Traffic Prediction- and Explainable Artificial Intelligence-based Dynamic Routing in Software-Defined Elastic Optical Networks

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***Abstract*—The recent research reveals a high potential and efficiency of machine learning (ML) algorithms applied to aid the optimization of telecommunication networks. Moreover, thanks to the tools of explainable artificial intelligence (XAI), it is possible to better understand and interpret the decisions of ML models, identify the features influencing them the most, and use that knowledge for further targeted optimization improvements. In this paper, we use these approaches to aid the optimization of the well-known and essential problem of dynamic routing in software-defined elastic optical networks (EONS). We use the XAI to verify which transmission and network state parameters influence the performance the most (expressed as a bandwidth blocking probability (BBP)) of a dynamic EON. The analysis reveals that two of the most relevant features are related to characteristics of the incoming traffic requests – the source node and the traffic prediction for the demand's source-destination nodes. Next, we use that data to propose six traffic prediction- and XAI-based demands ordering policies, which are used to improve a benchmark allocation algorithm. Then, we perform simulations to evaluate the policies' efficiency and compare them with reference methods. The results show that our targeted proposal is exceptionally efficient – the best policy allowed to reduce the BBP up to about 6.1%, representing 4203 Gbps of more served traffic compared to the best reference policy.**

***Index Terms*—traffic prediction, explainable artificial intelligence, software defined network, elastic optical network, network optimization, dynamic routing**

I. Introduction

Recently, telecommunication networks have risen to the extraordinary challenge of increasing users' expectations and tremendous traffic volumes. This is due to the COVID-19 pandemic and the following change of our working scheme (to mainly remote mode), increased interest in Internet contents on demand and a higher importance of social connections [1]. The growth phenomena force network operators and researchers to optimize the existing networks and adjust to the increasing requirements and traffic volumes. Besides ideas of new physical technologies, it is necessary to revisit and improve the algorithms used in control and management systems to use the existing and limited network resources better. That may be achieved by applying machine learning (ML) algorithms and computational intelligence methods [2]. Numerous successful applications of these methods have been proposed for optical networks, including the traffic prediction task [3], prediction-based routing and resource allocation [4], quality of transmission (QOS) estimation [5], survivability provisioning [6]. Due to the possibility of a incremental learning, ML algorithms may be especially beneficial when applied to (re-)optimize a dynamic network operation. Despite plenty of promising demo applications, adopting ML-based control systems in real networks is hindered due to their lack of trustfulness and the decision's complete understanding. Hopefully, the domain of explainable artificial intelligence (XAI) allows us to address these issues by providing methods able to explain and interpret the decisions of ML models and increase their trustfulness.

In this paper, we revisit a well known and extremely important problem of the dynamic routing in elastic optical networks (EONS) implementing the software defined networking (SDN) paradigm. We use explainable artificial intelligence (i.e., the shapley additive explanations – SHAP method) to analyze how different transmission and network state parameters (including the current traffic characteristics and its prediction for forthcoming time steps) influence the network performance expressed as the bandwidth blocking probability (BBP). We then identify the most important features and use them to improve the efficiency of a benchmark bit-rate allocation algorithm by proposing six demands ordering policies (which determine the demands allocation order in a particular time stamp). Based on simulations, we evaluate the performance of our proposals and compare them with reference policies.

The rest of the paper is organized as follows. Section II reviews the related works. Section III defines the considered optimization problem, while Section IV describes the applied optimization algorithm. Section V discusses the simulations and their results. Lastly, Section VI concludes the whole paper.

II. Related works

The problem of the traffic prediction in telecommunication networks has been extensively and fruitfully studied in the literature. Numerous efficient approaches have been proposed, including statistical methods (like auto-regressive integrated moving average, ARIMA) [7], simple supervised learning approaches (e.g., like linear regression (LR) [3], k nearest neighbors (KNN) [7]) and various neural network-based algorithms [8], [9]. The majority of papers focus on traffic forecasting in a normal network state. However, Refs. [10], [11] takes into account a special case of the prediction after

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a link failure. Traffic forecasting methods can then be used to optimize network performance directly. The authors of [7] propose an anycast demands relocation policy, which is controlled by the bit-rate prediction. Ref. [12] applies a forecasting of the traffic features to propose a resource (re)allocation procedure in optical data center networks. Then, the authors of [13] developed a traffic prediction algorithm for the resource allocation in network function virtualization architectures in which data centers are interconnected by an EON. Next, Ref. [14] study a problem of the efficient adaptation/reconfiguration of virtual network topologies using the traffic forecast. Lastly, paper [4] focuses on improving a dynamic routing in EONs using a bandwidth reservation mechanism controlled by the traffic prediction.

