM model of RU16 is shown in Figure 6 and the corresponding optimal values are provided in Table 2.

C. *Traffic forecasting based on LSTM Neural Networks*

Once the optimal LSTM NN structure has been determined, the model is trained using the history dataset and the corresponding synaptic weights are determined. The test set is applied to the LSTM model to evaluate its forecasting performance. A snapshot showcasing the performance accuracy of the LSTM model for RU16 is illustrated in Figure 7 a), where an RMSE of 0.16 is obtained corresponding to a forecasting error in the order of 0.3%.

D. *Prediction of operational parameters: Optimal Functional Split based on MLP Neural Networks*

Following a similar approach to the LSTM problem design, once the MLP network has been defined, the derived model is trained and validated using the training set obtained from the ILP formulation. Figure 7 b) shows the performance of the proposed model where it is observed that the MLP is able to identify the optimal functional split with a 95% accuracy.

E. *Total power consumption*

Finally, the performance of the proposed NN scheme is compared to the ILP based optimization approach presented in [4] in terms of total network power consumption. It is observed in Figure 8 that the power consumption over time for both schemes takes very close values, indicating the effectiveness of the proposed NN scheme to identify the optimal operational

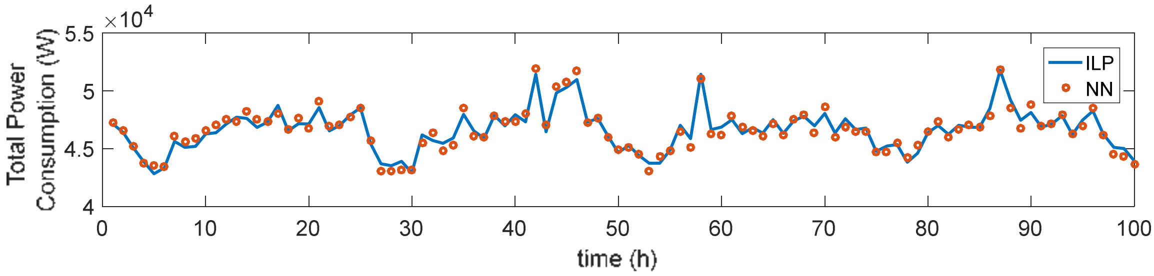

Figure 8: Total Power consumption when applying the ILP and the proposed NN scheme

strategies of every network element. This clearly shows that online optimal service provisioning can be achieved taking a practical low complexity approach adopting machine learning techniques that can be trained to take real time very close to optimal decisions. In this context, the training process plays a key role and can be performed taking advantage of the optimal decisions provided through offline tools based on ILP.

V. CONCLUSIONS

This study proposes a modeling framework to enable optimal online 5G service provisioning based on low computational complexity machine learning techniques such as NNs, exploiting optimal decisions taken through offline tools based on ILP for training purposes. The offline ILP model is first used to create a set containing the optimal design policies for converged 5G network environments. NNs then use the output of the ILP as a training set and after being trained, they can perform real time optimal decisions. To demonstrate the efficiency of the proposed technique, we consider the generic joint FH and BH service provisioning problem over a converged high capacity and flexibility optical transport aiming at minimizing the overall energy consumption of the 5G infrastructure. Our results indicate that the proposed approach adopting NN based real time service provisioning can provide very similar performance to the one derived adopting the high complexity but accurate ILP approach.

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