Recently, we also observe a research interest in the applications of explainable artificial intelligence to interpret and aid the optimization of network-related problems. Considering optical networks, which are in the scope of this paper, the majority of existing studies apply the SHAP [15] to explain the decisions of ML models. Selected problems are also solved by tree-based explainers or local interpretable model-agnostic explanations (LIME) framework [16]. In turn, Refs. [5], [17] make use of the SHAP for interpreting decisions of models estimating quality of service (QOS) parameters of light-paths in an optical network. Manuscript [18] studies a network failure detection problem using the SHAP. Authors of [19] cover a failure localization task using the same explainer. Ref. [20] focuses on a failure-cause identification using both – the SHAP and LIME approaches. Lastly, Paper [21] focuses on the traffic classification task using the deep SHAP explainer while the authors of [22] study failure identification and location in network function virtualization systems by utilizing explainable deep learning frameworks.

To summarize, the literature lacks a study on the practical application of the traffic prediction for optimizing dynamic routing in EONS. The only paper is [4], which uses forecasting to configure a bandwidth reservation mechanism. Moreover, no paper uses the XAI to explain which transmission and network state parameters influence the most the efficiency of a dynamic EON and no research focusing on the XAI application to improve that operation. The proposed paper fills the research gaps by applying the XAI to identify the features crucial for the dynamic routing and then proposing the traffic prediction- and XAI-based demands ordering policies, which improve the efficiency of a benchmark allocation algorithm.

III. Problem definition

The paper focuses on optimizing a dynamic routing and spectrum allocation (RSA) in software-defined EONS. This section gives network and traffic models and assumptions.

A. Network model

The network implements a software-defined networking [23] paradigm. Its architecture consists of three layers (planes): application (on the top), control (in the middle), and data (on the bottom). The application plane is the closest to the end users and serves as a source of traffic requests. The second edge layer, i.e., the data plane, is the closest to physical devices realizing the packets/frames switching. Note that the data plane in our study implements the EON paradigm. The central element of the architecture is the control plane, which is responsible for the network configuration and management. It can directly communicate with two other planes. In turn, it allows for a centralized management based on the observations of traffic patterns and requirements provided by the application plane as well as the monitoring state and resource availability in the data plane. For this paper, we assume that the control plane is responsible for (*i*) global monitoring and analyzing network traffic, (*ii*) creating traffic forecasting models, (*iii*) global monitoring and analyzing transmission and network state parameters as well as recourse availability, (*iv*) making decisions regarding routing and spectrum allocation (i.e., bit-rate allocation in the data plane). Note, in this contribution, we focus on the algorithmic nature of the control plane, i.e., traffic and network monitoring and analysis, as well as its application to efficient management of operations within the data plane. Therefore, we do not study in detail SDN physical realization and protocols for inter-layer communication.

B. Traffic model

The network is in its operational phase – in each time stamp, a number of traffic requests arrive (and need to be allocated), and a number expire (and free reserved resources). Each request is given as a tuple $d = (s, t, b, w)$, where $s(d)$ and $t(d)$ are the source and destination node, $b(d)$ is a bit-rate (in Gbps), and $w(d)$ is a holding time (in time stamps).

To generate a network traffic, we use the model introduced in [7]. It considers four transmission types (city to city, city to data center, data center to city, and data center to data center). It models their time process using sine functions with parameters related to network economic, demographic, and topological characteristics. In turn, the model allows us to estimate the entire bit-rate $f(t, i, j)$ existing between a pair of nodes $(i, j), i \neq j$ in each time stamp *t*. To verify whether a request arrives or expires in the time point *t*, it is necessary to compare the current total bit-rate value $f(t, i, j)$ with the previous observation $f(t-1, i, j)$ and already allocated demands. To simplify that process, we use the special algorithm proposed in [6], which translates the data provided by the traffic model into demands sets arriving in each iteration $t \in T$. To this end, it goes through all pairs of communicating nodes (i, j), takes into account the current bit-rate volume $f(t, i, j)$ and all previously offered and still existing demands (whose bit-rate is included in the value $f(i, j, t)$). The method also assumes that the maximum demand's bit-rate cannot exceed 250 Gbps while its duration is randomly chosen from the range $(0, 30]$. For more details on the traffic model and its translation into sets of demands, we refer to [7] and [6].

C. Routing and spectrum allocation

The data plane implements the EON architecture. Let $G = (V, E)$ denote a graph modeling the network topology wherein

V is a set of its nodes and E is a set of fiber-directed links. Each link offers the same spectrum width, which is divided into frequency slices $s \in S$. Note that adjacent frequency slices can be grouped into channels, each characterized by a first slice index and number of involved slices.

To realize an incoming request, it is necessary to assign it with a light-path $l = (p, c)$ and reserve its spectral resources for the period given by the request's holding time. Note that a light-path is a connection of a routing path *p* (from the source to the destination node) and a channel *c* tailored the request's bit-rate and the path length. Each established light-path must satisfy the constraints of the spectrum contiguity, continuity, and non-overlapping [24]. When it is impossible to assign a request with a light-path (due to resource unavailability following the realization of previously allocated bit-rates), the demand is rejected. We use the network physical model presented in [25] to calculate a channel width required to realize a given bit-rate on a specific routing path. We assume that an optical transponder utilizes three slices and uses one of four modulations: BPSK (supported bit-rate: 50 Gbps, transmission reach: 6300 km), QPSK (100 Gbps, 3500 km), 16-QAM (150 Gbps, 1200 km), 32-QAM (200 Gbps, 600 km). Signal regenerators are used when a selected path is longer than the modulation's range. Since they are expensive devices, we try to minimize their number and apply the distance-adaptive transmission (DAT) rule to select a modulation for a candidate bit-rate on a routing path [26]. The rule chooses the most spectrally efficient format that simultaneously minimizes the number of regenerators.

The network operation is simulated within T-iterations period. The optimization task aims to serve as much of the offered (incoming) bit-rate as possible within that time perspective. In other words, the goal is to minimize the bandwidth blocking probability, which is defined as a summed bit-rate of rejected demands divided by the total offered bit-rate.

IV. RSA ALGORITHM

To solve the RSA, we use an efficient benchmark algorithm called shortest path first routing and spectrum allocation (SFP-RSA). It was widely applied in numerous studies [4], [6].

Its idea is presented in Alg. 1. Firstly, the method initializes variables b_{off} and b_{rej}, which store the total offered and rejected bit-rate values, respectively. It also creates empty sets D_{cur} and L_{cur}, which will be then used to store, accordingly, the demands currently realized in the network and the light-paths established for them. Next, it moves to the main loop, simulating the network operation within T time points.

In each time step, the method's process consists of two phases: allocating new demands and releasing resources after expired requests. Thanks to SDN architecture, the allocation process has a general overview of the network – it monitors the resource availability on all links, receives and serves all incoming traffic requests. It is possible that more than one connection request appears at a specific time point. However, they cannot be simultaneously allocated due to the spectrum non-overlapping constraint. Therefore, the considered algorithm allows us to determine the order in which these demands are allocated. By default, the requests are handled according to the time they have come to the network (controller). However, the ordering policy is a mechanism we are going to improve using the XAI. Then, the demands are considered one by one according to the determined order. For each of them, the method calculates *n* shortest paths (using Yen's method with link lengths measured in kilometers) and tries to find a first-fit channel accommodating the required bit-rate. Note, when selecting a light-path we take into account only the path length and spectrum availability – we do not consider its QOS parameters. The demand is allocated if possible, and the algorithm moves to the next request. The demand is rejected if none of the *n* paths offers enough free spectrum. When all connections have been considered, the method moves to the existing (previously allocated) demands and checks which of them expire in the current time stamp. These requests are deleted and their resources are free. After T time stamps, the method calculates the final BBP value and terminates.

Algorithm 1: SPF-RSA algorithm

$b_{off} = b_{rej} = 0$; $D_{cur}, L_{cur} \leftarrow \emptyset$
for *each* $t \in T$ **do**
    $D_{off} \leftarrow$ GET_INCOMMING_DEMANDS(...)
    $D_{off} \leftarrow$ SORT_DEMANDS(D_{off})
    for *each* $d \in D_{off}(t)$ **do**
        $b_{off} = b_{off} + b(d)$
        $P_d \leftarrow$ GET_KSP(d, n, G)
        unallocated = True
        for *each* $p \in P_d$ **do**
            $c \leftarrow$ GET_FIRSTFIT_CHANNEL(d, p, G)
            if $c \neq \emptyset$ **then**
                Allocate demand d using $l = (p, c)$
                $L_{cur} = L_{cur} \cup l$; $D_{cur} = D_{cur} \cup d$
                unallocated = False
                break
        if *unallocated* **then**
            $b_{rej} = b_{rej} + b(d)$
    for *each* $d \in D_{cur}$ **do**
        $h(d) = h(d) - 1$
        if $h(d) = 0$ **then**
            Release resources of light-path $l = L_{cur}(d)$
            $L_{cur} = L_{cur} \setminus l$; $D_{cur} = D_{cur} \setminus d$
return BBP $= \frac{b_{rej}}{b_{off}}$

V. INVESTIGATION

In this section, we (*i*) apply the XAI to identify which transmission and network state parameters influence the most the network's BBP, (*ii*) use that data to design demands' ordering policies, (*iii*) evaluate the policies' efficiency based on simulations and comparison with reference procedures.

A. XAI *analysis of the network performance*

To analyze which transmission and network state parameters influence the most the network efficiency, we define a regression task $w_{d,t} \rightarrow \text{BBP}_{d,t}$. Let $w_{d,t}$ be a vector of a transmission and network state and let $\text{BBP}_{d,t}$ be the BBP associated with that vector (i.e., obtained after an attempt of the demand's d allocation in the time slot t and during the network state defined by that vector). Note that both $w_{d,t}$ and $\text{BBP}_{d,t}$ are a function of the time slot t and the demand d offered in that time slot. So, the estimation is performed for the operational network. The vector consists of features identified as potentially crucial for the network's BBP, accordingly:

1) source node of the demands d – $s(d)$,
2) destination node of the demand d – $t(d)$,
3) bit-rate of the demand d – $b(d)$,
4) holding time of the demand d – $h(d)$,
5) number of slices required for demand d on the selected path if allocated; -1, if rejected,
6) length of the selected path if allocated; -1, if rejected,
7) index of the selected modulation (0 – BPSK, 1 – QPSK, 2 – 16-QAM, 3 – 8-QAM) if allocated; -1, if rejected,
8) total offered bit-rate for the pair of nodes $(s(d), t(d))$ during x previous time steps,
9) total rejected bit-rate for the pair of nodes $(s(d), t(d))$ during x previous time steps,
10) total predicted bit-rate for the pair of nodes $(s(d), t(d))$ during x next time steps,
11) total currently allocated bit-rate for the pair of nodes $(s(d), t(d))$,
12) average number of free slices on the shortest path available for the pair of nodes $(s(d), t(d))$,
13) average spectrum fragmentation on the shortest path available for the pair of nodes $(s(d), t(d))$,
14) average number of free slices in the network,
15) average spectrum fragmentation in the network.

The parameters 1)–4) describe characteristics of the considered demand. The values 5)–7) give its allocation scheme if it is allocated. The features 8)–11) reflect the traffic observed or predicted for the pair of nodes related to the demand. Lastly, the values 12)–15) refer to the spectrum fragmentation and resource availability on the shortest path for the demand and in the entire network. Note, a link fragmentation is calculated as a width of the widest continuous set of free slices divided by the number of all free slices on that link. Following, a spectrum fragmentation in entire network is calculated as an average fragmentation over all links.

We use the following experimental protocol to evaluate how each defined feature influences the BBP. We consider EURO28 network topology (28 nodes and 82 links), which is presented in Fig. 1 [27]. There are $R = 7$ data centers located in the network based on real data available at https://www.datacentermap.com/. The network implements the EON architecture with $S = 320$ slices available on each fiber link and with the physical model described in Section III-C. We use traffic generation and translation models as given in Section III-B. The values of economic and demographic parameters were gathered from the official websites of the cities related to EURO28 as of December 2021. The distances between cities reflect real geographical distances given in kilometers. We consider the network traffic volume $B \in \{5, 10, 15, 20, 25, 30, 40, ..., 100\}$ Tbps and the simulation time $T = 1000$ iterations. We apply a highly efficient framework proposed and tuned in [7] for traffic forecasting. In more detail, we use multi-layer perceptron (MLP) regressor with *identity* activation function, *constant* learning rate, *lbfgs* solver and *(70,)* hidden layer sizes. We predict traffic for the next $x = 10$ time points based on the $m = 30$ last observations.

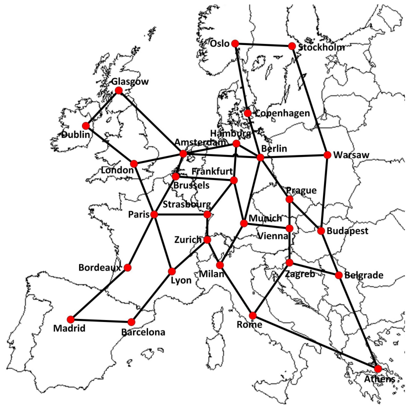


Fig. 1: EURO28 network topology

For each traffic volume, we simulate a network operation using the SPF-RSA with $n = 10$ shortest paths and with the default demands ordering policy. We save vectors $w(d, t)$ after an allocation attempt of each demand. Thus, the number of patterns is equal to the number of all offered requests and is not the same for considered cases – see Table I. Having that dataset, we tune extreme gradient boosting XGBoost regressor [28] using the standard k-fold cross-validation protocol with $k = 5$ [29] with the MSE metric. Due to the limited space of that paper, we do not show the regressor's tuning and evaluation process. Then, we use SHAP explainer to interpret the obtained results. It allows to estimate how each of the features influences the model's predictions by assigning it with a special SHAP value. The higher the absolute SHAP value is, the more important the related feature is in the problem. Since we focus on the BBP minimization, we interpret low (negative) SHAP values as potentially promising (impacting the less the BBP increase) and high (positive) values as potentially unbeneficial (significantly increasing the BBP).

Fig. 2 presents SHAP plots for two selected traffic loads $B = 15, 25$ Tbps. However, the dependencies for other values exhibit similar trends. For all traffic loads, four features are the most important: (*i*) fragmentation in the network, (*ii*) average number of free slices in the network, (*iii*) traffic prediction, (*iv*) demand's source node. Two first features represent a network state, which changes during the demands' allocation and release actions – the amount of free resources and the width of continuous free spectrum range decrease. For all configurations, low values of these parameters entail a significant BBP increase (positive SHAP values) and their high values

TABLE I: Characteristics of the training dataset for the BBP estimation task

average	AVERAGE NETWORK LOAD B [TBPS]												
number of	5	10	15	20	25	30	40	50	60	70	80	90	100
demands per time slot	106.6	146.6	175.0	196.0	211.6	227.6	252.9	275.1	294.2	309.2	334.3	337.0	351.2
patterns in dataset	106601	146580	175015	196093	211568	227591	252892	275144	294151	309197	324300	336952	351215

impact the BBP growth less importantly. Note, that we use non-standard fragmentation definition, which represents the width of the widest free channel to the number of all free slices. It is worth mentioning that the corresponding parameters defined for the demand's shortest path are much less important. It follows from the possibility of using longer paths when the shortest is almost fully utilized. The number of free slices is the parameter that cannot be directly controlled in the allocation since it mostly depends on the offered bit-rate. On the contrary, the problem of a spectrum fragmentation was widely considered in the literature, and numerous studies focus on its optimization [30]. Therefore, we do not pay attention to these two features. Then, the analysis shows the importance of traffic prediction, which can be easily calculated and used by the allocation procedure. Note that the bit-rate prediction is a parameter reflecting the future traffic volume, and simultaneously, it exposes the traffic pattern and trends, which may influence the current allocation and associated BBP. The plots show that low prediction values mostly relate to a low SHAP value (and BBP at the same time) while higher forecasts entail a higher SHAP value (and BBP). Lastly, the analysis identifies a demand source node as a critical parameter. It follows from the observation, that the cities' economic and demographic characteristics influence the traffic intensity and volume. That relationship is reflected in the applied traffic model. Since a node index does not represent a quantitative value, it is impossible to determine here a general relationship between a source node number and the BBP. That is also visible in the obtained plots – some cases show that low source node values are connected with low SHAP (and BBP) values (see for instance Fig. 2b) while others exhibit the opposite relationship (like in the example, Fig. 2a). Therefore, the source node has a significant impact on the BBP but its character depends on the network traffic load.

Summarizing, four parameters influence the BBP the most – the average number of free slices in the network (to reduce the BBP its value should be high), spectrum fragmentation (it should be high – according to the assumed definition), traffic prediction (which is preferable to be low) and transmission source node (for which it is impossible to give a general recommendation).

B. *Traffic prediction- and* XAI*-based ordering policies*

We propose six simple yet potentially efficient ordering policies based on the above analysis. To design policies, we use two parameters – traffic prediction and transmission source node. In the case of former one, we are going to use traffic forecast to sort the demands. In the latter one, we are going to use SHAP values obtained for network nodes when serving as source of transmissions. Since each demand is given by a source and destination node, that methodology does not allow to fully order the demands. Therefore, we also propose two ideas on how to order different demands with the same source node.

Let $sv\_src(i)$ be a weight of a network node i when serving as a source of a transmission. Its value is equal to the average SHAP value (over all pattern for which i is the source node) of the feature related to the demands source node. Similarly, let $sv\_dst(i)$ be a node weight when serving as a destination node. Its value is equal to the average SHAP value (over all pattern for which i is the destination node) of the feature related to the demands destination node. The proposed policies are as follows:

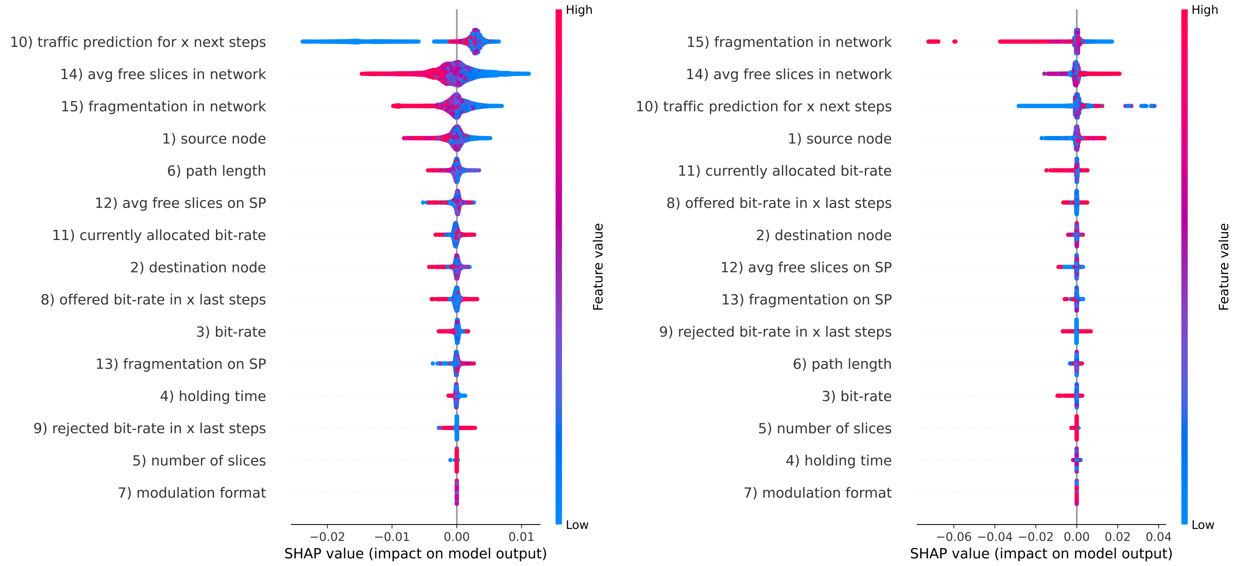
- TRAFF-ASC: The demands are handled in the ascending order of the traffic forecast for their source-destination nodes for the next x time steps.
- TRAFF-DSC: The demands are handled in the descending order of the traffic forecast for their source-destination nodes for the next x time steps.
- SRC-ASC: The demands are sorted in ascending value of the $sv\_src()$ metric of their source nodes. The demands with the same source node are then sorted in ascending order of the $sv\_src()$ metric of their destination node.
- SRC-DSC: The policy works similarly like the SRC-ASC, however, the demands are sorted in descending order.
- PAIR-ASC: Each pair of nodes $i, j \in V; i \neq j$ is assigned with a special weight $sv(i,j) = sv\_src(i) + sv\_src(j)$. Then, the demands are ordered in ascending value of the weight assigned to their source-destination pair of nodes.
- PAIR-DSC: The policy works similarly like the PAIR-ASC, however, the demands are sorted in descending order.

C. *Efficiency of the traffic prediction- and* XAI*-based routing*

This section evaluates the efficiency of the SPF-RSA applied with the proposed demands ordering policies. For the sake of simplicity, we refer to these algorithm versions using only the ordering policy name. The evaluation is divided into two parts. Firstly, we compare six proposed policies with each other and determine the best of them. Secondly, we compare the best policy with two reference ones:

- REF-DEFAULT: The demand are handled in the order they have appeared in the network. It is equivalent to the random handling policy.
- REF-NODE-BITRATE: The demands are handled according to the indexes of their source-destination pairs of nodes. So the order is as follows: (0,1), (0,2), (0,3),... . If multiple demands are offered for the same pair of nodes, they are handled in descending value of their bit-rate.

We consider the traffic volume equal to $B \in \{5, 10, 15, 20, 25, 30, 40, ..., 100\}$ Tbps. We run the



(a) $B = 15\ Tbps$ (b) $B = 25\ Tbps$

Fig. 2: SHAP plots for the BBP estimation problem

SPF-RSA for each value with various ordering policies. We repeat calculations five times and present the averaged results.

Fig. 3 compares six policies with each other. It shows that the lowest BBP for all traffic volumes was achieved when demands were sorted using the TRAFF-DSC. The second best policy was the PAIR-ASC. On the contrary, the worst results were yielded when the requests were ordered by the TRAFF-ASC. Note that the best and worst policies are connected with the traffic prediction. It means that the traffic pattern and trends have a crucial influence on the allocation process. During the highest network load, the gaps between these two approaches were tremendous – they reached up to several dozen of percent. Next, Fig. 4 compares the TRAFF-DSC's with two reference policies. It proves a high efficiency of the proposed approach, which provided the lowest blocking for the entire network load range. For the quantitative analysis, let a BBP *reduction gain* define a difference between the BBP obtained by the best reference policy (in our case – the REF-NODE-BITRATE) and the best proposed (the TRAFF-DSC). In other words, the parameter expresses how much the proposed method allows to reduce the BBP compared to the best reference. The analysis of the gains is reported in Table II. The TRAFF-DSC allowed to serve up to 6.1% more bit-rate, corresponding to 4203 Gbps of more served data (for $B = 50$ Tbps). Its average gain was 3.3%, representing 1976.1 Gbps of more allocated traffic. Therefore, the analysis proves that policy to be a simple yet highly efficient solution.

VI. Conclusions

In this paper, we focus on the well-known and significant problem of a dynamic routing in EONS. We use effective tools of the traffic prediction and the XAI to improve its optimization. First, we apply the SHAP explainer to determine which transmission and network state parameters influence the network's BBP the most. The analysis exhibits four crucial parameters, including the traffic prediction calculated for pairs of nodes related to network connections. On that background, we propose six traffic prediction- and XAI-based demands ordering policies, which can be used to improve the performance of a demands allocation method. Next, we perform simulations to evaluate the policies' efficiency and to compare them with reference procedures. The results prove the extremely high efficiency of our proposal – it allowed us to reduce the BBP up to about 6.1% (which corresponds to 4203 Gbps more served data) compared to the best reference method.

In future works, we plan to use the XAI to identify features crucial for improving the network survivability and use them to design efficient protection or restoration mechanisms.

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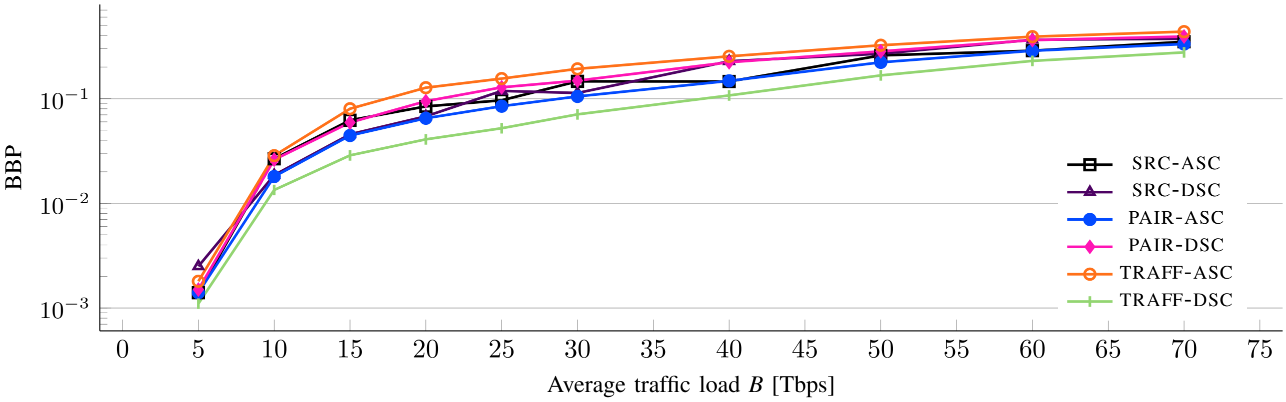

Fig. 3: Comparison of the proposed demands ordering policies – average BBP as a function of network load

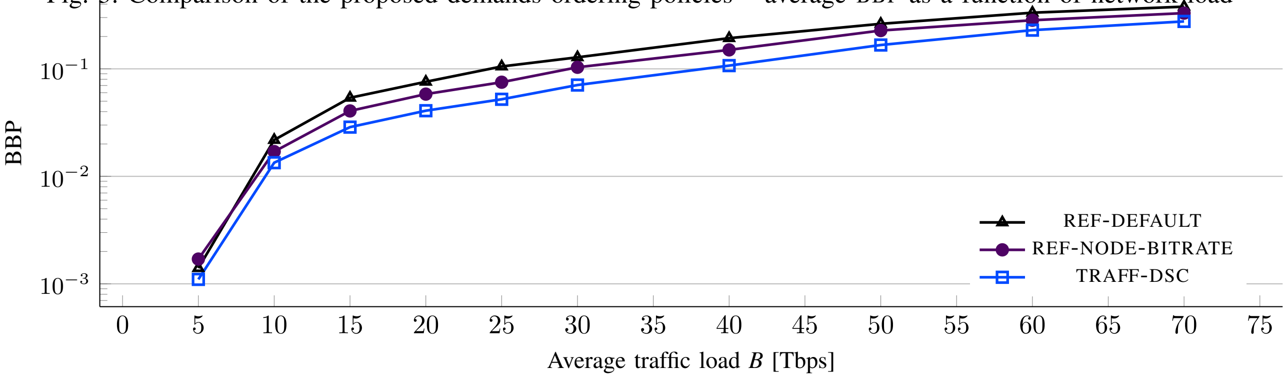

Fig. 4: Comparison of the best demands ordering policy with reference methods – average BBP as a function of network load

TABLE II: BBP reduction gain for the TRAFF-DSC ordering policy as a function of the network load

	MIN	MAX	AVG	AVERAGE NETWORK LOAD B [TBPS]									
				10	20	30	40	50	60	70	80	90	100
BBP reduction gain	0.1%	6.1%	3.3%	0.4%	1.7%	3.3%	4.3%	6.1%	5.4%	5.4%	4.7%	4.3%	4.2%
more served bit-rate [Gbps]	3.1	4203.0	1976.1	36.7	347.8	979.2	1715.6	3030.1	3246.4	3759.8	3741.0	3874.7	4203.0

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